

Review

Governing AI-Enabled Climate-Resilient Housing and Infrastructure Prioritization: A Caring Urban Governance Framework

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Abstract

Smart city governance increasingly relies on AI-enabled planning systems, digital twins, vulnerability scoring tools, and capital investment platforms to allocate climate-resilient housing and infrastructure investments. Yet existing smart-urbanism and adaptation frameworks do not adequately specify how such systems should encode well-being, equity, and climate uncertainty when translating urban data into ranked projects and funded portfolios. This paper develops the Caring Urban Governance Framework for AI-enabled urban prioritization through a structured scoping review and conceptual framework analysis integrating climate-risk decision-making under deep uncertainty, built-environment pathways affecting psychosocial well-being, and public-sector algorithmic accountability. The framework proposes a five-layer architecture linking urban form and infrastructure, climate exposure and environmental resources, psychosocial mediators of well-being, algorithmic design choices, and institutional governance, with explicit feedback loops. Its main outputs are an auditable decision architecture, eight mechanism-based propositions for empirical testing, an operational specification matrix for objective functions, equity constraints, robust logic, and documentation, and an analytical validation of construct clarity, coherence, literature congruence, and operationalizability. The analysis argues that aligning AI-enabled urban prioritization with SDG 11 requires treating well-being-supportive living conditions as a decision objective, constraining optimization with equity conditions, and institutionalizing auditability and contestability to reduce distributive and psychosocial harm in public investment planning.

Keywords: AI-enabled urban prioritization; caring urban governance; smart urbanism; algorithmic accountability; digital twins; climate adaptation; climate-resilient housing; infrastructure prioritization; psychosocial well-being; equity constraints



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1. Introduction

Smart-city governance is increasingly enacted through digital infrastructures and decision routines rather than through discrete technology projects [1–8]. Foundational scholarship conceptualizes smart cities through interacting dimensions of technology, people, and institutions [1–3], while more recent research shows that artificial intelligence is reshaping smart urbanism into more autonomous, data-intensive, and governance-relevant forms of urban decision-making [4,5]. In practice, municipal digitalization often operates as an integrated stack that combines administrative and sensor data, urban data platforms,

GIS analytics, dashboards, forecasting tools, and prioritization systems that rank, select, and sequence investments in climate-resilient housing and infrastructure [6–8]. This shift matters because some of the most consequential urban decisions are fundamentally allocation decisions: which housing stock receives resilience retrofits first, which neighborhoods obtain heat mitigation or flood protection, and which infrastructure assets are prioritized for hardening, redundancy, or relocation. Such decisions are central to SDG 11, particularly targets related to adequate housing, disaster risk reduction, inclusive planning, and equitable access to safe public and green space [9–11], and they sit at the core of urban adaptation practice under uncertainty and resource constraints [12].

In this article, AI-enabled urban prioritization systems denote algorithmic decision infrastructures used by city governments or their contractors to translate heterogeneous urban data into ranked projects, implementation sequences, or funded portfolios for climate-resilient housing and infrastructure planning. The term refers to the urban governance setting in which AI is embedded, not to a separate category of AI technology. It covers four types of systems relevant to municipal prioritization: (i) rule-based expert or scoring systems, (ii) statistical and machine-learning prediction models, (iii) optimization or recommendation engines, and (iv) scenario-simulation modules used in planning support systems or digital twins. The framework targets high-stakes allocation settings in which auditability, equity constraints, and contestability are governance requirements, and it does not endorse fully automated decision-making or surveillance-intensive deployments as legitimate substitutes for democratic oversight [4,5,8,13]. Within this governance landscape, AI and GIS increasingly function as decision infrastructures rather than merely as tools for “better information.” Vulnerability scoring tools translate heterogeneous indicators into ranked lists; digital twins and scenario environments support trade-off narratives and portfolio stress testing; planning-support and capital-prioritization systems can embed objective functions and constraints that shape investment sequences; and dashboards shape what is visible and therefore actionable [6–8,14]. While these systems often promise neutrality and evidence-based action, scholarship on smart urbanism has shown how computational governance can obscure normative choices, shift authority toward vendors and technical elites, and intensify surveillance, depoliticization, and inequity [15–20].

To avoid conceptual slippage, three governance terms are distinguished throughout the article. Urban governance refers here to the institutional arrangements through which public, private, and civic actors shape urban priorities, allocate authority, and render decisions accountable. AI governance refers to the rules, oversight practices, procurement requirements, risk-management procedures, and redress mechanisms that govern the design, deployment, and monitoring of AI-enabled decision systems [21–23]. Data governance refers more specifically to stewardship arrangements governing data collection, access, quality, sharing, protection, retention, and permissible reuse [21–23]. Distinguishing these levels clarifies that data governance is a component of AI governance, while both sit within the broader field of urban governance.

This paper proposes such an approach through the concept of the caring city. “Caring” is used here as a governance concept rather than a moral slogan: it denotes an institutional obligation to protect stability, safety, dignity, and the everyday environmental conditions that sustain urban well-being under climate stress. Care ethics scholarship emphasizes that care is institutional and distributive, organized through infrastructures and rules that allocate attention and protection [24,25]. Translating this insight into smart-city governance implies a sharp reframing: AI-enabled planning systems should be evaluated not primarily by throughput, prediction accuracy, or cost efficiency, but by whether they reliably protect well-being-supportive living conditions and do so equitably under climate uncertainty.

The relevance to urban mental well-being is not incidental. Urban planning shapes psychosocial outcomes through housing quality and stability, crowding, noise, perceived safety, access to restorative environments, and service reliability [26–28]. Climate risks compound these pathways: acute events and chronic hazards can destabilize housing, intensify stress burdens, disrupt social networks, and contribute to climate-related distress and anxiety [29–32]. Yet smart-city frameworks often treat well-being as a diffuse aspiration rather than a formal decision objective [1–4,15]. Conversely, climate-resilient planning scholarship and policy frameworks rarely specify how AI-governance mechanisms—such as objective functions, equity constraints, robustness logics, documentation, auditability, and contestability—should be built into deployed prioritization systems [12,21–23].

Accordingly, this paper develops a mechanism-level conceptual framework for governing AI-enabled prioritization systems used in climate-resilient housing and infrastructure planning. The framework is intended both as an analytical device for research and as a governance-oriented guide for the design, procurement, auditing, and contestation of such systems. It contributes in four ways. First, it synthesizes climate risk and adaptation, built-environment mental-health mechanisms, and algorithmic accountability into a single conceptual architecture for AI-enabled urban decision support. Second, it formalizes well-being-supportive living conditions as explicit terms in decision objectives and formalizes equity as auditable constraints rather than post hoc evaluation criteria. Third, it specifies robustness-oriented prioritization under deep uncertainty, shifting attention from single-scenario optimality to portfolio performance across plausible climate futures. Fourth, it advances eight refutable propositions and an operational guide that together support empirical evaluation through audits, quasi-experiments, and policy analysis. The article proceeds in five steps. Section 2 reviews smart-city governance, climate adaptation, and built-environment well-being scholarship and identifies the conceptual gap. Section 3 explains the structured scoping-review protocol, framework-construction method, and analytical validation. Section 4 defines the core constructs extracted from the literature. Section 5 presents the Caring Urban Governance Framework and its feedback loops. Sections 6–8 translate the framework into propositions, governance implications, boundary conditions, and a research agenda. Figure 1 summarizes the review and synthesis workflow. Section 7.6 later presents the operational specification matrix.

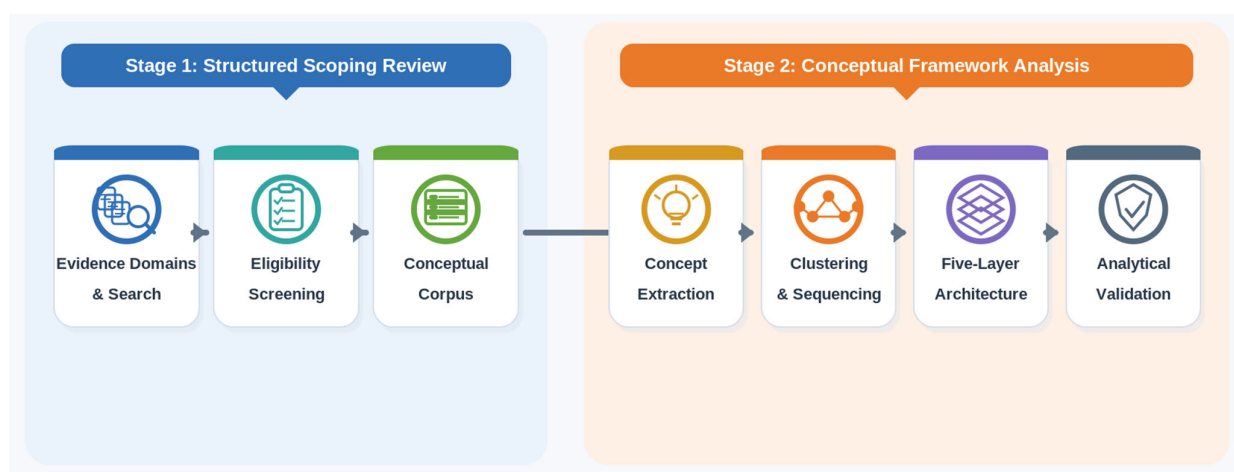


Figure 1. Structured scoping review and framework-derivation workflow.

