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Perspective

Towards building-scale urban analytics and simulation

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Abstract

Buildings serve as the basic cells of a city, forming a complex urban system that integrates physical and social characteristics. While urban analytics and simulation have traditionally been constrained by data availability and computational complexity, recent advancements in sensing, AI and high performance computing have made building-scale inquiry increasingly feasible. This perspective proposes and highlights Building-Scale Urban Analytics and Simulation through four key pillars. First, it calls for a unified modeling standard that aligns the semantic depth of building engineering with the geographic breadth of urban science. Second, it highlights the need for constructing comprehensive building datasets with full spatiotemporal coverage through AI-driven data foundations. Third, it advocates for the use of generative AI to diagnose building quality and efficacy. Fourth, it proposes a bottom-up simulation paradigm that integrates AI with generative rules to model complex morphological and behavioral transformations. This vision provides a critical bridge between building studies and urban studies.

Keywords

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urban simulation
applied urban model

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1 Introduction

Global building data products are progressing rapidly across temporal coverage, spatial extent, and attribute richness (Liu et al. 2023). This advancement is driven by diverse data sources including aerial, satellite, and ground-based imagery, as well as multi-source geospatial and social media data through increasingly abundant sensors. Meanwhile, this data abundance necessitates a corresponding evolution in computing facilities and infrastructure, which are developing fast to provide the power required for large-scale and high-precision urban computing (Zhang et al. 2025). The shift toward distributed and cloud-based environments makes it technically feasible to analyze and simulate large-scale and complex urban systems at the individual building level, moving beyond the limitations of traditional coarse-grained models.

The building scale is of particular significance because it constitutes the fundamental operational unit for a wide range of urban practices, which rely on building-level feasibility assessments and land parcel analysis. Urban regeneration, the comprehensive process of improving the physical, social, and economic conditions of existing urban areas, demands precise diagnostics of individual building conditions, including structural integrity, functional obsolescence, and vacancy status. Urban governance and management require building-granularity data for regulatory compliance, energy auditing, and public safety inspections. In each of these domains, decisions that are ultimately enacted at the building scale have traditionally been informed by coarse, aggregated data, resulting in a critical mismatch between the resolution of available information and the granularity of required action.

The convergence of massive data and high computational power is currently being catalyzed by the transformative evolution of AI technology (Liu et al. 2026). The breakthrough in large models offers the potential for automating feature extraction and modeling complex urban dynamics that were previously inaccessible. This technological readiness, combined with the growing demand for building-scale insights, is driving both building studies and urban studies toward a common frontier: analytics and simulation at the individual building level.

On one hand, building studies are expanding outward:

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building-scale data foundations increasingly inform neighborhood and district-level assessments. On the other hand, urban studies are deepening inward: fine-grained building data enables analysis of the socio-physical composition of urban spaces at unprecedented detail. While geometric layout and material performance are critical for physical simulation, the diagnosis of building quality and efficacy is paramount for urban regeneration. Building-Scale Urban Analytics and Simulation serves as the critical nexus where these trajectories converge (Figure 1). The perspectives presented in this paper are grounded in our systematic review of 291 studies, distilled from 3,305 publications (see the Electronic Supplementary Material for details. The Electronic Supplementary Material (ESM) is available in the online version of this article.).

2 Towards unified building modeling standards

2.1 Data standards

In building studies, the Industry Foundation Classes (IFC) provides the primary standard for Building Information Modeling, offering high-fidelity semantic details for the lifecycle management of individual buildings (Li et al. 2024). Conversely, in urban studies, the City Geography Markup Language serves as the open data model for the storage and exchange of virtual 3D city objects, focusing on the geographic and topological relationships within the broader city landscape.

2.2 Current limitations of building modeling standard

The integration of urban and building studies is currently hindered by divergent modeling standards. Our systematic review of 291 studies reveals an ontological mismatch: CityGML treats buildings as spatial shells with limited semantic depth, while IFC focuses on internal components without a unified geographic coordinate system. This leads to data fragmentation where building function is defined through fundamentally different frameworks; urban studies rely on land-use classifications integrating Points of Interest, zoning codes, and socio-economic indicators to characterize function at the city scale, whereas building studies employ room-level functional typologies derived from spatial programming and occupancy schedules that capture internal organization in detail. Consequently, there is no standardized protocol for translating the high-fidelity details of a building model into the macroscopic data structures required for city-wide simulation.

2.3 Towards AI-driven semantic integration of building models

Achieving semantic interoperability between building and urban modeling frameworks represents the single most critical prerequisite for building-scale urban analytics. The fundamental barrier to cross-domain research is not the absence of data, but the lack of a shared ontological foundation. Integrating definitions of buildings from building engineering (e.g., IFC) and urban science (e.g., CityGML) demands more than a shared file format; it requires a common semantic ontology that maps concepts across disciplines. Future efforts should employ AI-driven ontology matching and automated semantic mapping to reconcile divergent attribute definitions, coordinate reference systems, and levels of detail. Such integration would enable, for

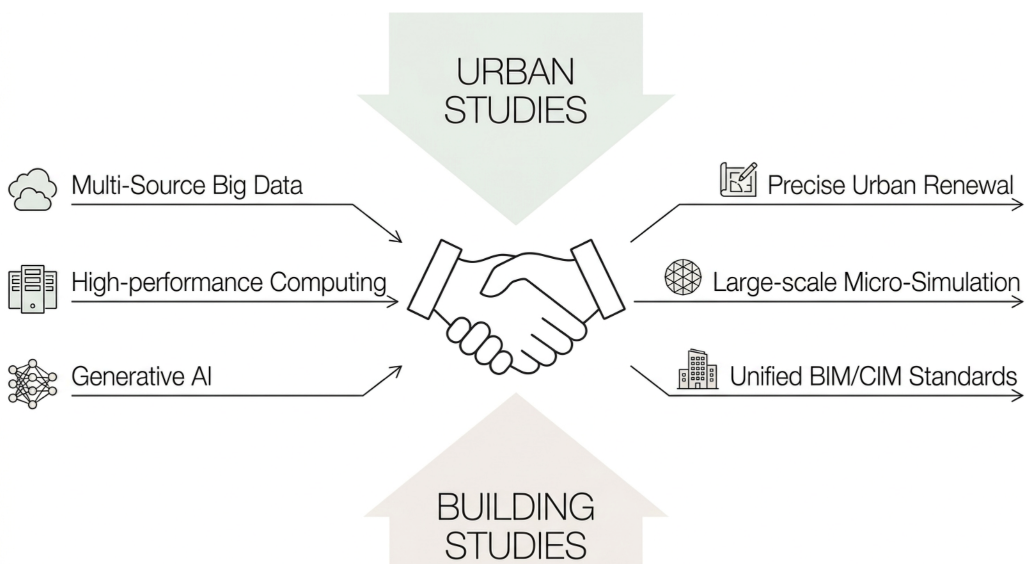

Fig. 1 Intersection of building and urban studies

example, the automatic translation of an IFC model's detailed room-level thermal properties into CityGML-compatible attributes suitable for district energy simulation. This semantic unification is the prerequisite upon which the data construction efforts discussed in Section 3 depend: without agreed-upon standards for what building attributes mean across scales, even the most comprehensive datasets remain siloed.

