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The Urban Intelligence Model from AI-Enabled Insight to Public Action and Institutional Learning

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Abstract

Cities use artificial intelligence, urban data platforms, and Digital Twins to perceive conditions and anticipate risks. Yet analytical capacity does not by itself ensure legitimate decisions, coordinated intervention, evaluation, or institutional learning. This article asks how the literature represents the transformation of urban data into public action and to what extent existing frameworks integrate the capabilities involved. A scoping review retrieved 2,209 records from Scopus, Web of Science, and IEEE Xplore, producing 1,397 unique records after deduplication. Title and abstract screening mapped the field, while a full-text comparison examined the frameworks that directly challenged the proposed model. The review shows that individual capabilities and recursive lifecycles are increasingly integrated, with the closest challengers approaching an end-to-end architecture. The remaining problem is less the absence of stages than the continuity between technological, organizational, and institutional functions. In response, the Urban Intelligence Model differentiates seven recursive capabilities - Perceive, Interpret, Anticipate, Deliberate, Act, Evaluate, and Learn - and identifies three institutional boundaries where intelligence fails to become legitimate action or cumulative learning. An illustrative application to urban flooding in Recife demonstrates the model's diagnostic use. The contribution is a domain-independent conceptual architecture whose empirical validity and operational maturity require subsequent testing.

Keywords: urban intelligence; artificial intelligence; urban governance; Digital Twins; institutional learning; decision-making; Recife

1. Introduction

Artificial intelligence, sensor networks, data platforms, and Digital Twins are expanding what cities can observe, simulate, and predict. These technologies can reveal emerging risks, compare intervention scenarios, and shorten analytical cycles. Their public value, however, depends on what happens after a signal or forecast is produced. Information must be interpreted in context, translated into legitimate choices, connected to authority and resources, converted into coordinated action, evaluated against outcomes, and incorporated into future institutional practice.

This distinction is especially important in recurrent urban crises. Flooding, heat, mobility disruption, and infrastructure failure are rarely caused only by a lack of data. A city may possess sensors, models, dashboards, and technical expertise while continuing to reproduce the same vulnerabilities. The problem may lie at the transition from forecast to public decision, from decision to implementation, or from evaluated experience to durable institutional change. In such cases, more accurate prediction improves only one part of a wider urban-intelligence process.

Research on smart cities and urban intelligence already provides substantial elements of this process. City-intelligence studies connect data to urban performance (Kourtit, 2021); Digital Twin research links monitoring and simulation to governance (Deng et al., 2021); data-driven public-policy research examines the use of large-scale information in government decisions (Hossin et al., 2023); and anticipatory-governance scholarship considers how generative AI may shape urban futures and public authority (Cugurullo & Xu, 2025). More recent studies map AI

across the policy cycle (Lnenicka et al., 2026), integrate Digital Twins through a climate-intervention lifecycle (Ali et al., 2026), frame cities as complex adaptive systems (Das, 2026), institutionalize resilience capabilities (Varzeshi et al., 2026), and connect data governance to policy learning (Piana, 2025). The literature therefore cannot be characterized simply as lacking integrated or recursive frameworks.

The unresolved issue is analytical differentiation. Existing approaches pursue different domains and theoretical purposes, and they do not consistently distinguish the functions through which urban evidence becomes authorized public action and cumulative institutional learning. Even frameworks that cover an extensive lifecycle may combine interpretation with prediction, treat deliberation as an implicit governance activity, or represent learning as feedback without specifying how evaluated experience changes rules, routines, responsibilities, models, and resource allocation. The critical gap is thus not the existence of individual capabilities or feedback loops, but the ability to diagnose discontinuities between them.

This article addresses that problem through two questions: RQ1 asks how the literature conceptualizes the transformation of urban data and technological intelligence into public decision-making, coordinated action, evaluation, and institutional learning. RQ2 asks to what extent existing urban-intelligence frameworks represent these capabilities as an integrated and adaptive decision cycle. The study combines a structured scoping review with an adversarial comparison of the frameworks most capable of challenging the proposed architecture.

The resulting Urban Intelligence Model (UIM) differentiates seven recursive capabilities: Perceive, Interpret, Anticipate, Deliberate, Act, Evaluate, and Learn. Its proposed contribution is not ownership of these functions or of cyclical reasoning. It lies in treating the transitions between them as explicit diagnostic objects and in identifying three institutionally consequential boundaries: Intelligence-to-Decision, Decision-to-Action, and Evaluation-to-Learning. Failures at these points are conceptualized as urban-intelligence bottlenecks.

The model is illustrated through recurrent flooding in Recife, Brazil, where advanced observation and forecasting can coexist with fragmented authority, implementation constraints, and limited institutional accumulation. The application is conceptual rather than an empirical validation or technological proof of concept. It is used to show how the model can organize a concrete urban problem and generate testable propositions for later field research. The remainder of the article establishes the conceptual background, reports the review method and findings, presents the UIM, compares it with its strongest challengers, and discusses its implications and limitations.

2. CONCEPTUAL BACKGROUND

2.1. Urban Intelligence as a Public Capability

Urban intelligence is often associated with the capacity to collect, process, and use information about city systems. This technological dimension is necessary but insufficient. Intelligence becomes public capability only when evidence can influence collectively consequential choices and when institutions can organize the authority, coordination, and resources required to act. The unit of analysis is therefore not a platform or algorithm alone, but the socio-technical process through which urban conditions become interpretable, actionable, and reviewable.