2. Smart-City Governance, AI-Enabled Prioritization, and the Conceptual Gap

2.1. Smart Urbanism as a Governance Project

Smart-city scholarship no longer treats smartness as a purely technological attribute. Foundational work conceptualizes smart cities through interacting dimensions of technology, people, and institutions [1–3], while more recent research shows that AI is reshaping smart urbanism into more autonomous, data-intensive, and governance-relevant forms of urban decision-making [4,5]. Accordingly, smart-city projects are not only technological initiatives; they are also governance projects that configure authority, visibility, participation, and accountability through digital systems and vendor partnerships [4,8,15,19]. These dynamics matter most where smart systems shift from monitoring to prioritization, because they begin to influence who is protected first, where investment flows, and which needs become visible in the decision process [6,8,16].

Smart-city governance debates, therefore, hinge on a recurring tension. Computational systems can expand analytic capacity, yet they can also narrow the space of political contestation by presenting value-laden decisions as technical outputs [6,16]. City dashboards and benchmarking projects make certain aspects of the city legible while pushing others outside the frame [6]. Vulnerability indices can standardize attention to risk, but they can also impose classifications that may misrepresent lived vulnerability, particularly for marginalized groups [33,34]. Digital twins can support participatory visualization and scenario learning [8,35]. Yet they can also consolidate technical authority, especially when models are difficult for non-specialists to interrogate or contest [8,16].

2.2. The Prioritization Turns: From “Smart Services” to AI-Enabled Capital Allocation

A decisive development in smart urbanism is the emergence of AI-enabled capital-allocation tools: systems that can rank places or projects for intervention, support retrofit sequencing, and structure emergency or adaptation portfolios [5,36]. These tools often combine GIS layers, multicriteria decision analysis, predictive modeling, and portfolio optimization [5,36]. They are frequently embedded in urban data platforms and real-time dashboards, creating a pipeline from data capture to decision recommendation [7].

Climate-resilient housing and infrastructure prioritization tools are a particularly high-stakes expression of this shift. They typically combine hazard layers such as heat and flooding, exposure and asset layers such as housing stock and critical infrastructure, and socioeconomic indicators used as vulnerability proxies [12,33,36,37]. They can then generate ranked lists or optimized portfolios to support capital budgeting and implementation sequencing. Their legitimacy depends on whether they represent vulnerability adequately and incorporate uncertainty explicitly, and on whether the resulting trade-offs are open to inspection and contestation [12,21,23,33,37]. It also depends on whether they protect well-being-supportive living conditions rather than merely optimizing cost-effectiveness [26–28].

2.3. Why Existing Smart City Models Under-Theorize Psychosocial Outcomes

The smart-city literature frequently invokes “quality of life,” but often without a mechanism-level account of how digital decisions shape psychosocial outcomes [1–4,15]. This is a conceptual weakness because climate-resilient housing and infrastructure investments directly affect mediators of mental well-being, including housing stability, perceived safety, thermal comfort, noise exposure, service reliability, and access to restorative environments [26,28,38,39]. When prioritization systems ignore these mediators, they may select portfolios that reduce aggregate hazard exposure while intensifying stress burdens, for example, by privileging asset-value or amenity protection in ways that heighten displacement pressure without adequate safeguards [40,41].

This omission is not simply a missing variable; it is a governance problem. Without explicit representation of psychosocial mediators, the decision system has no formal reason to protect them. In computational terms, what is absent from the objective function or the constraint set remains vulnerable to erosion through trade-offs. As scholarship on algorithmic fairness and sociotechnical systems makes clear, systems optimize the objectives they are given; fairness and harm reduction do not emerge automatically from data quality alone [42–44].

2.4. *Why Do Climate-Resilient Planning Frameworks Omit Algorithmic Governance Mechanisms*

Climate adaptation and resilience scholarship offers robust conceptual tools for analyzing hazard, exposure, vulnerability, infrastructure interdependencies, and adaptive capacity [12,45,46]. Yet much of this literature addresses decision-making primarily as an institutional planning process rather than as a socio-technical pipeline in which algorithms shape prioritization and, in turn, the distribution of protection and risk [12,45]. Uncertainty is acknowledged, but it is often operationalized through scenario narratives rather than encoded directly into the decision logic of the prioritization tools procured and used by cities [47,48]. As a result, in much of this literature, the governance of AI-enabled prioritization—documentation, auditing, contestability, and redress—remains implicit rather than being treated as an integral component of adaptation capacity [12,45,47,48].

2.5. *The Conceptual Gap*

The conceptual gap can be stated precisely. Smart urbanism provides powerful digital governance architectures, but it does not adequately theorize psychosocial well-being and equity as decision primitives [4,15,16,26,28,38,39]. Climate-resilient planning, by contrast, offers a mature vocabulary for risk, exposure, vulnerability, interdependence, and uncertainty, yet it still under-specifies how algorithmic design and governance structures distribute outcomes in practice [12,45–48]. The result is a practical and theoretical mismatch: cities deploy AI-enabled prioritization systems for climate-resilient housing and infrastructure without a coherent conceptual framework linking environmental conditions relevant to mental well-being, algorithmic decision logic, and accountable governance arrangements.

The present framework builds on, but departs from, three adjacent model traditions. First, unlike broad smart-city frameworks that treat digitalization primarily as an urban-systems attribute, it isolates AI-enabled prioritization as a distinct governance locus [1–4]. Second, unlike planning support systems and digital-twin models that emphasize scenario exploration and visualization, it specifies how objective functions, equity constraints, and documentation rules shape allocation outcomes [8,35,49–51]. Third, unlike general public-sector AI governance frameworks, it introduces climate uncertainty, psychosocial mediators, and distributive protection as domain-specific requirements for urban housing and infrastructure prioritization [21–23]. This positioning clarifies that the contribution of the present study lies not in introducing a new technological model, but in specifying how AI-enabled prioritization systems should be governed as socio-technical decision infrastructures under conditions of climate uncertainty and distributive responsibility.

2.6. *Governance Comparison: Two Orientations for AI-Enabled Urban Prioritization*

The comparison below does not distinguish between cities that use AI and those that do not. Instead, it compares two governance orientations applied to the same class of AI-enabled prioritization systems: an efficiency-dominant smart/AI urbanism orientation and a caring urban governance orientation. The analytical difference lies in how objectives are defined, how equity is treated, how uncertainty is handled, and how accountability and participation are institutionalized.

The comparison concerns governance choices applied to the same class of AI-enabled prioritization systems; it does not compare cities that use AI with cities that do not. Table 1 summarizes the two governance orientations.

Table 1. Governance comparison of two orientations for AI-enabled urban prioritization.