3 Construction of building datasets

3.1 Trends in building data construction

In building studies, data construction historically relies on high-fidelity, site-specific methodologies including engineering surveys, on-site measurements, and the aggregation of administrative records such as building permits, utility consumption data, census housing records, and local historical building codes. The field has increasingly transitioned toward digital twins through Terrestrial Laser Scanning and Scan-to-BIM workflows that transform physical structures into semantically rich digital assets, though these methods remain labor-intensive and difficult to scale across entire cities.

In contrast, urban studies focus on scalability through active and passive sensing. Aerial photogrammetry, drone-based LiDAR, and fused multi-source datasets such as optical imagery with radar backscatter enable machine learning and deep learning models to predict building footprints and heights over vast areas with increasing accuracy. In data-sparse regions, geostatistical methods like Kriging are employed to estimate missing attributes by analyzing the spatial continuity of the built environment.

3.2 Current limitations in data coverage and resolution

Significant imbalances in spatiotemporal resolution and coverage hinder both macro-scale regeneration and micro-scale transformation. For urban studies, the primary deficiency lies in the absence of vector-based longitudinal data and deep semantic attributes necessary for tracking city evolution. While global building footprints are expanding, essential indicators such as precise construction age, occupancy status, and renovation history remain scarce in large-scale datasets, preventing accurate capture of stock dynamics like demolition or retrofit rates.

For building physics studies, existing urban datasets often lack the geometric fidelity and physical parameters required for high-precision simulation. Performance models depend on detailed indoor structures and precise material properties that are typically absent from city-scale products. Most open-source building data provide only Level of Detail (LOD) 1 (extruded footprints with flat roofs) or LOD 2 (simplified roof structures) representations, while LOD 3 (detailed architectural features including windows and doors) and LOD 4 (full interior structures) remain largely unavailable at the urban scale. This results in data islands where engineering-grade information is too localized for city-wide application, while global datasets are too coarse for building performance evaluation.

3.3 Building an AI-driven foundation for global coverage

The most urgent research priority for building data construction is the development of an AI-driven data foundation that transcends the constraints of direct sensing. Next-generation models should utilize multi-modal generative intelligence to infer latent building attributes from environmental context. By evaluating spatial relationships between a building, its neighborhood morphology, and historical urban textures, machine learning and deep learning models can predict variables that are traditionally difficult to acquire, such as vacancy status, construction age, or specific socio-economic functions. Furthermore, generative modeling provides a robust methodology for spatiotemporal reconstruction, synthesizing missing historical information rather than relying on static snapshots. A particularly promising direction is the use of generative AI foundation models pre-trained on diverse urban imagery to enable zero-shot or few-shot inference of building attributes in data-sparse regions, dramatically reducing the cost of global-scale data construction. Such reasoning-based approaches enable a truly comprehensive digital foundation that reflects the complex rules of urban growth and decay, providing the essential input layer upon which all subsequent diagnostic and simulation efforts depend. With such a comprehensive data foundation in place, the critical next step is to develop diagnostic frameworks capable of interpreting these data, the subject of Section 4.

4 Diagnosing building quality and efficacy

While Section 3 addresses the construction of spatiotemporally complete building datasets, this section turns to how these data are interpreted and evaluated. Building quality and efficacy are higher-order diagnostic attributes that cannot be directly sensed but must be inferred through analytical frameworks combining physical, social, and functional indicators.

4.1 Scope of building quality and efficacy

Building quality is a multidimensional concept comprising physical quality (structural integrity and material maintenance), construction quality (workmanship standards), perceptual quality (user satisfaction), and functional quality (suitability for intended use) (Zhong et al. 2019). Building efficacy focuses on the dynamic utilization state of the built environment and encompasses three critical dimensions: vacancy, representing absolute idling where buildings remain entirely unoccupied; inefficiency, where actual usage intensity falls significantly below designed carrying capacity; and functional mismatch, denoting the misalignment between original design intent and current operational reality (Li and Long 2024). Diagnosing these attributes is essential for precise urban regeneration and evidence-based governance.

4.2 Limitations of current diagnostic approaches

Current assessment methodologies suffer from confused conceptual definitions and inconsistent metrics. Building quality is frequently conflated with narrow building design aesthetics or technical performance indicators, leading to a neglect of long term structural and management health. Distinguishing between building performance and building quality is fundamental to refined urban regeneration. Building performance involves quantifiable physical indicators such as thermal energy consumption, ventilation, and structural performance, which are typically treated as independent metrics. Furthermore, building efficacy lacks clear formal definitions and sufficient empirical research. This deficiency is often due to the difficulty of obtaining high resolution internal usage data, such as electricity or water consumption, at the individual building level to validate occupancy and functional utility.

4.3 Towards AI-driven diagnosis

The most critical frontier in building quality and efficacy diagnosis lies in the development of AI-driven, multi-modal assessment frameworks that fundamentally transform how buildings are evaluated. Future systems should integrate multi-modal data fusion to overcome the limitations of single-source observations. AI models can execute physical appearance assessments by identifying material aging or structural cracks from remote sensing and street-view imagery. These visual assessments should be synthesized with social sensing data, such as mobile signaling patterns and resident complaint texts processed by large language models (a form of generative AI), to monitor occupancy dynamics and social performance in real time. Critically, future diagnostic systems must move beyond per-building evaluation toward urban-scale comparative diagnosis, benchmarking individual buildings against neighborhood and city-wide baselines to identify relative underperformance. This multi-modal, multi-scale approach facilitates a paradigm shift from static physical checks to dynamic socio-technical evaluations, enabling continuous building health monitoring that supports proactive rather than reactive urban regeneration strategies. These diagnostic insights, in turn, provide the essential input for the next frontier: building-scale urban simulation that can project how interventions reshape urban form over time.