This view does not oppose technological and institutional explanations. It connects them. Sensing and data integration extend perception; analytical models support interpretation; simulation and AI expand anticipation; governance arrangements structure deliberation; administrative and operational systems condition action; monitoring and assessment support evaluation; and changes to routines, policies, responsibilities, and models constitute institutional learning. A city may be advanced in one capability and weak in the next, making aggregate labels such as smart or data-driven inadequate for diagnosis.

2.2. AI Digital Twins and the Problem of Continuity

AI and Digital Twins make the problem of continuity more visible. They can integrate heterogeneous data, detect patterns, simulate scenarios, and update representations of urban systems. These functions can improve the speed and quality of perception, interpretation, and anticipation. They do not automatically determine which risks deserve priority, whose interests should prevail, which institution is authorized to decide, how resources will be mobilized, or

how responsibility will be assigned when an intervention fails.

The same limitation applies to feedback. Operational feedback can recalibrate a technical system without producing policy or organizational learning. Institutional learning requires evaluated experience to alter future capacity: rules, procedures, budgets, competencies, interorganizational relationships, data practices, or the assumptions embedded in models. The distinction is consequential because a technically closed loop may coexist with a politically and administratively open one.

Accordingly, the UIM uses capabilities and transitions as separate analytical dimensions. Capabilities indicate what a city can perform; transitions indicate whether outputs can cross technological, organizational, and institutional boundaries. This distinction makes it possible to locate a bottleneck without assuming that every urban problem follows a rigid linear sequence. The model is recursive: action changes the city, evaluation produces new evidence, and learning modifies the conditions under which subsequent perception and decision occur.

3. METHODOLOGY

3.1. Research Design

This study adopts a conceptual research design supported by a structured scoping review to investigate how international literature has conceptualized urban intelligence and, particularly, how technological capabilities are connected to public decision-making, coordinated action, evaluation, and institutional learning.

The documentation of the review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) (Tricco et al., 2018) and by the PRISMA-S recommendations (Rethlefsen et al., 2021) to improve the transparency and reproducibility of the literature search strategy.

A scoping review was selected because the purpose of the study is not to estimate the effect of a specific intervention, but to map and compare conceptual approaches across an interdisciplinary body of literature encompassing smart cities, urban intelligence, artificial intelligence, digital twins, urban governance, public decision-making, adaptive governance, and institutional learning.

The review has two related purposes. First, title and abstract screening maps the technological, governance, and adaptive streams relevant to urban intelligence. Second, focused full-text assessment tests the UIM against frameworks that most directly challenge its proposed integration and diagnostic contribution.

3.2. Review Questions (RQs)

The scoping review was guided by the following research question:

RQ1: How does the existing literature conceptualize the transformation of urban data and technological intelligence into public decision-making, coordinated action, evaluation, and institutional learning?

A complementary question was formulated to examine the degree of integration among these processes:

RQ2: To what extent do existing urban intelligence frameworks represent these capabilities as an integrated and adaptive decision cycle?

3.3. Search Strategy

A structured literature search was designed to identify studies addressing the relationship between urban intelligence, technological capabilities, public decision-making, governance, evaluation, adaptation, and institutional learning. The search strategy combined terms representing three complementary conceptual dimensions: (i) urban intelligence and smart cities; (ii) decision-making and governance; and (iii) feedback, adaptation, evaluation, learning, and related technological approaches.

Searches were conducted in Scopus, Web of Science Core Collection, and IEEE Xplore, selected to provide complementary coverage of interdisciplinary research across urban studies, public governance, computer science, engineering, and digital technologies. The searches included records available in the databases up to 11 August 2026. No geographical restriction was applied.

Rather than relying on a single broad query, three complementary search strategies were used. Search Strategy 1 (S1) captured the general intersection between urban intelligence and

decision processes:

S1: ("urban intelligence" OR "smart cit*" OR "urban AI") AND ("decision making" OR "decision-making" OR governance OR deliberation) AND (learning OR feedback OR adaptive OR evaluation OR "digital twin*")

Search Strategy 2 (S2) was designed to capture studies describing more complete sensing-to-action processes, including research that did not explicitly employ the term urban intelligence:

S2: ("smart cit*" OR "urban intelligence" OR "urban governance") AND (sensing OR perception OR monitoring) AND (anticipat* OR predict* OR simulation) AND (decision* OR deliberat* OR governance) AND (action OR implementation OR intervention) AND (evaluat* OR learning OR feedback)

Search Strategy 3 (S3) targeted concepts associated with adaptive and closed-loop decision processes that emerged as particularly relevant to the research questions:

S3: ("smart cit*" OR "urban intelligence") AND ("public decision*" OR "decision-making" OR governance OR deliberation) AND ("adaptive governance" OR "institutional learning" OR "policy learning" OR "organizational learning" OR "closed-loop decision*" OR "policy cycle" OR OODA OR "adaptive decision*" OR "governance feedback")

The three strategies were adapted to the syntax and search fields supported by each database while preserving their conceptual equivalence. Searches were primarily conducted in titles, abstracts, and keywords, where supported by the database interface. Database-specific syntax, indexing structures, and available filtering options were taken into account rather than forcing technically identical queries across platforms.

The three strategies were intentionally complementary. S1 provided broad coverage of the relationship between urban intelligence and decision-making; S2 emphasized the operational sequence connecting urban sensing, anticipation, decision, action, and evaluation; and S3 increased sensitivity to governance, adaptation, feedback, and institutional-learning approaches that might otherwise remain outside technology-centered smart-city searches.

The searches yielded 2,209 search occurrences before consolidation and deduplication: 984 in Scopus, 648 in Web of Science, and 577 in IEEE Xplore. Across the three strategies, S1 returned 1,519 occurrences, S2 returned 419, and S3 returned 271. Because the same publication could be retrieved by more than one strategy and indexed in more than one database, these figures represent search occurrences rather than unique studies. Consolidation and duplicate removal are described in Section 3.5.