Governance Dimension	Efficiency-Dominant Smart/AI Urbanism Orientation	Caring Urban Governance Orientation
Planning objective	Service optimization, performance metrics, cost-effectiveness, and aggregate risk reduction [1–4]	Well-being-supportive living conditions and distributive protection [26–28,52], with service reliability treated as a planning objective where relevant
Equity treatment	Equity acknowledged in policy language or evaluated ex post; allocation rules remain weakly constrained [4,15–17]	Equity encoded ex ante through service floors, disparity caps, or group-protective constraints that bound acceptable trade-offs [53–55]
Climate uncertainty	Point estimates, single-scenario risk maps, or forecast-specific optimization [12,47,48]	Robustness-oriented prioritization across plausible futures, scenario stress-testing, and regret-aware portfolio design [12,47,48,56]
Data politics	Data treated primarily as input for efficiency and comparability, with limited attention to missingness or representational harm [6,7]	Data categories, proxy choices, and missingness treated as distributive design decisions requiring stewardship, documentation, and community scrutiny [23,33,34,42,44]
Accountability	Limited explanation, vendor opacity, and one-off transparency claims [16,57,58]	Documentation, auditing, contestability, and redress treated as core governance requirements across the system lifecycle [21–23,57,59–62]
Participation	Consultation focused mainly on outputs or interface design [8,63–65]	Co-governance of problem framing, indicator selection, constraint design, and oversight over time [63–65]
Psychosocial well-being	General “quality of life” language without mechanism-level representation in decision logic [1–4,15]	Psychosocial mediators—stability, safety, agency, restorative access, and social support—explicitly represented in objectives, constraints, or evaluation criteria [26–28,38,39,52]

3. Materials and Methods

3.1. Study Design and Framework-Construction Method

This study adopts a two-stage qualitative research design. Stage 1 consists of a structured scoping review intended to map the multidisciplinary literature relevant to AI-enabled urban prioritization in climate-resilient housing and infrastructure planning. The scoping-review component was reported in accordance with the PRISMA extension for Scoping Reviews (PRISMA-ScR) [66]. Stage 2 applies conceptual framework analysis to synthesize the reviewed literature into an integrated governance framework [67]. This design is appropriate because the article seeks to build a conceptually explicit and governance-ready framework from fragmented multidisciplinary literatures rather than test a single causal hypothesis using primary empirical data. For the purposes of this article, a framework is understood as a network of linked concepts that explains a phenomenon, structures empirical inquiry, and guides applied intervention [67]. The framework developed here is intended for municipal planning departments, housing and infrastructure agencies, procurement units, oversight bodies, and researchers evaluating AI-enabled pri-

oritization systems. Its purpose is not to replace political judgment, but to make the design, governance, and scrutiny of such systems conceptually explicit and operationally auditable.

3.2. Structured Scoping Review Protocol and Search Strategy

Consistent with the review design outlined above [66], the scoping review covered three evidence domains aligned with the governance problem examined in this article: (A) climate-risk decision-making under deep uncertainty and robustness-oriented adaptation planning; (B) built-environment pathways relevant to psychosocial well-being; and (C) AI governance, algorithmic accountability, and fairness in public-sector decision systems. Searches were conducted in Scopus and Web of Science as the core bibliographic databases. Google Scholar was used only for backward and forward citation chaining and for locating foundational institutional frameworks not consistently indexed in the two core databases. Search strings combined terms such as “smart city,” “urban governance,” and “urban planning” with “AI,” “algorithmic governance,” “digital twin,” and “prioritization,” and then paired them with “climate adaptation,” “housing resilience,” “infrastructure prioritization,” “mental well-being,” “equity,” “auditing,” “contestability,” and “redress.” The purpose of the search was not to assemble an exhaustive technical AI corpus, but to identify literature capable of informing the governance design of high-stakes urban prioritization systems. For PRISMA-ScR reporting purposes, the source-identification process was grouped into core bibliographic database records from Scopus and Web of Science and supplementary sources identified through Google Scholar citation chaining, reference lists, and institutional frameworks.

3.3. Eligibility Criteria and Screening Logic

Consistent with the structured scoping-review logic outlined above [66] and the conceptual framework approach adopted in this study [67], sources were included when they met at least one of three criteria. First, they defined concepts or mechanisms relevant to urban allocation decisions, including objective functions, constraints, uncertainty handling, documentation, auditing, participation, or redress. Second, they addressed urban planning, public administration, or public-sector decision workflows. Third, they provided foundational conceptual or institutional guidance necessary to interpret AI governance in cities.

Sources were excluded when they were purely technical machine-learning studies with no governance relevance, when they lacked traceable conceptual or methodological claims, or when their relevance to high-stakes urban prioritization could not be established through triangulation with the broader literature. Preference was given to peer-reviewed scholarship and major institutional frameworks, with deliberate emphasis on the recent literature from 2020 onward, while retaining foundational studies required for conceptual continuity.

The final conceptual corpus comprised 85 cited sources spanning peer-reviewed journal articles, scholarly books, and major institutional frameworks. Conceptual saturation was treated as having been reached when iterative reading and coding no longer produced new concept families relevant to the five-layer architecture or to the governance elements operationalized in Sections 4–7 [67]. Potential selection bias was addressed through triangulation across the three evidence domains, the use of two core bibliographic databases, backward and forward citation chaining, and the exclusion of purely technical AI studies without urban-governance relevance. These steps were intended to reduce selection bias while preserving the multidisciplinary breadth required for the development of the framework. The source-selection process proceeded through identification, deduplication, title/abstract and relevance screening, full-text eligibility assessment, and final inclusion. The PRISMA-ScR flow diagram is included in the main text to document these steps.

3.4. Concept Extraction, Integration, and Derivation of the Five-Layer Architecture

The five-layer architecture was derived through a three-step analytical procedure [67]. First, extracted concepts were coded according to their primary locus of intervention: urban form and infrastructure, climate exposure and environmental resources, psychosocial mediators, algorithmic design, or institutional governance. Second, concepts addressing the same governance problem were clustered through axial comparison into higher-order families such as representation, objective specification, equity constraints, uncertainty handling, documentation, auditing, participation, and redress. Third, these families were sequenced along the workflow of municipal prioritization, from the conditions being represented to the rules that transform those representations into ranked projects and, ultimately, to the institutional mechanisms that authorize, audit, and correct those outputs. The resulting five-layer architecture should therefore be understood as an analytical reconstruction of a socio-technical decision pipeline rather than as a merely illustrative diagram.

To make this procedure more concrete, the derivation of equity constraints and psychosocial mediators can be used as an example. Equity constraints emerged through the joint reading of algorithmic fairness scholarship and environmental-justice literature [42,43,53–55,68]. During coding, service floors, disparity caps, and equal-opportunity conditions were grouped under the governance problem of distributive protection and were therefore positioned in Layer 4 as formal decision constraints on prioritization outputs. By contrast, psychosocial mediators such as housing stability, perceived safety, and restorative access were coded as human-consequence constructs [26–28,38,39]. They were therefore positioned in Layer 3, where they define what the system should protect rather than how it computes rankings. This distinction helped separate normative outcomes from computational design mechanisms within the final architecture.

3.5. Operationalization Logic for Propositions and Specification Guide

Within the conceptual framework approach adopted here [67], the eight propositions were formulated as mechanism-based claims linking specific design or governance mechanisms to directional expectations about prioritization outputs and distributive outcomes. Because the manuscript does not present a case study, the results of this study are reported as conceptual outputs rather than empirical findings. These outputs include the defined constructs, the five-layer architecture, the mechanism-based propositions, and a conceptual specification guide that makes objective terms, equity constraints, robustness logic, and documentation artifacts explicit and auditable. To improve practical interpretability, Section 7.6 also includes a brief hypothetical illustration of how a municipality could apply the framework within a prioritization workflow.

3.6. Analytical Validation of the Framework

Because this article develops a conceptual framework rather than evaluating a deployed municipal system, validation is analytical rather than empirical [67]. The framework was assessed against four criteria. First, construct clarity: the major terms used in the framework—including AI-enabled urban prioritization systems, psychosocial mediators, equity constraints, robustness, documentation, and contestability—must be explicitly defined. Second, internal coherence: the layers and feedback loops must form a non-contradictory account of how urban conditions, algorithmic design, and institutional governance interact. Third, literature congruence: each layer and proposition must be traceable to the reviewed literature. Fourth, operationalizability: the framework must yield auditable design elements and empirically testable propositions. Table 2 summarizes this validation logic [67].

Table 2. Analytical validation matrix for the Caring Urban Governance Framework.

Validation Criterion	Validation Question	Evidence in the Article	Output
Construct clarity	Are the key concepts explicitly defined and differentiated?	Introduction defines AI-enabled urban prioritization systems, urban governance, AI governance, and data governance; Section 3.1 defines the framework and intended target users.	Reduces conceptual ambiguity
Internal coherence	Do the layers and feedback loops operate as one socio-technical system?	Sections 4 and 5 link urban conditions, psychosocial mediators, design choices, and institutional oversight	Supports framework logic
Literature congruence	Is each major construct grounded in the reviewed literature?	Section 2 synthesis, cited Table 1, Sections 4.1–4.6, and Sections 6 and 7	Strengthens scholarly traceability
Operationalizability	Can the framework guide practice and future empirical testing?	Sections 6–8 specify propositions, audit points, governance requirements, an operational specification matrix, and scope conditions	Enables application and future validation

Table 2 specifies the criteria used to assess the conceptual framework in the absence of a case-based empirical test.