5 AI-driven bottom-up simulation

5.1 Evolution of urban simulation

Urban simulation is undergoing a significant transition from macroscopic spatial interaction models, such as gravity models, toward microscopic agent-based modeling. Traditional macroscopic approaches often overlook the granular dynamics of individual entities, whereas agent-based modeling provides a framework to capture the heterogeneous behaviors of urban actors. The rapid development of AI, spanning traditional machine learning, generative AI, and agentic AI, provides the necessary tools to enhance both the behavioral fidelity and computational efficiency of these simulations (Liu et al. 2025), allowing for the representation of complex urban systems at the individual building level. The emergence of urban building energy modeling (Yan et al. 2025) exemplifies this trend of scaling building-level analysis to the urban scale.

5.2 Limitations of current simulation approaches

Despite these advances, current building-scale urban simulations face several critical limitations. Most agent-based models rely on simplified behavioral rules and fixed utility functions that cannot represent the complex reasoning underlying real-world decisions about building development and adaptation. Geometric modeling through shape grammar and socio-economic simulation typically operates as separate, loosely coupled modules, preventing coherent representation of how physical form and human activity co-evolve. Furthermore, existing urban building energy models remain largely static, capturing performance at discrete time points without modeling the morphological and functional transitions that reshape demand patterns over decades. These fragmented approaches, while technically sophisticated in individual components, fail to capture the emergent dynamics arising from the continuous interaction between micro-scale building changes and macro-scale urban spatial restructuring.

5.3 Next generation of building-scale simulation

The most transformative prospect for building-scale simulation lies in the deep integration of geometric evolution logic with interdisciplinary semantic reasoning. This represents the central challenge and opportunity for the field. Shape grammar must transcend preset design rules in this paradigm, evolving into a dynamic generation engine that fuses multi-dimensional knowledge, including building evolution patterns, urban planning expertise, and human behavioral logic (Yin et al. 2024; Burke et al. 2025). When this geometric engine is combined with cognitive bottom-up agents, large language model-based agents (agentic AI) can perform complex logical reasoning by synthesizing environmental context, socio-economic incentives, and physical constraints. This enables agents to drive specific morphological transformations such as building expansion or functional adaptation through a reasoning-based process rather than fixed utility functions. Crucially, this closed-loop framework, where data-driven graph networks manage spatial interactions while agents make decisions based on integrated knowledge, provides a high-fidelity pathway for understanding how building transformations self-organize into macro-scale urban spatial patterns (Figure 2). Advancing this AI-driven, bottom-up simulation paradigm is essential for moving urban prognosis from extrapolation of historical trends toward genuine scenario reasoning under novel conditions.

6 Conclusions

This perspective calls for urban studies to embrace the building scale as its essential frontier for achieving fine-grained urban governance and sustainable management of existing building stocks. We identify four critical and interrelated actions that the research community should undertake. First, we call for a unified modeling standard to bridge the semantic gap between building engineering and urban science, enabling seamless data interoperability across scales and disciplines. Second, comprehensive building datasets with full spatiotemporal coverage should be constructed through AI-driven data foundations that transcend the constraints of direct sensing. Third, AI-driven assessment frameworks should be developed to diagnose building quality and efficacy through multi-modal data fusion, shifting from static physical examinations to dynamic, continuous socio-technical evaluations that directly inform urban regeneration strategies. Fourth, a new generation of bottom-up simulation should be advanced, integrating large language model agents with generative morphological rules to model complex building-level transformations and their emergent urban-scale consequences. Together, these four pillars provide a transformative framework for urban prognosis at building-level resolution, offering the high-fidelity insights necessary for creating resilient and sustainable human settlements.

Electronic Supplementary Material (ESM): The Electronic Supplementary Material contains the complete systematic literature review, including: review methodology and framework (Figure S1 in the ESM), research classification system (Table S1 in the ESM), temporal distribution analysis (Figure S3 in the ESM), building attribute definitions (Figure S4 in the ESM), data sources and datasets (Tables S2–S6 in

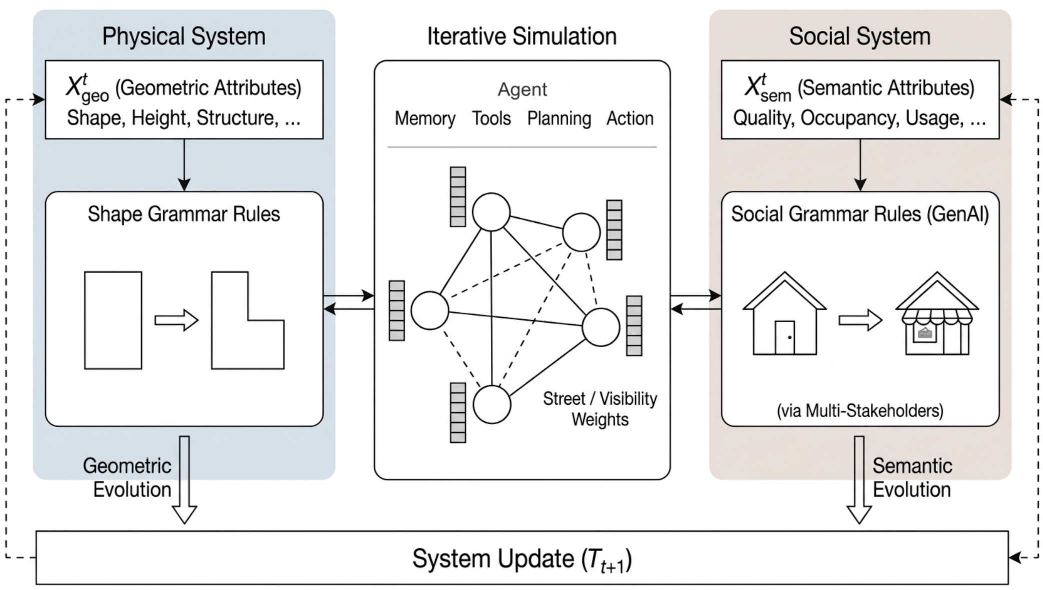

Fig. 2 AI-driven building-scale urban simulation based on agents and graphs

the ESM), and methodological landscape (Figure S5 in the ESM). The ESM is available in the online version of this article at 10.1007/s12273-026-1461-9.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval

This study does not contain any studies with human or animal subjects performed by any of the authors.