Search strategies, information sources, execution dates, and retrieval counts were documented to enhance transparency and reproducibility drawing on PRISMA-ScR and PRISMA-S reporting principles (Tricco et al., 2018; Rethlefsen et al., 2021).

Table 1. Records retrieved by database and search strategy

Database	S1	S2	S3	Total
Scopus	712	168	104	**984**
Web of Science	458	90	100	**648**
IEEE Xplore	349	161	67	**577**
Total search occurrences	**1,519**	**419**	**271**	**2,209**

Note. Counts represent search occurrences before consolidation and deduplication. The same study may have been retrieved by multiple search strategies and databases.

Source: Authors' elaboration.

3.4. Eligibility Criteria

Studies were eligible for inclusion when they: (i) addressed urban intelligence, smart cities, urban governance, or closely related urban decision contexts; (ii) examined at least one capability associated with sensing, interpretation, anticipation, decision-making or deliberation, implementation, evaluation, feedback, adaptation, or institutional learning; and (iii) presented a conceptual framework, empirical application, methodological approach, or review relevant to the transformation of urban information into public decision or action.

Journal articles, conference papers, conference reviews, book chapters, and review articles indexed in the selected databases were considered. Studies published in English were included, and no geographical restriction was applied. Because database coverage and indexing periods

differed across Scopus, Web of Science, and IEEE Xplore, no common lower publication-year threshold was imposed beyond the records effectively retrieved through the search strategies described in Section 3.3.

Studies were excluded when they: (i) addressed technological applications without a meaningful connection to urban decision-making, governance, or public action; (ii) focused exclusively on technical optimization, communication protocols, hardware architectures, image processing, or algorithmic performance without relevant implications for the research questions; (iii) used terms such as smart city, urban intelligence, or related expressions only as contextual labels; or (iv) provided insufficient information to assess conceptual relevance.

Particular care was taken not to exclude studies merely because they addressed only part of the urban decision process. Since one objective of the review was to determine whether the relevant capabilities were fragmented across different research traditions, partial frameworks could provide important evidence for the conceptual synthesis. Conversely, studies integrating several capabilities were retained for closer examination as potential challenger frameworks.

Because the purpose of the review was conceptual mapping rather than effect estimation, studies were not excluded solely on the basis of methodological design. The eligibility criteria were therefore intentionally broad enough to capture technological, governance, policy, and adaptive perspectives relevant to the research questions.

3.5. Study Selection

The three database searches generated 2,209 search occurrences. Records retrieved from Scopus, Web of Science, and IEEE Xplore were exported and consolidated into a single dataset. Because the three complementary search strategies intentionally overlapped, the same study could be retrieved by more than one search strategy and indexed in more than one database. Duplicate occurrences were therefore identified within and across databases, primarily through DOI and normalized-title matching.

Following deduplication, 812 duplicate occurrences were removed, leaving 1,397 unique records for title and abstract screening.

The remaining records were screened at the title and abstract level according to the eligibility criteria described in Section 3.4. Studies clearly unrelated to urban decision-making, governance, public action, evaluation, adaptation, or institutional learning were excluded. Particular attention was given to excluding records in which smart city, urban intelligence, or related terminology served only as an application context for predominantly technical research without a substantive connection to the research questions.

When titles and abstracts provided insufficient information to determine eligibility, records were retained for further examination rather than excluded on the basis of uncertainty alone. Potentially relevant studies were subsequently examined in greater detail to assess their contribution to the conceptual dimensions addressed by the review.

In addition to conventional relevance screening, the review incorporated an adversarial conceptual screening procedure. Studies presenting comparatively integrated approaches, including closed-loop architectures, Urban Digital Twins, AI-supported decision processes, policy cycles, adaptive governance, feedback mechanisms, and institutional or policy learning, were deliberately prioritized for closer examination. These studies were designated challenger frameworks because they represented the literature most capable of questioning whether the proposed Urban Intelligence Model (UIM) provided a distinct conceptual contribution.

The adversarial procedure was designed to reduce confirmation bias in the conceptual synthesis. Rather than searching only for evidence supporting the proposed integration problem, the review actively examined frameworks capable of contradicting it. Accordingly, the presence of multiple UIM-related capabilities within an existing framework was treated as evidence requiring the proposed contribution to be narrowed or reformulated, rather than as evidence to be excluded.

The analytical procedure therefore reflected two complementary logics: broad relevance to the research questions and high integrative relevance to the conceptual challenge posed by RQ2. The resulting set of studies provided the basis for the conceptual coding described in Section 3.6 and for the adversarial comparison reported in Section 4.

3.6. Data Extraction and Conceptual Coding

Data extraction was conducted using a structured conceptual coding framework developed iteratively from the research questions and refined during the screening process. The objective

was not to measure the frequency of isolated keywords, but to identify the functions performed within urban decision processes and the relationships established among them.

For each relevant study, information was extracted concerning its research context, principal technological or institutional approach, role of data and analytical systems, relationship with public decision-making, mechanisms of implementation and evaluation, and presence of feedback, adaptation, or learning. Technologies such as artificial intelligence, predictive analytics, Internet of Things (IoT), and Urban Digital Twins were coded according to the functions they performed within the decision process rather than treated as urban-intelligence capabilities in themselves.

Through iterative comparison across the literature, seven analytical capabilities were used to organize the conceptual synthesis: Perceive, Interpret, Anticipate, Deliberate, Act, Evaluate, and Learn. Perceive refers to the capacity to observe relevant urban conditions; Interpret to transforming observations into meaningful representations; Anticipate to exploring possible future states and consequences; Deliberate to considering alternatives and forming institutionally legitimate public choices; Act to translating authorized decisions into intervention; Evaluate to assessing observed outcomes against objectives, expectations, or alternative scenarios; and Learn to incorporating evaluated experience into subsequent institutional capacity.