4. Results

This section reports the results of the conceptual framework analysis: (i) a set of defined constructs linking climate risk under deep uncertainty, psychosocial mediators of well-being, and algorithmic accountability; (ii) the Caring Urban Governance five-layer architecture with explicit feedback loops; and (iii) mechanism-based propositions and a conceptual specification guide that operationalize objectives, equity constraints, robustness logic, and documentation artifacts as auditable elements of an urban decision infrastructure.

4.1. Climate Risk, Resilience, and Deep Uncertainty

Climate risk is commonly defined as the potential for adverse consequences arising from the interaction of hazard, exposure, and vulnerability, shaped by adaptive capacity and societal development pathways [12]. Urban risk is compounded by infrastructure interdependence and cascading failures [46], and by social vulnerability patterns that are historically produced and unevenly distributed [33,53,69]. For prioritization systems, a core implication is that risk is not simply a property of geography; it is co-produced by built form, institutional capacity, and social inequality.

A second implication is uncertainty. Climate and socio-economic futures are characterized by deep uncertainty: probabilities may be unknown or contested, models may be structurally incomplete, and value judgments about acceptable risk and equity are not reducible to technical parameters [48]. Planning under deep uncertainty, therefore, requires approaches that are robust across plausible futures rather than optimal for a single forecast [47,56]. In the context of long-lived housing and infrastructure assets, this robust orientation is especially salient because maladaptive lock-in can persist for decades.

4.2. Urban Well-Being and Mental Health as Planning-Relevant Outcomes

Urban well-being is shaped by social determinants and built environment conditions that structure stress exposure, safety, agency, and restorative opportunities [52,70]. The built environment affects mental health through pathways such as crowding, noise, housing

quality, neighborhood disorder, and access to supportive and restorative spaces [26–28]. Green and blue spaces are linked to mental well-being via stress reduction, attention restoration, social interaction, and thermal regulation pathways [38,39,71].

Climate change adds psychosocial burdens through acute events and chronic stressors, including displacement risk, loss of predictability, and climate-related distress and anxiety [29–32]. The governance implication is that adaptation strategies and the tools used to prioritize them cannot be evaluated solely by physical exposure reduction; they must also be assessed by whether they protect the mediating conditions that sustain mental well-being.

4.3. Psychosocial Mediators

A psychosocial mediator is an intermediate condition linking material urban environments to mental well-being outcomes. The present framework focuses on mediators that are theoretically grounded, relevant to climate-resilient housing and infrastructure, and plausibly representable in planning systems without claiming to “measure mental health” directly. Core mediators include:

- Housing stability and security, including predictability of shelter and tenure-related stress burdens [27].
- Perceived safety and environmental threat, shaped by physical conditions and residents’ sense of security [26].
- Control and agency, including residents’ perceived ability to manage risks and influence decisions [52,70].
- Restorative and cooling access, including proximity and accessibility of green/blue spaces and other heat-relief opportunities [12,28,71].
- Social cohesion and support, which are relevant to coping with chronic stress and climate-related disruption [72,73].

The conceptual move is to treat these mediators as legitimate planning objects that should inform capital allocation decisions and the constraints governing them.

4.4. AI-Enabled Planning Systems as Socio-Technical Decision Infrastructures

Planning support systems (PSS) and spatial decision support systems have long sought to structure complex choices through scenario modeling, multi-criteria evaluation, and visualization [50,51,74]. Yet decades of PSS scholarship warn against the assumption that technical capacity automatically translates into planning value; implementation gaps reflect institutional, political, and communicative constraints [14,75]. Contemporary AI-enabled planning systems inherit these challenges while adding new ones: opacity of machine learning models, drift over time, and greater stakes as systems move from exploration to recommendation and ranking [21,59–62].

Within smart city governance, AI-enabled planning systems increasingly take the form of integrated pipelines that connect urban data platforms, indicator generation, vulnerability scoring, and portfolio recommendation in capital planning [6–8]. Digital twins extend this pipeline by providing simulation and scenario environments, often anchored in 3D city models and GIS layers [35,76,77]. These systems are not neutral assistants; they structure visibility, urgency, and justification [6,16].

4.5. Objective Functions, Equity Constraints, and Robustness Logic

Because climate-resilient housing and infrastructure prioritization often involves ranking or portfolio selection, it can be conceptualized as an optimization problem [49,50] even when agencies do not use formal optimization language. Three constructions are therefore essential.

An objective function specifies what the system is designed to improve, e.g., minimizing climate risk, minimizing service disruption, maximizing coverage of interventions, or minimizing cost. If psychosocial mediators are excluded, the system has no formal reason to protect them; if they are included, trade-offs become explicit and governance can interrogate them.

An equity constraint limits the feasible set of solutions. Its purpose is to prevent unacceptable disparities or guarantee minimum levels of protection. In urban prioritization, such constraints may take the form of service floors or disparity caps grounded in distributive-justice commitments [53,55], or equal-opportunity conditions when predictive models are used [54]. Environmental-justice scholarship underscores why such constraints matter: average improvement is not sufficient if marginalized groups remain systematically exposed [53,55,69].

Fairness constraints, however, are not interchangeable, and different criteria can conflict in practice, especially when outcome prevalence differs across groups [43,44,54,68]. For that reason, the choice among equity constraints should be treated as an explicit governance decision. Public agencies should state which fairness principle is prioritized, justify that choice in relation to statutory duties and planning goals, and document the trade-offs that follow.

Robustness logic addresses uncertainty. Rather than optimizing for a single forecast, it seeks options that perform acceptably across plausible futures [47,48,56]. This is especially important for long-lived housing and infrastructure assets, where maladaptive lock-in can be costly and difficult to reverse.

4.6. Algorithmic Accountability, Documentation, Auditing, and Contestability

Algorithmic-governance scholarship emphasizes that transparency alone is insufficient; accountability requires institutionalized practices of documentation, auditing, and redress [57–60]. Documentation frameworks such as model cards and datasheets clarify intended use, data provenance, limitations, and failure modes [61,62]. Risk-management guidance emphasizes ongoing monitoring and lifecycle governance rather than one-time evaluation [21]. For public-sector systems, contestability matters: affected communities should have meaningful routes to challenge decisions, obtain explanations, and seek remedy [23,60]. In the context of housing and infrastructure prioritization, where decisions influence stability and safety, contestability is not peripheral; it is a legitimate governance condition [23,60].

5. The Caring Urban Governance Framework

5.1. Framework Overview and Core Premise

The Caring Urban Governance Framework integrates the constructs defined in Section 4 into a single governance architecture. Its logic runs from material urban conditions (Layers 1–2), to human consequences (Layer 3), to decision rules (Layer 4), and finally to institutional accountability structures (Layer 5). The core premise is governance-centered: AI-enabled prioritization becomes publicly legitimate only when well-being-supportive living conditions are treated as explicit decision objectives, equity is encoded as binding constraints, and uncertainty is handled through robustness-oriented prioritization rather than brittle optimality. These requirements are not moral adornments; they are design and governance commitments that can be specified in procurement, audited in operation, and contested in public deliberation.

5.2. Five-Layer Architecture

The framework is structured as a five-layer architecture to clarify mechanisms and loci of intervention. In brief, Layer 1 defines the urban assets and infrastructures at stake; Layer 2 captures hazard exposure and environmental resources; Layer 3 identifies the psychosocial conditions that should be protected; Layer 4 translates those inputs into rankings or portfolios; and Layer 5 governs the authority, oversight, and correction of those outputs. This summary is intended to orient readers before the fuller layer-by-layer explanation below.

Layer 1: Urban form and infrastructure

This layer represents housing stock characteristics, building performance, drainage and flood-control systems, cooling and heat-refuge infrastructure, and mobility and access networks. It also includes the interdependencies that can generate cascading service failures [46,78]. For prioritization systems, Layer 1 includes both the assets to be intervened upon and the service consequences of interventions.

Layer 2: Climate exposure and environmental resources

Layer 2 captures hazards and exposure (heat, flooding, storms) and environmental resources that affect both climate risk and well-being, such as tree canopy, blue-green infrastructure, and accessible cooling opportunities [12,71]. This layer also includes spatially uneven exposure patterns shaped by historical development and inequity [33,53,69].

Layer 3: Psychosocial mediators

Layer 3 includes the psychosocial mediators through which housing and infrastructure conditions influence mental well-being: stability/security, perceived safety, agency, restorative access, and social cohesion [26–28,52]. Importantly, this layer clarifies that “resilience” is not only an engineering property; it is experienced through everyday conditions that structure stress and control, especially for vulnerable residents.