Author contribution statement

Yecheng Zhang: writing—original draft, visualization, investigation, formal analysis. Ying Long: funding acquisition, project administration, writing—review & editing

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Electronic Supplementary Material for

Towards building-scale urban analytics and simulation

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This supplementary material accompanies the perspective article and provides the complete systematic literature review underpinning the main text, including review methodology, analytical framework, temporal and thematic analysis of 291 studies (2010–2026, Updated to 29 March 2026), building attribute definitions, data sources, methodological landscape, and conceptual frameworks.

S1 Introduction

Under multi-source risk disturbances, refined urban governance requires research to be more practical, prioritizing precise diagnosis in urban physical examination and resilience enhancement in urban regeneration (Qin et al. 2025; Wang et al. 2024a). However, the majority of urban studies have traditionally focused on macro scales, such as the city, grid, block, or street levels (Liu et al. 2025; Shi et al. 2024; Che et al. 2024). In urban systems, buildings serve as the basic units that represent both physical and social attributes, including geometric form, spatial distribution, function, and quality (Zhu et al. 2025; Gong et al. 2025; Alabi et al. 2025). Consequently, the need for building-scale urban studies has increased due to their critical role in understanding ownership patterns and human interactions, particularly during development and redevelopment processes (Iarkov et al. 2025; Ruokamo et al. 2024).

As a new paradigm of urban studies, Building-Scale Urban Analytics and Simulation (BSAS) needs to be introduced into urban governance to address the practical need for refined spatial management. Drawing on related research (Yap et al. 2025; Burke et al. 2025; Xie et al. 2025), this study defines BSAS as a domain that takes buildings as the basic unit to characterize urban problems by modeling their geometric and semantic attributes. By integrating building details with advanced urban models, BSAS aims to bridge the gap between static examination and dynamic simulation. Specifically, this methodology operates through two key modules: the urban analytics module creates a detailed profile of urban micro-spaces to guide urban physical examination, while the urban simulation module provides dynamic strategies for enhancing resilience in urban regeneration.

Conceptually, the proposed BSAS functions as a critical component of the City Intelligence Model (CIM) by extending intelligent governance to the building level. However, it is essential to distinguish this paradigm from existing approaches to clarify its unique position. First, unlike City Geography Markup Language (CityGML), which primarily serves as a standardized data format for 3D geospatial modeling and often lacks mechanisms for active urban problem diagnosis (Li and

Zeng 2024; Florio et al. 2025), BSAS explicitly focuses on the interplay between building attributes and urban issues. Second, distinct from Building Information Modeling (BIM) and its underlying Industry Foundation Classes (IFC) standard, BSAS adopts a macroscopic perspective. While BIM and IFC prioritize high-fidelity semantic details for the lifecycle management of individual buildings (Jahangir et al. 2025), BSAS analyzes buildings as interconnected nodes within broader urban systems. Finally, BSAS extends beyond Building Performance Simulation (BPS). Whereas BPS acts as a specialized analytical domain within the BIM ecosystem to evaluate physical environmental performance (Yan et al. 2025; Badmus and Sutley 2025), BSAS targets the sociotechnical objectives of urban governance and spatial resilience.

Recently, advancements in remote sensing and computational capabilities have significantly enhanced the feasibility of building-scale urban analysis and simulation Li et al. 2025a; Huo et al. 2025; Cao and Weng 2024). Consequently, this study aims to systematically synthesize this emerging trend through a systematic review. Specifically, it defines the concept of BSAS and analyzes related studies across four dimensions: attribute definition, dataset extraction, research types, and research methods. Furthermore, this study identifies the importance, research gaps, and key scientific problems in the field, ultimately constructing the comprehensive framework for Building-Scale Urban Analytics and Simulation.

S2 Literature review

S2.1 Review Methodology and Framework

Protocol Definition. This study employs a Systematic Literature Review (SLR) to synthesize relevant literature. It is particularly effective for interdisciplinary topics such as 'building-scale analytics and simulation,' where the knowledge base remains fragmented despite a proliferation of publications.

Data Retrieval. To ensure comprehensive coverage, the Web of Science (WoS) Core Collection was selected as primary databases (Fig. S1). The search strategy employed 'Topic Search' (TS) for WoS. Guided by the preliminary scope, search queries utilized Boolean logic to combine terms related to the research subject, attributes, dynamic processes, and analytical methods. After removing duplicates, the initial identification yielded 3,305 records from WoS.

Selection Process. To ensure relevance and quality, rigorous eligibility criteria were established: (a) peer-reviewed journal articles; (b) accessible full texts; (c) publications in English; (d) subject areas limited to architecture, planning, geography, remote sensing, and GIS; and (e) publication dates between 2010 and 2025. The screening proceeded in three distinct stages following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow (Fig. S1). First, filtering by inclusion criteria reduced the initial pool to 771 (WoS). Second, a content screening of titles and abstracts excluded irrelevant studies, narrowing the selection to 414. These studies were systematically cataloged based on metadata to support the subsequent review.