The coding process deliberately distinguished conceptually adjacent functions. Prediction or simulation was not automatically coded as deliberation; decision support was not automatically coded as public decision-making; implementation was distinguished from the authorization of action; feedback was distinguished from evaluation; and evaluation was distinguished from institutional learning. These distinctions were introduced to avoid overstating the degree of integration represented by individual studies.

Particular attention was also given to the transitions between capabilities. The analysis examined whether studies merely presented adjacent functions or explicitly described mechanisms through which the output of one capability informed, constrained, authorized, or modified the subsequent capability. This distinction allowed the review to examine not only which elements of an urban-intelligence process were represented in the literature, but also whether continuity among those elements was conceptually articulated.

For the challenger frameworks identified during the adversarial screening, conceptual coverage was classified as substantively represented (✓), partially represented (Partial), or insufficient evidence for classification (–). A capability was coded as substantively represented only when the study provided clear conceptual or operational evidence corresponding to the definition adopted in the review. Partial was used when a related function was present but did not fully correspond to the analytical construct, while the absence symbol indicated that the available evidence was insufficient to support classification. These codes indicate conceptual coverage and should not be interpreted as measures of study quality.

Two additional dimensions were examined for the challenger frameworks: explicit transitions and the institutional boundary between analytical intelligence and public decision-making. The first assessed whether relationships among capabilities were themselves represented as part of the framework rather than inferred solely from the coexistence of adjacent functions. The second examined whether the framework recognized, explicitly or substantively, that analytical or predictive outputs do not by themselves constitute legitimate public decisions, which also involve institutional authority, accountability, competing objectives, and public values.

Importantly, the coding framework was used as an analytical device rather than as an assumption of novelty. No presumption was made that the seven capabilities, their combination, or their recursive organization were absent from the existing literature. On the contrary, the challenger analysis was explicitly designed to identify frameworks containing comparable or more comprehensive structures and, where necessary, to narrow or reformulate the proposed contribution of the UIM.

The resulting coding supported two complementary forms of synthesis: a broader comparison of the principal technological, governance, and adaptive streams identified in the literature, and a focused adversarial comparison of the most integrative challenger frameworks. The results of these analyses are presented in Section 4.

4. REVIEW RESULTS AND CONCEPTUAL SYNTHESIS

4.1. Search and Selection Results

The searches retrieved 2,209 occurrences: 984 from Scopus, 648 from Web of Science, and 577 from IEEE Xplore. By strategy, S1 returned 1,519 occurrences, S2 returned 419, and S3 returned 271. Deduplication removed 812 occurrences and produced 1,397 unique records.

The final documented title and abstract screening status comprised 1,240 provisionally included records, 113 exclusions, and 44 records retained for targeted source or full-text verification. The broad set was used as an evidence map of the research landscape rather than presented as a corpus of 1,240 full-text studies. The 44 unresolved records did not support any substantive finding reported below.

Adversarial screening flagged 157 possible challengers from titles and abstracts and prioritized 25 for closer reading. Full-text assessment and supplementary targeted searching then identified the five frameworks compared in Table 2. Selection for that table depended on conceptual proximity to the UIM, not on representativeness or study quality.

This two-level design separates the broad mapping function of the scoping review from the narrower integration test. The first identifies relevant technological, governance, and adaptive streams; the second examines whether highly integrated frameworks already differentiate the seven capabilities, their transitions, and the institutional boundary between analytical intelligence and authorized public action.

4.2. Main Conceptual Streams Identified

The evidence map revealed three overlapping streams. Technological and analytical studies emphasize sensing, data integration, AI, prediction, simulation, and Digital Twins. They strengthen the capacity to observe and model urban conditions, but decision support does not by itself establish legitimate choice or implementation (Deng et al., 2021; Kourtit, 2021).

Public-policy and governance studies begin with authority, interests, participation, and institutional constraints. They explain how evidence enters formulation, adoption, implementation, and evaluation, while often treating urban sensing and computational anticipation as external inputs (Hossin et al., 2023; Lnenicka et al., 2026).

Adaptive-governance and resilience studies emphasize feedback, evaluation, institutionalization, and learning. They show that implementation must be monitored and revised, but they do not always connect these processes to a differentiated sensing-to-decision architecture.

The streams increasingly intersect, yet they retain different entry and exit points. This observation motivated the adversarial test: the relevant question is not whether prior studies contain particular capabilities, but whether strong frameworks connect them and make their transitions analytically explicit.

4.3. Challenger Frameworks and the Integration Test

The adversarial procedure selected frameworks that most directly challenged the proposed integration problem. Digital Twin, AI-policy, adaptive-systems, resilience, and participatory-governance approaches were included because each connects multiple parts of the urban-intelligence process.

This comparison requires a conservative interpretation of novelty. Prediction, decision support, implementation, evaluation, feedback, adaptation, and closed-loop reasoning all precede the UIM. The test therefore examines functional differentiation: whether a study substantively represents Perceive (P), Interpret (I), Anticipate (An), Deliberate (D), Act (Ac), Evaluate (E), and Learn (L), and whether it specifies transitions and an institutional boundary between analytical intelligence and legitimate public choice.

A check mark indicates substantive representation, Partial indicates a related but non-equivalent function, and a dash indicates insufficient evidence. The coding evaluates conceptual coverage, not study quality or purpose.