Layer 4: Algorithmic design layer

For governance purposes, Layer 4 is the bounded locus of AI within the framework. It includes any auditable ruleset or model—rule-based, statistical, machine-learning, optimization-based, or simulation-based—that performs one or more of three functions: representing need through scoring or classification, prioritizing projects through ranking or portfolio selection, and exploring uncertainty through scenario stress-testing. In this sense, AI is treated neither as a black box nor as a substitute for planning judgment; it is a governable decision layer whose objectives, constraints, and outputs remain institutionally accountable. Layer 4, therefore, specifies how data and models translate into prioritization outputs. It includes:

- Data selection and classification, including the politics of categories and missingness [33,34].
 - Indicator construction and vulnerability scoring, including proxy choices and aggregation rules [33,37,79].
 - Objective function specification, including explicit inclusion of psychosocial mediators and service reliability.
 - Equity constraints, including floors, caps, and equal-opportunity conditions [53–55].
 - Robustness-oriented uncertainty handling, including scenario ranges, stress tests, and regret-based selection [47,48].
 - Explainability and documentation, enabling scrutiny and monitoring [61,62,80].
- Layer 4 is where “smartness” most directly becomes governance: these design choices determine whose needs are visible, which trade-offs are permitted, and how errors can persist.

Layer 5: Governance and institutional layer

Layer 5 is the institutional envelope that shapes the legitimacy of Layers 1–4. At the level of urban governance, it concerns authority, accountability, and coordination across public, private, and civic actors. At the level of AI governance, it includes procurement rules, impact assessment, auditing capacity, participatory oversight, and redress mechanisms [21,23,59,60]. At the level of data governance, it includes stewardship arrangements that govern data quality, access, permissible reuse, retention, and protections against surveillance and extractive data practices that erode trust [23,81–83]. Taken together, the five layers should be read as an explanatory sequence rather than as a checklist of disconnected components. Operationally, the framework works in five steps. First, information on urban form and infrastructure is assembled in Layer 1. Second, this representation is combined in Layer 2 with climate exposure and environmental-resource data. Third, Layer 3 interprets those conditions through psychosocial mediators that define what meaningful protection should entail. Fourth, Layer 4 translates the combined inputs into ranked projects or portfolios through scoring, prediction, optimization, and scenario exploration. Fifth, Layer 5 determines whether those outputs are authorized, documented, audited, and contestable. The framework therefore explains where normative choices enter AI-enabled urban prioritization and where corrective intervention remains possible.

5.3. Feedback Loops and Dynamic Behavior

The framework is explicitly dynamic; it anticipates feedback loops that can either stabilize caring outcomes or amplify harm.

1. Investment-to-risk loop: capital allocation reshapes exposure and vulnerability over time; poorly chosen investments can create new lock-ins, while robust portfolios reduce future regret [47,56].
2. Investment-to-mediator loop: housing and infrastructure interventions reshape psychosocial mediators, e.g., stability and perceived safety, thus affecting well-being trajectories [27].
3. Algorithm-to-investment loop: prioritization outputs become implementation sequences, reshaping Layer 1 and redistributing protection and services.
4. Governance-to-algorithm loop: procurement, auditing, and oversight determine whether objectives and constraints are explicit, whether documentation exists, and whether contestability is meaningful [21,60].
5. Outcome-to-legitimacy loop: experienced harms and benefits shape trust and participation, which in turn affects the legitimacy and quality of subsequent governance processes [6,57].

5.4. Figure Description (Conceptual)

Figure 2 illustrates the Caring Urban Governance Framework for climate-resilient housing and infrastructure prioritization. Layers 1–3 represent the urban and human conditions that must be protected; Layer 4 translates those inputs into rankings or portfolios through algorithmic design; and Layer 5 governs authorization, auditing, participation, and correction. Arrows indicate both data inputs to prioritization and feedback loops through implementation, oversight, and legitimacy.

Figure 3 reports the PRISMA-ScR source-selection flow corresponding to the structured scoping-review procedure described in Sections 3.1–3.3.

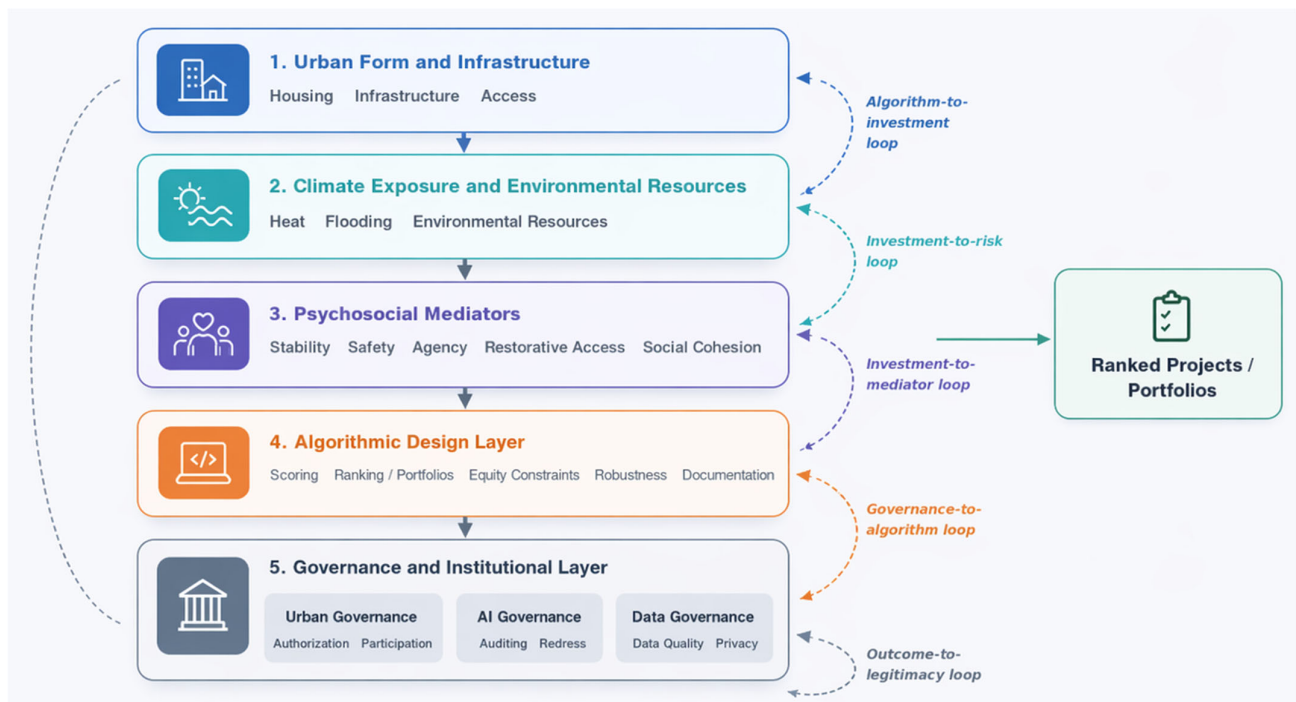


Figure 2. Caring Urban Governance Framework for climate-resilient housing and infrastructure prioritization.