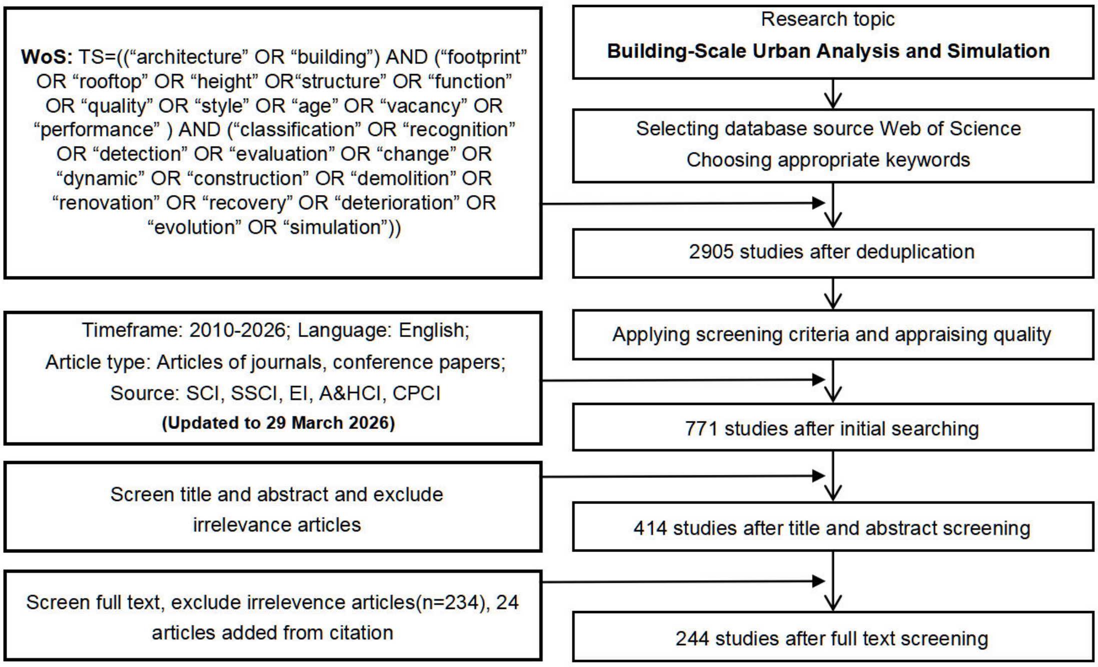


Fig. S1. *The process of systematic review.*

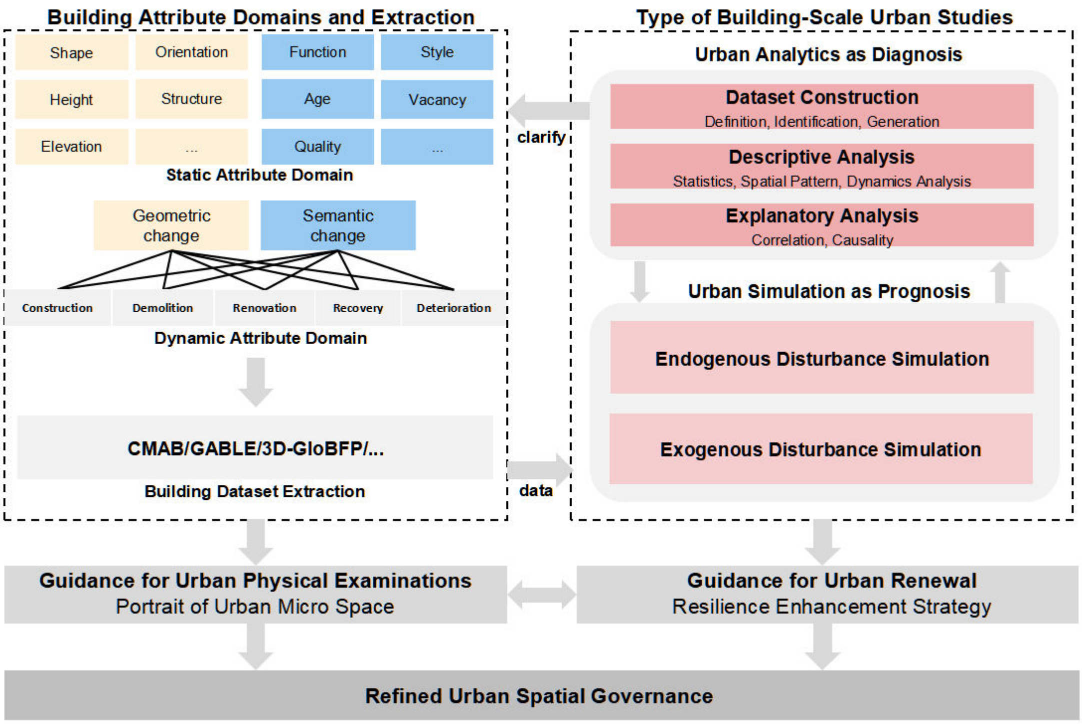


Fig. S2. *The framework of building-scale urban analytics and simulation.*

Framework Development. The analytical framework guiding this review (Fig. S2) was developed through an iterative process. Initially grounded in core definitions from the introduction, the classification evolved through systematic synthesis to distinguish Urban Analytics as Problem Diagnosis (focusing on attribute extraction) from Urban Simulation as Development Deduction (focusing on disturbance modeling). This conceptual evolution culminated in the comprehensive structure presented in Fig. S2

Central to this framework is a building ontology that bifurcates attributes into static and dynamic categories. Static attributes describe a building's state at a specific snapshot, encompassing geometric data and semantic details such as function, age, and quality metrics. In contrast, dynamic attributes capture changing states across spatiotemporal scales, covering lifecycle events like construction, renovation, and demolition. Notably, studies strictly focused on Building Performance Simulation (BPS) were excluded. Despite their frequency in the initial retrieval, BPS studies address micro-environmental physics rather than the macro-scale governance patterns central to this review.

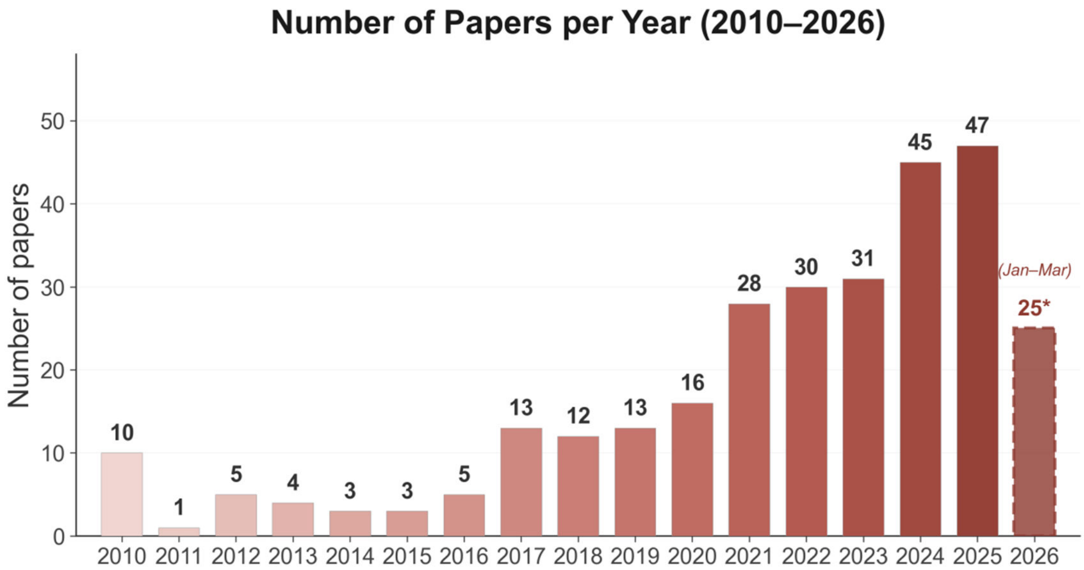
Based on this framework, we constructed a hierarchical classification system (Table S1) comprising two core domains. Building-Scale Urban Analytics characterizes existing building stocks through sub-categories of dataset construction, descriptive analysis, and explanatory analysis. Building-Scale Urban Simulation models future scenarios by distinguishing between simulations of endogenous and exogenous disturbances. Mapping methodologies to these categories reveals a distinct technical landscape: deep learning dominates attribute identification, spatial analysis underpins descriptive studies, and agent-based modeling drives the simulation of complex urban dynamics.