Table 2. Adversarial comparison of selected challenger frameworks

Challenger study	PERCEIVE	INTERPRET	ANTICIPATE	DELIBERATE	ACT	EVALUATE	LEARN	Explicit transitions	al boundary	Main unresolved issue relative to the integration problem
Ali et al. (2026) - IUCT	✓	✓	✓	✓	✓	✓	✓	✓	✓	A highly integrated seven-stage lifecycle with explicit continuity and adaptation, but developed specifically for Digital Twins and urban-heat mitigation.
Lnenicka et al. (2026)	Partial	✓	Partial	✓	✓	✓	Partial	Partial	✓	Maps AI actions across the public-policy cycle and clearly addresses institutional legitimacy, but does not model the mechanisms connecting one phase to the next.
Das (2026) - Complex Adaptive Systems	✓	✓	✓	✓	Partial	✓	✓	✓	✓	Integrates technological, governance, participation, and feedback loops, but authorized intervention is not differentiated as a distinct functional transition.
Varzeshi et al. (2026) - SURF	Partial	✓	Partial	✓	✓	✓	✓	✓	✓	Provides a strong institutionalization, implementation, evaluation, and learning architecture; perception and anticipation remain supporting inputs rather than distinct capabilities.
Piana (2025) - FUTURA	Partial	✓	✓	✓	✓	✓	✓	✓	✓	Offers participatory governance, foresight, implementation, evaluation, and learning, while urban perception is primarily an informational input rather than a differentiated capability.
UIM	✓	✓	✓	✓	✓	✓	✓	✓	✓	A domain-independent diagnostic architecture with three explicit institutional boundaries; empirical validation remains required.

Note. ✓ = substantively represented; Partial = related capability represented but not fully equivalent to the UIM construct. The comparison evaluates conceptual coverage, not study quality.

Source: Authors' elaboration.

Table 2 confirms that completeness alone cannot support the UIM's contribution. The Integrated Urban Climate Twin (IUCT) is the closest challenger: its seven-stage Digital Twin lifecycle addresses implementation, evaluation, adaptation, lifecycle discontinuity, and governance in urban-heat mitigation. It therefore rules out a generic claim that the UIM uniquely integrates stages, transitions, or bottlenecks.

The remaining challengers narrow the claim further. Lnenicka et al. (2026) map AI across the policy cycle and separate technological support from legitimate decision-making, but do not model the mechanisms connecting successive phases. Das (2026) integrates technological and governance feedback loops. SURF provides a phase-gated architecture for institutionalization, implementation, evaluation, and learning, while FUTURA combines foresight, human oversight, implementation, evaluation, and learning within participatory data governance.

The comparison consequently shifts the contribution from completeness to diagnostic differentiation. The UIM distinguishes seven functions and examines whether information, authority, resources, and evaluated experience cross three named boundaries: Intelligence-to-Decision, Decision-to-Action, and Evaluation-to-Learning. Failures at these boundaries are treated as urban-intelligence bottlenecks across policy domains.

4.4. Research Gap and Conceptual Synthesis

The review does not reveal a shortage of urban-intelligence capabilities. The gap lies in continuity across technological, institutional, and organizational domains. Frameworks frequently explain individual functions or connect several adjacent stages, yet fewer treat changes in agency between stages as diagnostic objects.

The first discontinuity arises when forecasts or simulations enter public deliberation. Analytical evidence must acquire institutional meaning through authority, accountability, stakeholder interests, legal constraints, and public values. The second arises when authorized choices encounter budgets, responsibilities, procurement, coordination, and operational capacity. The third occurs when evaluation fails to alter rules, routines, priorities, models, or information requirements.

These discontinuities connect three domains: technological and analytical intelligence (Perceive, Interpret, Anticipate); public decision and governance (Deliberate, Act, Evaluate); and adaptive institutional intelligence (Evaluate, Learn, renewed Perceive). A city may perform strongly within one domain while losing continuity at the boundary to the next.

The resulting research gap is therefore transition-oriented: existing capabilities are increasingly sophisticated, but their conversion into legitimate decision, coordinated intervention, and cumulative institutional learning remains uneven. The UIM addresses this gap by representing both the seven capabilities and the boundaries through which their outputs must pass.

5. THE URBAN INTELLIGENCE MODEL (UIM)

5.1. Conceptual Foundations

The Urban Intelligence Model defines urban intelligence as a decision-centered socio-technical capacity: the ability to transform heterogeneous urban signals into legitimate public choice, coordinated intervention, evaluated outcomes, and institutional learning.

The model does not equate intelligence with data volume, predictive accuracy, AI sophistication, or Digital Twin infrastructure. These resources contribute only when connected to institutions capable of deliberation, authorization, implementation, evaluation, and learning. Prediction is not decision, decision is not action, and evaluation is not learning.

The UIM therefore organizes seven distinct but interdependent capabilities: Perceive, Interpret, Anticipate, Deliberate, Act, Evaluate, and Learn.

Figure 1. The seven-stage Urban Intelligence Model (UIM)



Source: Authors' elaboration.

The stages form a recurrent cycle rather than a rigid sequence. Learning can revise what the city observes, how it interprets signals, which futures it models, and how subsequent decisions are implemented. Urban intelligence therefore depends on both stage capacity and continuity between stages.

The model's central proposition is that a city becomes more intelligent when it can preserve this continuity across technological, institutional, and organizational boundaries, not merely when it strengthens isolated technical components.

5.2. The Seven-Stage Urban Intelligence Cycle

The seven capabilities are analytically distinct, although they may overlap or operate concurrently in practice:

(1)PERCEIVE – Capture relevant signals about urban conditions through sensors, administrative records, geospatial systems, mobility data, citizen reports, environmental monitoring, and other sources.