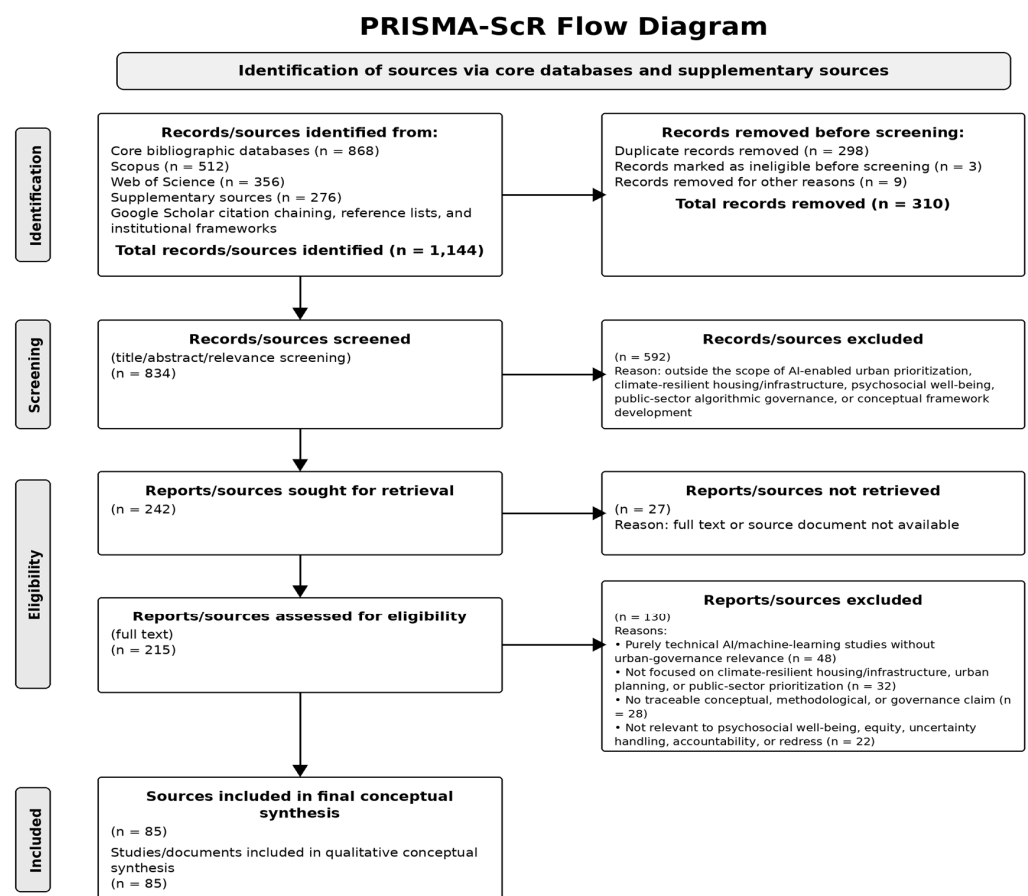


Figure 3. PRISMA-ScR flow diagram documenting source identification, deduplication, screening, eligibility assessment, and final inclusion in the conceptual synthesis, following PRISMA-ScR reporting guidance [66].

5.5. Situating the Caring Urban Governance Framework Within Digital Urban Governance Architectures

Smart-city governance is increasingly enacted through digital architectures that integrate data, models, and decision workflows [6–8]. The Caring Urban Governance Framework can be directly situated within four common components of contemporary digital urban governance.

(i) Urban data platforms and dashboards. Urban data platforms aggregate administrative, sensor, and third-party data into standardized schemas, enabling indicators, benchmarking, and dashboard visualization [6,7]. In conventional architectures, dashboards often privilege what is quantifiable and operationally convenient, contributing to a “visualized facts” epistemology that can conceal normative choices [6]. In a caring architecture, the platform must do more than aggregate data: it must support traceability (provenance and lineage), publish data dictionaries and indicator construction rules, and enable public scrutiny of what is counted and what is absent. Caring governance therefore treats the platform as an accountability substrate rather than a data lake.

(ii) Vulnerability scoring tools and risk indices. Many cities rely on composite indices to prioritize interventions. Such tools can bring systematic attention to risk and inequity, but they also embed classification politics and aggregation choices that can misrepresent lived vulnerability, especially where data coverage is uneven [33,34,37]. A caring architecture requires that vulnerability scoring tools be paired with equity constraints and participatory validation: indices should be contestable, their proxy assumptions explicit, and their error patterns audited for representational harms [37,42–44].

(iii) Digital twins and scenario environments. Urban digital twins extend GIS and PSS traditions by integrating 3D city models, simulation capabilities, and interactive visualization that can support scenario deliberation [35,76,77]. Digital twins are often framed as instruments of prediction and optimization, yet their governance risk lies in epistemic authority: when models become persuasive narratives, they can crowd out contestation [8,16]. The Caring Urban Governance Framework positions the digital twin not as an oracle but as a robustness engine: it should be used to stress-test portfolios across plausible climate futures and to document uncertainty rather than to present a single “best” answer [47,48]. Within that process, it can also be used to explore distributional consequences.

(iv) Capital investment prioritization systems (CIPS). The most consequential component is the system that converts risk indicators and project options into ranked lists or portfolios. These systems often involve multicriteria evaluation, optimization, and scheduling [49,50,56]. In conventional smart governance, the objective function is frequently implicit (cost efficiency, aggregate risk reduction), and equity is often externalized to political negotiation after outputs are produced [4,15–17]. The Caring Urban Governance Framework requires that CIPS explicitly encode (a) psychosocial mediators as decision objectives where relevant, (b) equity as constraints that define unacceptable trade-offs, and (c) robustness criteria that privilege strategies with acceptable performance under uncertainty [56]. Documentation must specify intended use, limitations, and governance responsibilities, enabling auditing and public accountability [59,61,62].

Positioning the Caring Urban Governance Framework within this architecture clarifies that the framework is not an abstract ethical overlay. It is an intervention into the digital machinery of smart governance, aimed at making AI-enabled capital allocation systems accountable to SDG 11 commitments and to well-being-supportive urban living conditions.

6. Propositional Development

The propositions are organized to follow the causal logic of the framework. Propositions 1–3 address representation and objective specification. Propositions 4–5 address

uncertainty handling and co-benefit design. Propositions 6–8 address oversight, auditing, and stewardship. Each proposition is presented in a parallel format comprising (i) mechanism, (ii) directional expectation, and (iii) an empirical test route suitable for smart-city governance research, including audits, quasi-experiments, and policy evaluation. Together, these propositions define the design and governance requirements that are translated into procurement rules, impact-assessment procedures, documentation standards, monitoring routines, and participatory oversight mechanisms in Section 7.

Proposition 1. *Objective alignment with psychosocial mediators.*

P1. Mechanism. When prioritization systems formally include psychosocial mediators (e.g., housing stability, perceived safety, restorative access) as terms in the decision objective, these mediators become protected against trade-off erosion.

Directional expectation. Systems with mediator-inclusive objectives will generate investment portfolios that more consistently improve well-being-supportive living conditions than systems that optimize only hazard reduction and cost.

Empirical test route. Comparative policy evaluation of portfolio outputs before and after objective revisions, combined with mixed-method assessment of mediator-relevant indicators and resident-reported experiences.

Anchoring sources: Evans [26]; Evans et al. [27]; Hartig et al. [28]; Marmot [52].

Proposition 2. *Representation bias and invisible vulnerability.*

P2. Mechanism. Uneven data coverage and proxy construction under-represent marginalized communities, leading vulnerability models to systematically mis-estimate need where lived vulnerability is poorly captured.

Directional expectation. Under-represented neighborhoods will be systematically under-prioritized for climate-resilient housing and infrastructure investments even when aggregate model performance appears acceptable.

Empirical test route. Data and model audit linking missingness and proxy bias to prioritization outcomes, supplemented by participatory validation or targeted ground-truthing of high-risk areas.

Anchoring sources: Barocas & Selbst [42]; Bowker & Star [34]; Cutter et al. [33]; Mehrabi et al. [44].

Proposition 3. *Efficiency-first optimization and distributive divergence.*

P3. Mechanism. Optimization that maximizes aggregate risk reduction without binding equity constraints can tend to concentrate investment where marginal returns are highest, which can mirror existing advantages (better data, lower costs, higher asset values).

Directional expectation. Unconstrained systems will widen spatial disparities in climate protection and well-being-supportive living conditions compared with constrained systems that enforce service floors or disparity caps.

Empirical test route. Counterfactual simulation comparing unconstrained versus equity-constrained portfolios on the same project universe, evaluating disparity metrics and distributional coverage.

Anchoring sources: Hardt et al. [54]; Schlosberg [53]; Walker [55].

Proposition 4. *Robustness logic reduces maladaptive lock-in.*

P4. Mechanism. Robustness-oriented decision rules select strategies that perform acceptably across plausible futures, reducing regret and lock-in to brittle solutions.

Directional expectation. Portfolios chosen under robustness criteria will show fewer failure modes and lower regret under alternative climate scenarios than portfolios optimized for a single forecast.

Empirical test route. Scenario stress-testing of portfolios within a digital twin or planning model, comparing regret and service failure outcomes across plausible hazard trajectories.

Anchoring sources: Lempert et al. [48]; Hallegatte [47]; Haasnoot et al. [56]; IPCC [12].

Proposition 5. *Nature-based and thermal comfort pathways with anti-displacement conditions.*

P5. Mechanism. Integrating restorative access and thermal comfort into prioritization objectives supports dual pathways: climate risk reduction (heat mitigation) and psychosocial restoration; however, interventions can trigger exclusionary pressures or displacement without safeguards.

Directional expectation. When restorative access objectives are paired with anti-displacement safeguards and equity constraints, portfolios will deliver larger well-being co-benefits and fewer adverse distributional effects than portfolios that treat green or blue infrastructure solely as amenity or aesthetic improvement.

Empirical test route. Policy evaluation comparing intervention areas with and without explicit anti-displacement safeguards, assessing changes in access, perceived comfort and safety, and displacement pressure indicators.