Table S1. *Research type, description, methods and typical studies in building-scale urban studies*

Research Type I	Research Type II	Research Type III	Description	Methods	Studies
Building-scale Urban analytics	**Attribute Extraction**	**Definition**	Defining metrics for attributes like building function, age, style, quality, performance, vacancy.	Literature review	(Zhang et al. 2025b)
		Identification	Using multi-source data (remote sensing, street view, etc.) to extract or predict building footprints, height, age, function, and style.	Deep Learning (CNN, U-Net), Machine Learning (Random Forest, SVM),	(Dionelis et al. 2025; Chen et al. 2025; Gong et al. 2025)
		Generation	Rule constraint driven or AI driven generation of building geometry and semantic attributes.	Generative Artificial Intelligence, Genetic Algorithm, etc.	(Ikeno et al. 2021; Bittner et al. 2018)
	Descriptive Analysis	**Statistics**	Compiling descriptive statistics of building attributes at various scales.	Spatial Autocorrelation (Moran's I, LISA), Kernel Density Estimation, Geographically Weighted Regression.	(Iarkov et al. 2025; Huuhka and Lahdensivu 2016)
		Spatial Pattern	Identifying geographic concentrations and distributions of building characteristics.		(Du et al. 2024; Lin et al. 2021)
		Dynamics Analysis	Monitoring building lifecycle events like demolition, renovation and post-disaster recovery over time.	Econometric Models (Regression, Panel Data), Structural Equation Modeling (SEM), Qualitative Comparative Analysis (QCA).	(Yang 2024; Liu et al. 2024; Coccossis et al. 2021)
	Explanatory Analysis		Uncovering the relationships between building stock characteristics and socio-economic/policy factors, and identifying the driving forces of building stock evolution.		(Marmolejo et al. 2024; Klika et al. 2025; Chen et al. 2023a)
Building-scale Urban simulation	**Endogenous Disturbance Simulation**		Refers to changes and fluctuations arising from internal interactions and agent agency within the urban system. This includes both top-down macro-regulation (government) and bottom-up socio-economic activities (residents, firms).	Agent Based Modeling, System Dynamics, Cellular Automata.	(Burke et al. 2025; Yin et al. 2024)
	Exogenous Disturbance Simulation		Refers to impacts (e.g., natural hazards, physical abrupt changes) originating outside the urban socio-economic system that urban entities cannot inherently mitigate or directly control.	Spatial Analysis, Physics-Based modeling, Explainable Machine Learning.	(Wang and van de Lindt 2021; Qin et al. 2025; Nie et al. 2024; Guo et al. 2025; Cao et al. 2021; Liu et al. 2020)

S2.2 Temporal Distribution and Research Focus

The temporal analysis based on the Web of Science (WoS) dataset reveals a robust upward trajectory in building-scale urban analytics and simulation over the past fifteen years. Fueled by the increasing availability of open data and advancements in computational power, research volume has surged recently. Notably, the last five years alone account for 65.2% of the cumulative publications (Fig. S3a). Regarding the specific research focus, the international literature demonstrates a distinct prioritization of foundational data capabilities. As illustrated in the category distribution (Fig. S3b), Dataset Construction constitutes a substantial proportion of the research volume (131 papers), significantly outweighing other categories. This trend suggests that the global research community currently prioritizes establishing robust data infrastructures, viewing them as the essential prerequisite for subsequent descriptive profiling and complex simulations.



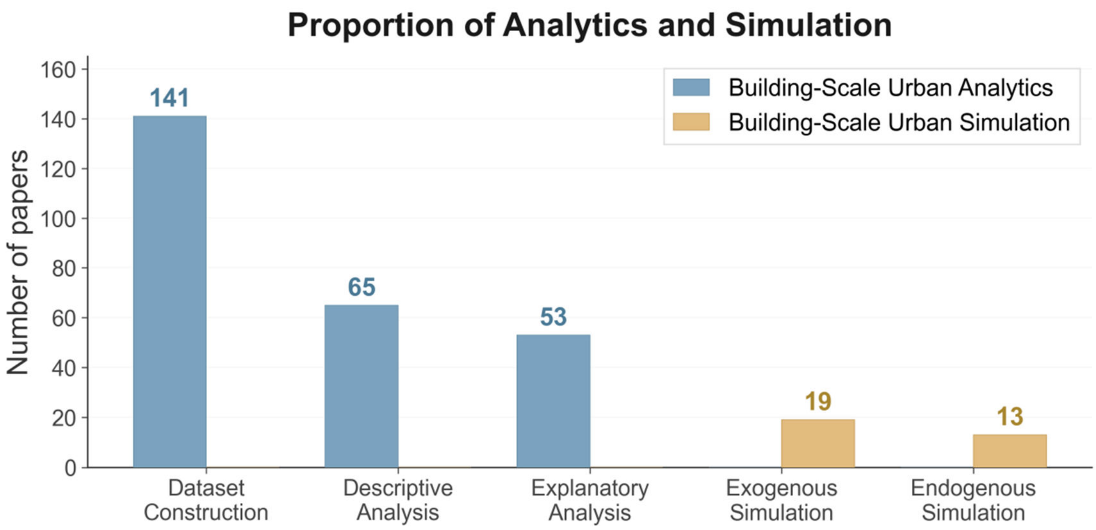


Fig. S3. *Temporal distribution and structural characteristics of building-scale urban studies (2010 –2025). (a) Annual publication volume in WoS; (b) Distribution of research categories.*

S2.3 Research Types of Building-Scale Urban Analytics and Simulation

Based on the extensive review of 291 studies, building-scale urban studies emerges as a rapidly developing field. However, research efforts often remain isolated, lacking a coherent structural organization. To synthesize these findings, this review proposes a hierarchical classification framework (Table S1) and quantifies the field's focus. At the primary level (Research Type I), the research landscape presents a significant structural imbalance. Urban Analytics occupies an absolutely dominant position, accounting for 89% (259 papers) of the total studies. This indicates that the vast majority of work concentrates on understanding, quantifying, and explaining the state of the urban building stock. In contrast, Urban Simulation, which focuses on modeling the lifecycle dynamics in response to disturbances, remains a marginal domain, accounting for a mere 11% (32 papers). This disparity reflects the current status of urban governance where the field prioritizes filling the gap in urban physical examination, while the development of decision support tools for urban regeneration is in its early stages.