(2)INTERPRET – Integrate and contextualize observations to identify patterns, anomalies, dependencies, vulnerabilities, and emerging problems. Interpretation converts data into a meaningful account of current conditions.

(3)ANTICIPATE – Explore possible future states using prediction, scenarios, simulation, AI, and Urban Digital Twins. This capability asks what may happen, under which conditions, and

with what consequences.

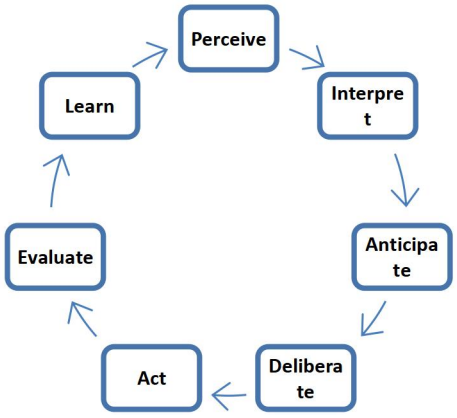
(4)DELIBERATE – Compare possible actions in light of evidence, legal competence, public values, stakeholder interests, distributional effects, political priorities, and resource constraints. Deliberation produces an institutionally legitimate choice.

(5)ACT – Translate an authorized choice into coordinated physical, regulatory, administrative, or service intervention. Action requires responsibilities, resources, procurement, communication, and operational coordination.

(6)EVALUATE – Compare observed outcomes with objectives, expectations, counterfactuals, or predicted trajectories. Evaluation determines what followed from the intervention and what the evidence means.

(7)LEARN – Use evaluated experience to change knowledge, rules, routines, priorities, capabilities, models, responsibilities, or information requirements. Learning changes future institutional capacity.

Figure 2. The seven-stage Urban Intelligence Model (UIM)



Source: Authors' elaboration.

Figure 2 emphasizes recursion: Learn reconfigures subsequent Perceive, Interpret, and Anticipate activities. Learning may reveal missing variables, weak indicators, inappropriate models, or institutional blind spots; it must therefore alter more than computational parameters.

An intelligent city is thus not simply the one with the strongest technology. It is the one that can connect observation, knowledge, anticipation, legitimate decision, coordinated action, evaluation, and persistent institutional adaptation.

5.3. Critical Transitions and Urban Intelligence Bottlenecks

Possessing all seven capabilities does not ensure an effective cycle. We define an urban intelligence bottleneck as a transition in which the output of one stage cannot be converted into the capability required by the next because of technical limitations, fragmented data, incompatible systems, weak authority, unclear responsibilities, legal constraints, insufficient resources, political disagreement, or absent evaluation mechanisms.

The effective level of urban intelligence is therefore constrained by transition continuity. The UIM highlights three boundaries where the nature of agency changes and failure is especially consequential.

5.3.1 - The Intelligence-to-Decision Boundary

The transition from Anticipate to Deliberate separates analytical evidence about possible futures from institutionally authorized choice. AI, predictive analytics, and Digital Twins can estimate risks and compare interventions, but they do not determine which public objective should prevail or who is accountable for the decision.

Crossing this boundary requires legal authority, public values, stakeholder participation, transparency, and political accountability. Failure produces an intelligence-to-decision bottleneck: the city may understand what could happen yet remain unable to decide legitimately and in time.

5.3.2 - The Decision-to-Action Boundary

The transition from Deliberate to Act separates an authorized decision from intervention in the real city. Implementation depends on budgets, procurement, organizational responsibility,

technical capacity, coordination, and operational timing.

Failure produces a decision-to-action bottleneck: a legitimate decision exists, but fragmented authority or insufficient capacity prevents execution.

5.3.3 - The Evaluation-to-Learning Boundary

The transition from Evaluate to Learn separates evidence about results from persistent institutional change. Dashboards, indicators, and post-intervention data provide feedback, while evaluation assigns meaning relative to objectives and expectations. Learning occurs only when this evidence changes future rules, routines, priorities, responsibilities, models, or resource allocation.