Anchoring sources: Gascon et al. [38]; Twohig-Bennett & Jones [39]; Anguelovski et al. [40,41]; WHO [71].

Proposition 6. *Participatory oversight improves indicator validity and legitimacy.*

P6. Mechanism. Participatory oversight introduces lived experience into problem framing and indicator selection, exposing mis-specified proxies and strengthening contestability.

Directional expectation. Systems with institutionalized participatory oversight will tend to exhibit higher legitimacy (trust and acceptance) and more contextually relevant indicators than otherwise similar systems without such oversight.

Empirical test route. Comparative process evaluation across governance models, measuring changes in objectives and constraints after participation and assessing trust, contestation uptake, and perceived agency.

Anchoring sources: Arnstein [63]; Healey [64]; Cardullo & Kitchin [65]; Diakopoulos [57].

Proposition 7. *Documentation and auditing reduce persistent distributive error.*

P7. Mechanism. Documentation (datasheets and model cards) and auditing create institutional capacity to detect bias drift, performance drift, and distributive harms and to implement corrective action.

Directional expectation. Prioritization systems with strong documentation and routine audits will show lower persistence of systematic distributive errors than systems governed only by transparency statements or one-time evaluations.

Empirical test route. Cross-sectional governance audit scoring documentation and monitoring practices, linked to observed correction rates and identified bias incidents over time.

Anchoring sources: Mitchell et al. [61]; Gebru et al. [62]; Raji et al. [59]; NIST [21].

Proposition 8. *Data stewardship increases participation and reduces surveillance-related trust erosion.*

P8. Mechanism. Data stewardship arrangements that limit repurposing, clearly allocate stewardship responsibility, and protect residents from surveillance can help reduce trust erosion and support more trustworthy participation and data-sharing arrangements.

Directional expectation. Cities with explicit stewardship and contestability arrangements should be better positioned to sustain public cooperation and trustworthy data-sharing conditions than cities where data practices are opaque or vendor-dominated.

Empirical test route. Comparative institutional analysis of stewardship models linked to participation rates, public trust indicators, and documented disputes over data access, reuse, and oversight.

Anchoring sources: Austin & Lie [83]; Houser & Bagby [84]; Crawford [81]; Zuboff [82].

7. Governance and Planning Implications

The Caring Urban Governance Framework implies that AI-enabled capital allocation must be treated as a public accountability domain rather than a narrow IT procurement matter. Drawing directly on the framework layers and the eight propositions, this section translates the conceptual model into governance requirements for procurement, impact assessment, documentation, monitoring, and democratic oversight in climate-resilient housing and infrastructure prioritization.

7.1. Procurement as a Governance Lever for Objective and Constraint Transparency

Procurement decisions often determine whether a prioritization system will be auditable or inscrutable. Caring governance requires that procurement standards mandate:

1. Objective function transparency: the system must publish and maintain a clear statement of objectives, including how psychosocial mediators and service reliability are represented where relevant [26–28,52,61,62].
2. Equity constraints as enforceable requirements: equity is not a reporting metric but a feasibility condition (floors, caps, equal-opportunity constraints where predictive models are used) [53–55].
3. Robustness-oriented uncertainty handling: the system must demonstrate performance under scenario ranges and document how decisions change across plausible futures [47,48,56].
4. Documentation deliverables: model cards, datasheets, data dictionaries, and decision logs as contractual requirements [61,62].
5. Audit interfaces: the system must support independent auditing, including reproducible evaluation pipelines and access to relevant logs under appropriate safeguards [59].

These requirements directly address critiques of vendor-driven smart city governance in which proprietary systems shape public decisions while limiting scrutiny [16,17].

7.2. Algorithmic Impact Assessment as Planning Due Diligence

Algorithmic Impact Assessment (AIA) can be positioned as a planning instrument analogous in intent, though not identical in form, to environmental impact assessment [21,60]. For AI-enabled housing and infrastructure prioritization, AIA should minimally specify:

- Decision context and scope (what decisions the system influences).
- Affected populations and equity-relevant groups.
- Data provenance, representational adequacy, and proxy risks.
- Objective functions and equity constraints, including rationales and trade-offs.
- Uncertainty handling (scenarios, stress tests, robustness criteria).

- Monitoring and re-evaluation cycles (drift detection).
- Contestability and redress procedures [21,60].

Institutionalizing AIAs makes caring operational: it creates a governance routine that forces explicitness about objectives, constraints, and risks.

7.3. Documentation, Explainability, and the Limits of Transparency

Smart city systems often promise “transparency” while providing little that supports accountability [57–60]. Caring governance distinguishes transparency from accountability. Documentation must enable three functions:

- Interpretability for planners: the system must allow planners to understand why a portfolio was selected and how trade-offs were handled.
- Auditability for oversight bodies: the system must support reproducible evaluation of bias, performance, and constraint compliance.
- Contestability for affected residents: the system must provide explanations suitable for challenge and remedy where decisions impose harm.

Explainability methods can support these aims, but they do not substitute for governance structures that define responsibilities and remedies [57,59,60]. Documentation frameworks such as model cards and datasheets are therefore treated as governance artifacts rather than academic add-ons [61,62].

7.4. Auditing and Monitoring as Continuous Governance

AI-enabled prioritization systems are not static: data, urban conditions, and institutional priorities change; models can drift; and vulnerability patterns can shift under new climate extremes [21,59]. Caring governance therefore requires continuous monitoring aligned with risk management principles [21]. Auditing should include:

- Representation audits (coverage and missingness by neighborhood and group).
- Constraint compliance audits (floors and caps enforced).
- Performance audits (predictive validity where prediction is used, and error distribution).
- Outcome audits (distribution of investments and service improvements).
- Process audits (whether participation, contestation, and corrections occur).

This emphasis aligns smart city governance with a lifecycle view of AI risk rather than a deployment-and-forget mentality.

7.5. Participatory Oversight and Democratic Contestability

Participation in smart city projects often focuses on user experience or consultation around outputs [65]. Caring governance requires participatory oversight at the level of decision primitives: what counts as need, which mediators are protected, which constraints are non-negotiable, and how uncertainty is handled. Arnstein’s ladder remains relevant because participation is frequently symbolic; caring governance requires institutionalized roles for affected residents in oversight rather than episodic engagement [63,64]. Smart citizenship scholarship underscores that inclusion is not guaranteed by “open data” or digital platforms; it depends on power, resources, and institutional design [65].

7.6. Operational Specification Matrix for Applying the Caring Urban Governance Framework

Table 3 translates the framework into auditable design and governance requirements for municipal AI-enabled prioritization systems. It is conceptual and normative; it does not report empirical findings.

Table 3. Operational specification matrix for applying the Caring Urban Governance Framework.

Governance Element	Minimum Specification	Example Audit Artifact	Example Application
Decision objective	State what the system is optimizing and why; specify whether psychosocial mediators are included	Problem statement; objective-function note; procurement brief	“Minimize combined flood risk, housing instability risk, and heat-related service disruption subject to budget”
Equity constraints	State non-negotiable floors, caps, or group protections	Constraint register; fairness memo; compliance dashboard	Minimum retrofit eligibility for high-deprivation tracts; cap on protection gaps between deprivation quintiles
Data and representation	Document data sources, missingness, proxies, update cycle, and excluded populations	Datasheet; data dictionary; coverage audit	Explain whether informal housing, hidden homelessness, or cooling-center use are captured
Uncertainty handling	Evaluate portfolios across plausible futures and disclose scenario sensitivity	Stress-test report; regret table; scenario log	Compare project portfolios under low, medium, and high heat/flood futures
Documentation and explanation	Record intended use, model limits, known failure modes, and override procedures	Model card; decision log; override log	Explain why a neighborhood moved up or down in priority after a data or policy change
Participation and contestability	Define who can review, challenge, or amend assumptions and outputs	Participation plan; public notice; appeals protocol	Resident review panel can contest proxy choices or displacement assumptions
Monitoring and correction	Re-audit after deployment and specify thresholds for recalibration or suspension	Periodic audit report; incident register; correction plan	Suspend or recalibrate the model if false negatives cluster in deprived or protected groups

To illustrate applications, consider a municipality allocating a fixed resilience budget across heat-vulnerable rental housing, flood-prone drainage corridors, and neighborhood cooling infrastructure. Using Layers 1 and 2, the city assembles data on housing conditions, infrastructure interdependencies, heat exposure, flood risk, tree canopy, and cooling access. Layer 3 introduces psychosocial mediators such as housing stability, perceived safety, and restorative access as protection goals rather than background context. Layer 4 then applies a prioritization model that minimizes combined heat and flood harm while enforcing equity constraints across high-deprivation neighborhoods and stress-testing the resulting portfolio across alternative climate scenarios. Layer 5 requires that the resulting rankings be documented, reviewed through participatory oversight, and audited before implementation. This example illustrates how the framework structures a municipal prioritization workflow without presupposing a specific software platform or case-study city.