Within the dominant Urban Analytics category, the research paradigms (Research Type II) demonstrate a clear progressive logic, starting with Dataset Construction as the foundation. Ideally, this involves the Definition of metrics for attributes like quality or vacancy (Dionelis et al. 2025), followed by Identification, utilizing multi-source data to extract attributes like height and function (Gong et al. 2025; Li et al. 2025b; Wang et al. 2024b). Notably, Generation is also integral to this phase, where computational methods like GANs are employed to synthesize new urban forms or fill data gaps based on learned rules (Sun et al. 2022). In this framework, generative AI serves primarily as a method for data synthesis and completion. Following dataset construction, Descriptive Analysis aims to reveal spatial distributions and temporal evolution, encompassing inquiries into Spatial Patterns, statistical summaries, and Dynamics Analysis such as detecting past demolition or renovation events (Yang 2024). Finally, studies conducting Explanatory Analysis focus on Correlation and are dedicated to revealing the causal mechanisms between building attributes and socio-economic influencing factors (Klika et al. 2025).

The Urban Simulation domain (Research Type II) is strictly defined by its focus on dynamic responses to disturbances, comprising two distinct directions. The first is Exogenous Disturbance Simulation, which assesses the impact of external forces. This includes research on Chronic Stresses, such as simulating the influence of morphology on heat islands (Guo et al. 2025), and Acute Shocks, such as modeling vulnerability to earthquakes or floods (Wang and van de Lindt 2021). The second direction is Endogenous Disturbance Simulation, which models internal socio-economic lifecycle dynamics. This typically adopts either a Top-down perspective to evaluate renewal strategies (Burke et al. 2025) or a Bottom-up micro-approach using agents to model complex decision-making behaviors (Yin et al. 2024).

S2.4 Definition of Building Attributes

All reviewed literature involves one or more building attributes, which serve as the fundamental units for this examination. Systematizing these concepts and categories is the first step in constructing an indicator system for urban diagnosis (Fig. S4), facilitating a comprehensive understanding of urban space at the building scale and laying the foundation for identification, evolution analysis, and problem response.

Building attributes can be categorized into two main types: static and dynamic. These represent distinct yet interconnected aspects of urban form and function (Fig. S4). Static Attributes describe the state of a building or building stock at a specific point in time. These attributes are typically the focus of data extraction, identification, and cross-sectional analysis. They include geometric attributes (e.g., shape, size, height), semantic attributes (e.g., function, age, quality, style).

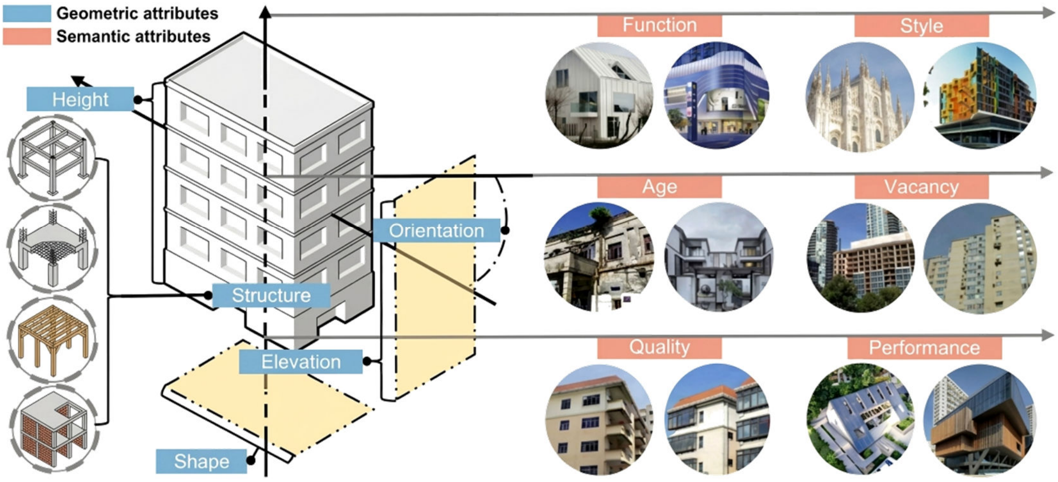


Fig. S4 *Visualization of building attributes.*

The quantitative review of the literature reveals significant disparities in the research focus on these static attributes within the field of urban analytics (Table S2). Geometric attributes are the most frequently studied category overall. Accounting for 30.8% of the literature, this category covers morphological indicators such as building footprint, height, volume, and floor area ratio (Guo et al. 2025; Liu et al. 2021; Chen et al. 2024). Building function follows at 17.3%, serving as a core element for understanding urban activities (Gong et al. 2025; Li et al. 2025b; Zheng et al. 2024). Building style (15.8%) and building quality (14.0%) are also prominent. These two categories typically constitute the assessment of the physical and aesthetic condition of buildings (Youns and Grchev 2024; Ma et al. 2026; Liang et al. 2023). Building performance (9.6%) and building age (8.8%) represent significant but slightly smaller portions of the research (Egerlid et al. 2025; Dionelis et al. 2025; Nachtigall et al. 2023). In contrast, specific semantic attributes such as building price and vacancy (3.4%) currently receive relatively little attention (Klika et al. 2025; Li and Long 2024).

Conversely, Dynamic Attributes involve processes that alter the state or stock of buildings over time. This review identifies five primary dynamic processes. An analysis of the literature (Table S3) indicates an equally uneven distribution of research on these dynamics. The most prevalent category is Deterioration (45.4%), a term often used broadly to denote long-term gradual transformations or the aging and degradation processes of buildings (Yang 2024; Zheng et al. 2021). Renovation is the second largest theme (28.9%), typically driven by energy efficiency and adaptive reuse goals, referring to significant alterations where the basic structure remains intact (Iarkov et al. 2025; Lim et al. 2025; Beneito et al. 2024). Next is Recovery (11.2%), which refers to repair or reconstruction activities following destructive events such as disasters (Stevenson et al. 2010; Wang and van de Lindt 2021; Opabola and Galasso 2024). Construction (7.9%) and Demolition (6.6%), as the fundamental processes of inflow and outflow in building stock, have received relatively less attention (Zhuo et al. 2024; Huuhka and Lahdensivu 2016). Understanding the interaction between static attributes (e.g., how age or quality influences renovation decisions) and these dynamic processes is vital for simulating and predicting the future trajectory of urban building stock.