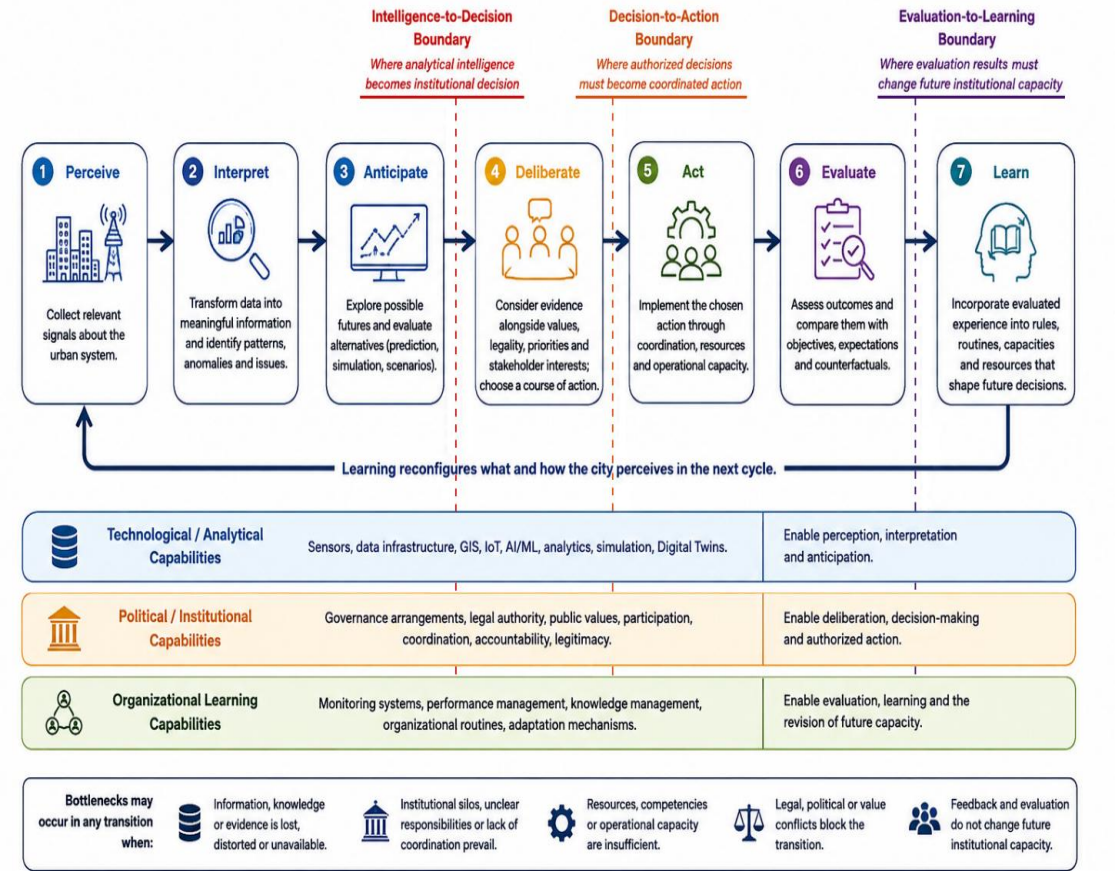
Failure produces an evaluation-to-learning bottleneck: institutions repeatedly identify the same problem without changing the conditions that reproduce it. The return from Learn to Perceive closes the adaptive cycle by revising what the city monitors and how it interprets subsequent signals.

5.3.4 - Bottlenecks as a Diagnostic Property of the UIM

The bottleneck perspective changes the assessment of urban intelligence maturity. A city may possess extensive sensing, AI, and Digital Twin infrastructure while producing weak outcomes because evidence does not become decision, decisions do not become action, or evaluation does not become learning.

The diagnostic principle is straightforward: improve urban intelligence where the cycle loses continuity, not automatically where technology is least sophisticated. Investment should therefore target the constraining stage or transition rather than assume that additional sensing or predictive accuracy will improve the whole system.

Figure 3. Urban Intelligence Model (UIM): Critical Transition and Bottlenecks



Source: Authors' elaboration.

5.4. Role of AI and Urban Digital Twins

AI and Urban Digital Twins are enabling technologies within the UIM. AI can integrate heterogeneous data, detect patterns, classify events, generate predictions, and compare scenarios. Digital Twins add dynamic representations in which observed conditions, models, and simulations can support alternative-intervention analysis.

Their strongest contribution lies in Perceive, Interpret, Anticipate, and parts of Evaluate. At

the Intelligence-to-Decision Boundary, however, analytical superiority does not establish legitimate choice. Public decisions still require authority, accountability, legal competence, stakeholder interests, distributional judgment, and public values.

Technology can also compare observed and expected outcomes and update computational models after implementation. Such recalibration is not equivalent to institutional learning. The Evaluation-to-Learning Boundary is crossed only when evaluated experience changes organizational routines, public policy, responsibilities, priorities, resources, or future information requirements.

The relationship is therefore complementary: AI helps cities understand and anticipate; Digital Twins help them represent, simulate, and compare; the UIM explains how these capabilities may become public action and institutional learning. Technological sophistication cannot compensate for discontinuity across institutional boundaries.

6. ILLUSTRATIVE APPLICATION: URBAN FLOODING IN RECIFE

6.1. Why Urban Flooding?

Urban flooding in Recife provides a concise illustration of the UIM because the problem combines environmental signals, infrastructure, mobility, land use, social vulnerability, emergency response, and institutional coordination. The application is conceptual and does not constitute empirical validation.

The relevant question is not only whether flooding can be predicted, but whether the city can maintain continuity from observation and interpretation to timely public decision, coordinated action, evaluation, and institutional learning.

6.2. Applying the UIM to Urban Flooding

The cycle begins by combining rainfall, canal and river levels, tides, drainage conditions, topography, mobility, historical records, and citizen reports. Interpretation identifies abnormal accumulation, drainage limitations, exposed infrastructure, and vulnerable populations. AI, hydrological models, scenarios, and a Digital Twin can then estimate how flooding may evolve and compare possible interventions.

Prediction must cross the Intelligence-to-Decision Boundary. Authorities must weigh urgency, legal responsibility, resources, social vulnerability, mobility impacts, and distributional consequences before authorizing warnings, traffic measures, emergency assistance, drainage operations, or longer-term infrastructure investments. The Decision-to-Action Boundary tests whether agencies can coordinate and implement that choice in time.

After intervention, observed outcomes can be compared with predictions and objectives. Learning occurs only when this evaluation changes protocols, responsibilities, infrastructure priorities, models, monitoring, or resource allocation. The application of each capability is summarized in Table 3.

6.3. Flooding as an Urban Intelligence Bottleneck Problem

The UIM reframes persistent flooding as a possible continuity problem. A city may possess sensors, geospatial databases, predictive AI, and a Digital Twin yet respond poorly because forecasts do not reach decision-makers, decisions are delayed, agencies cannot mobilize resources, or recurrent evaluations do not alter protocols and investments.

In these cases, additional sensing or predictive accuracy may produce limited gains because the constraint lies at the Intelligence-to-Decision, Decision-to-Action, or Evaluation-to-Learning Boundary. The diagnostic question becomes whether flood intelligence produces timely action and better preparation for the next event.