7.7. Operational Alignment with SDG 11

The framework advances SDG 11 at the level of decision design rather than at the level of rhetoric [9–11]. By treating housing stability, retrofit sequencing, and service reliability as explicit allocation concerns, it speaks directly to Target 11.1 on safe and adequate housing [9–11]. By requiring participatory oversight and contestability in the definition of indicators, objectives, and constraints, it supports Target 11.3 on inclusive and participatory urbanization [9–11]. By requiring robustness-oriented adaptation planning and distributive protection under heat, flood, and infrastructure stress, it supports Targets 11.5 and 11.B on disaster risk reduction and integrated resilience planning [9–11]. By incorporating restorative access, cooling opportunities, and blue-green infrastructure into prioritization logic, it also supports Target 11.7 on safe, inclusive, and accessible public space [9–11].

7.8. Avoiding “Caring Washing” in Smart City Governance

A predictable risk is that caring language becomes branding while the underlying system remains efficient-first and opaque. The Caring Urban Governance Framework therefore treats caring as auditable commitments: explicit objectives, enforceable constraints, robust logic, documentation, audits, and contestability. Without these, caring cannot be evaluated and becomes performative.

8. Boundary Conditions, Scope, and Research Agenda

This section operationalizes the scope conditions implied by Sections 5–7. It specifies where the framework is most applicable, where it should not be used, and which empirical strategies can test the eight propositions advanced above. The purpose is not to introduce a separate argument, but to delimit the claims made by the framework and guide future validation.

8.1. Primary Domain of Applicability

The framework is designed for urban governance contexts where the decision problem is to prioritize climate-resilient housing and infrastructure investments under constrained budgets and uncertain futures. It applies most directly when:

- A city uses GIS and data platforms to develop risk and vulnerability layers.
- Prioritization involves ranking projects or selecting portfolios.
- Institutional capacity exists (or can be built) for documentation, auditing, and participatory oversight.

The framework is intentionally not a general theory of smart cities. It targets a specific and consequential smart governance function: AI-enabled allocation of climate resilience investments.

8.2. Where the Framework Should Not Be Applied

The Caring Urban Governance Framework should not be used to legitimize:

- Fully automated prioritization without meaningful human accountability and democratic oversight [21,23,60].
- Surveillance-intensive data practices, especially where they elevate perceived threat or erode trust in marginalized communities [81–83].
- Adaptation strategies that treat displacement as a default solution, absent strong protections and consent mechanisms [41].

8.3. Global North/Global South, Data-Poor Contexts, and Informal Settlements

Data availability and institutional capacity vary widely. In data-poor contexts, algorithmic systems can worsen invisibility: marginalized communities and informal or weakly recorded settlements may be poorly represented in administrative records, leading prioritization tools to misrepresent need [33,34,37]. Caring governance in such contexts requires:

- Participatory mapping and community-generated data can supplement official records and help reduce invisibility in data-poor contexts [33,34,85]. Such practices should, however, be accompanied by safeguards against extraction and harm [81–83].
- Stronger data stewardship and contestability protections, given heightened risks of surveillance, exclusion, or coercive intervention [81–83].
- Robustness-oriented approaches that explicitly recognize uncertainty in both climate projections and baseline data [47,48].

The framework’s governance layer, therefore, becomes more, not less, central in Global South and informal settlement contexts.

The framework can also be misapplied in real-world settings. Risks include treating it as a justification for fully automated allocation, relying on poorly validated proxies for psychosocial conditions, or invoking ‘care’ rhetorically without enforceable constraints, documentation, and contestability. These risks reinforce that the framework should be used as a governance discipline rather than as a technical template that can be deployed without institutional safeguards.

8.4. Research Agenda for Smart City Governance Scholarship

The framework yields a research agenda oriented towards falsification and governance learning, and this agenda follows directly from the causal mechanisms specified in Section 6 and the governance requirements elaborated in Section 7:

1. Scenario stress-testing in digital twins: robustness versus single-scenario optimization effects on portfolio regret [47,56].
2. Comparative institutional studies: how AIAs, procurement standards, and stewardship models shape system behavior and public trust [21,60].
3. Mediator-oriented evaluation: how investments change well-being-supportive living conditions, not only hazard exposure [26,28].
4. Equity constraint design research: how constraints are negotiated, institutionalized, and contested across different political contexts [53,63,64].

9. Discussion

Smart city governance is increasingly implemented through AI-enabled planning systems that translate data into prioritized investments [4–8]. This prioritization turn is a defining feature of contemporary smart urbanism because it relocates normative urban questions—who is protected first, who receives infrastructure investments, and whose risks count—into computational systems that can obscure trade-offs behind technical outputs [6,15–20]. Existing smart city frameworks provide limited conceptual tools for governing these systems when decisions materially shape climate resilience and the living conditions that structure mental well-being [1–5,15,16,26–28].

This conceptual analysis advances a governance-centered alternative: the Caring Urban Governance Framework for AI-enabled climate-resilient housing and infrastructure prioritization. The framework responds to conceptual fragmentation by integrating climate risk and deep uncertainty, psychosocial mediators of urban well-being, and algorithmic governance mechanisms (objective functions, equity constraints, robustness logic, documentation, auditing, and contestability). Its five-layer architecture clarifies where harms and protections are produced, and its feedback loops explain why system behavior cannot be understood as a static mapping from data to decisions. The eight propositions translate the framework into refutable claims and specify evaluation routes consistent with smart city governance as an empirical and institutional practice.

This study has several limitations. First, it is a conceptual framework article and does not yet provide a municipal case study, comparative audit, or quasi-experimental test of the propositions. Second, although the review protocol has now been made explicit, the synthesis remains constrained by the availability of English-language scholarship and may underrepresent practice-based and Global South knowledge. Third, the framework is designed for high-stakes housing and infrastructure prioritization systems and should not be generalized to all urban AI applications. Fourth, the psychosocial mediators specified here are planning-relevant proxies for well-being rather than direct clinical measures of mental health and therefore require contextual calibration in empirical applications. Fifth, practical implementation may also be constrained by fragmented data infrastruc-

tures, limited audit capacity, uneven procurement expertise, and restricted staff time for participatory oversight.

For smart city scholarship, the central implication is that “smartness” is not a technical attribute; it is a governance arrangement [1–8,15–20]. Digital twins, vulnerability scoring, dashboards, and capital prioritization systems should be treated as public institutions with distributive consequences [6–8,16]. For practitioners, the implication is operational: caring must be specified in procurement, encoded in constraints and objectives, validated through participatory oversight, and maintained through continuous audit and redress mechanisms. Without these commitments, smart-city systems risk optimizing a narrow conception of performance while intensifying inequity, psychosocial stress, and distrust. Such outcomes would run counter to the inclusion, safety, resilience, and public-space commitments reflected in SDG 11 targets 11.1, 11.3, 11.5, 11.7, and 11.B [9–11].

10. Conclusions

This study developed the Caring Urban Governance Framework as a conceptually explicit and operationally auditable approach to governing AI-enabled climate-resilient housing and infrastructure prioritization. The framework addresses a key gap in existing smart-city and climate-resilience models by integrating psychosocial well-being, equity constraints, and climate uncertainty directly into the decision logic of AI-enabled prioritization systems.

The analysis demonstrates that AI-enabled urban prioritization systems are not merely technical tools but socio-technical decision infrastructures that shape the distribution of protection, resources, and risks. As such, their legitimacy depends on how objectives are defined, how equity is enforced, and how uncertainty is handled within governance structures. The five-layer architecture clarifies where these decisions occur and how they can be made transparent, auditable, and contestable.

From a practical perspective, the framework provides a governance-oriented basis for municipalities to design, procure, and evaluate AI-enabled prioritization systems in alignment with SDG 11 [9–11]. In particular, it emphasizes that well-being-supportive living conditions must be treated as explicit decision objectives, and that distributive protection must be enforced through formal constraints rather than post hoc evaluation.

Future research should focus on empirical validation of the framework through comparative case studies, algorithm audits, and scenario-based evaluations of prioritization systems. Such work is necessary to assess how the proposed mechanisms operate in practice and to refine the framework in different institutional and geographic contexts.

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