6.4. From Flooding to a General Urban Intelligence Architecture

Although flooding is the illustrative case, the UIM is domain-independent. Mobility, public health, environmental management, energy, safety, and infrastructure maintenance require the same conversion of heterogeneous information into public decision, action, evaluation, and learning.

The domain changes the data and institutions involved, but not the diagnostic question: where does the process lose continuity, and which capability or boundary constrains improvement?

Table 3. Illustrative application of the UIM to urban flooding in Recife

UIM stage	Flooding application	Guiding question
① **Perceive**	Rainfall, canals, tides, drainage, mobility, citizen reports	What is happening?
② **Interpret**	Integrate signals and identify affected areas/vulnerabilities	What does it mean?
③ **Anticipate**	AI, scenarios, hydrological models, Digital Twin	What may happen?
④ **Deliberate**	Compare interventions, constraints, priorities and impacts	What should be done?
⑤ **Act**	Alerts, traffic measures, response teams, drainage interventions	Can the decision be implemented?
⑥ **Evaluate**	Compare predicted, intended and observed outcomes	What happened because of the action?
⑦ **Learn**	Modify protocols, infrastructure, models, responsibilities and monitoring	What must change for the next cycle?

Source: Authors' elaboration.

7. DISCUSSION

7.1. From Technological Intelligence to Urban Intelligence

The review and Recife application support a shift from technological intelligence to urban intelligence. Sensors, AI, Digital Twins, participation, implementation structures, and evaluation systems may coexist without forming an effective decision cycle if their outputs cannot cross institutional boundaries.

The UIM therefore changes the unit of analysis from isolated assets to process continuity. Its contribution is not the presence of seven capabilities, already distributed across the literature, but their functional differentiation within a domain-independent diagnostic architecture.

7.2. Urban Intelligence Bottlenecks and the Limits of Technological Maturity

Technological maturity may overstate effective urban intelligence. A city can collect extensive real-time data and produce accurate forecasts while failing to decide, implement, or learn. Outcomes are constrained by the stage or transition that interrupts the cycle.

This has a practical implication for investment: governments should diagnose the binding bottleneck before acquiring additional technology. More sensors or better models add little when the principal constraint is legitimacy, coordination, implementation capacity, or institutional learning.

7.3. Implications for AI, Digital Twins, and Public Governance

AI and Digital Twins expand observation, interpretation, prediction, simulation, and evaluation, but they do not remove questions of authority and accountability. At the Intelligence-to-Decision Boundary, public institutions remain responsible for reconciling evidence with rights, equity, legal competence, competing objectives, and distributional effects.

The distinction becomes more important as autonomous or agentic systems shorten analytical cycles. Greater computational autonomy does not justify automatic public authority; it increases the need to specify where automation ends, institutional judgment begins, and accountability remains located.

7.4. From Reactive Management to Institutional Learning

Feedback makes outcomes observable, evaluation assigns meaning, and institutional learning changes future capacity. Cities may repeatedly measure the same vulnerability without learning if protocols, priorities, responsibilities, models, and resource allocations remain unchanged.

Recife illustrates this distinction: recurrent flooding may persist not because information is absent, but because evaluated experience does not cross the Evaluation-to-Learning Boundary.

7.5. Limitations and Research Agenda

The UIM is a conceptual simplification of decision processes that may be nonlinear,

concurrent, contested, and distributed across institutions. Its seven-stage structure should be interpreted as a diagnostic architecture, not as a deterministic sequence.

The Recife application demonstrates analytical use but not empirical validity. Future studies should reconstruct actual decision processes through interviews, administrative records, operational data, and comparative cases, testing whether the proposed capabilities and boundaries explain observed successes and failures.

The importance of stages and transitions may vary across policy domains, institutions, and temporal scales. Operationalization should therefore measure both capability strength and transition effectiveness, supporting an Urban Intelligence Maturity framework without assuming that the same bottleneck dominates every context.

A further research priority concerns autonomous AI and Digital Twins: how much analytical autonomy can be delegated, where institutional judgment must begin, and how responsibility should be allocated when automated recommendations shape public action.

8. CONCLUSION

This study examined how urban data and technological intelligence are transformed into public decision-making, coordinated action, evaluation, and institutional learning. The review answers RQ1 by showing that these functions are widely represented but distributed across technological, governance, policy, resilience, and learning traditions. It answers RQ2 by showing that recent frameworks increasingly connect substantial parts of the cycle; the strongest challengers therefore rule out a broad claim that urban-intelligence research lacks integrated stages, feedback, or lifecycle reasoning.

The remaining contribution of the UIM is more precise. It functionally differentiates Perceive, Interpret, Anticipate, Deliberate, Act, Evaluate, and Learn, while making their transitions explicit objects of diagnosis. The Intelligence-to-Decision, Decision-to-Action, and Evaluation-to-Learning Boundaries identify where analytical outputs must cross questions of legitimacy, authority, coordination, resources, accountability, and institutional change. Urban-intelligence bottlenecks arise when a capable stage cannot transfer usable outputs to the next function.

The Recife flooding illustration indicates how this architecture can distinguish a forecasting deficit from a governance or implementation deficit, and recurrent measurement from genuine institutional learning. It does not validate the model empirically. The UIM remains a conceptual simplification of processes that may be concurrent, contested, and distributed across organizations. Future research should reconstruct actual decision episodes, measure capability and transition effectiveness, compare policy domains and cities, and examine how autonomous AI changes the allocation of judgment and responsibility. The model should therefore be judged not as a terminal account of urban intelligence, but as a testable architecture for locating why technological insight does - or does not - become effective public action and cumulative learning.

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