Table S2. Specific Categories and Count of Building Static Attributes. The number of studies involving this attribute is in parentheses.

Domain	Attribute Type	Specific Classes
Geometry (93)	**Building Scale (168)**	Area, Building Height, Building Volume
	Building Morphology (157)	Orientation, Roof Type, Compactness, Surface Area
	Building Density (105)	Building Coverage, Floor Area Ratio, Frontal Area Index
Semantics (199)	**Building Function (50)**	Residential, Commercial, Office, Industrial, Public Services, Transport, Mixed-use, etc.
	Building Style (47)	Modernist, Classical, Gothic, Brutalist, Art Deco, International Style, Vernacular, Parametricism, etc.
	Building Quality (42)	Physical: Cracks, subsidence, material aging; Design: Aesthetics, layout, stylistic coordination; Functional: Adaptability, accessibility; Construction: Workmanship, compliance; Management: Maintenance status; Perceived: Visual quality
	Building Performance (29)	Thermal, Ventilation, Optical/Lighting, Acoustic, Structural Performance
	Building Age (27)	Specific Construction Year, Construction Era (e.g., 1980s), Historical Period (e.g., Pre-war)
	Building Occupancy (7)	Housing Vacancy, Office Vacancy

Table S3. Specific Categories and Count of Building Dynamic Attributes

Attribute Type	Description	Typical Literature
Deterioration (41)	Represents the long-term process of building aging/deterioration. Such research typically focuses on the building's lifecycle rather than state changes at a specific moment.	(Yang 2024; Zheng et al. 2021)
Renovation (24)	Typically driven by goals of energy efficiency and adaptive reuse; refers to major retrofitting or alterations carried out while maintaining the basic structural integrity.	(Iarkov et al. 2025; Lim et al. 2025; Beneito et al. 2024)

Recovery (11)	Repair or reconstruction activities conducted following disruptive events such as disasters.	(Stevenson et al. 2010; Wang and van de Lindt 2021; Opabola and Galasso 2024)
Construction (7)	The fundamental process of inflow into the building stock.	(Zhuo et al. 2024)
Demolition (6)	The fundamental process of outflow from the building stock.	(Huuhka and Lahdensivu 2016)

Among these attributes, it is necessary to clarify the distinction between "Building Quality" and "Building Performance." As shown in Table S2, Performance (accounting for 9.6%) typically refers to quantifiable physical indicators, such as thermal/energy consumption, ventilation, optical, or structural performance, which are treated as relatively independent in urban-scale research. In contrast, Quality (14.0%) is a multidimensional concept that must be clearly distinguished from building performance and address the common confusion with "design quality" (Ma et al. 2026; Barreca 2022). A rigorous definition comprises several discrete aspects. Among them, physical quality is the most frequently analyzed type, involving material robustness, structural integrity (e.g., cracks), and maintenance levels (Lodge et al. 2023; Mydin et al. 2014). Next is construction quality, which reflects workmanship standards during the building process (Chen et al. 2025), and perceived quality, which represents user subjective evaluation and satisfaction (Sulaiman et al. 2012; Bacevice and Ducao 2022). Other important but currently less studied aspects include functional quality, which assesses a building's suitability for its intended use (Liang et al. 2023; Baglio et al. 2020), and management quality, covering facility operations and compliance (Zalejska-Jonsson 2020).

S2.5 Existing Research Paradigms for Building Attribute Extraction

With the rise of machine learning and multi-source big data, a surge of data-driven research has emerged in the field, embodying an implicit "cognition" or understanding of building attributes. This cognition is reflected not only in the inference of static attributes, such as geometric morphology (e.g., height, Chen et al. 2024; Li et al. 2020), function (Gong et al. 2025; Li et al. 2025b), age (Dionelis et al. 2025; Nachtigall et al. 2023), and style (Cantemir and Kandemir 2024), but also in assessments of building quality and vacancy status (Ma et al. 2026; Lodge et al. 2023). Equally, this understanding extends to the modeling and prediction of dynamic attributes, including renovation (Iarkov et al. 2025; Lim et al. 2025), demolition (Huuhka and Lahdensivu 2016; Rashidian et al. 2021), construction (Zhuo et al. 2024), and post-disaster recovery (Stevenson et al. 2010; Wang and van de Lindt 2021).

Fundamentally, this relies on specific inference logic using proxy indicators. In static inference, for instance, the shadow length of a building in optical imagery, combined with the solar elevation angle, serves as the physical basis for estimating height (Sun et al. 2019; Kadhim and Mourshed 2018). The composition of Points of Interest (POI) surrounding a building—such as the density of restaurants and shops—is used as a core semantic clue to identify commercial functions (Qin et al. 2025; Wang et al. 2021a). Spatiotemporal activity patterns derived from mobile signaling or taxi trajectories (e.g., day-night differences) are employed to distinguish between office and residential functions (Nie et al. 2022). Furthermore, facade styles in street view images and the morphological patterns of building textures serve as effective proxies for inferring construction age (Dionelis et al. 2025; Nachtigall et al. 2023; Benz et al. 2023), while deep learning models are trained to identify visual cues such as broken windows and overgrown vegetation to assess building quality or vacancy status (Zou and Wang 2021; Li and Long 2024; Lodge et al. 2023).

In dynamic modeling, this cognition manifests as a predictive logic. For example, renovation decisions are largely viewed as a function of static attributes, such as high age, specific function, or low energy efficiency (Iarkov et al. 2025; Beneito et al. 2024). Demolition events can be directly detected via the signal of a "building" transitioning to "non-building" in multi-temporal remote sensing imagery (Rashidian et al. 2021). In post-disaster scenarios, the volume of building permits issued (Stevenson et al. 2010) or the appearance of blue tarpaulins in aerial imagery (Gonsoroski et al. 2023) serve as key proxy indicators to quantify the progress and speed of recovery.

Table S4 systematically summarizes the common data sources, key methodologies, and proxy indicators used in the literature to infer or model these two types of attributes (static and dynamic).

Table S4. Proxy Indicator System for Building Attribute Extraction

Category	Attribute Type	Proxy Indicators	Typical Literature
Static Attributes	Geometry	Shadow length in remote sensing vs. solar elevation angle; Repetitive patterns of windows and floors in street view imagery.	(Sun et al. 2019; Yan and Huang 2022)
	Building Function	Category and density of POI/AOI; Spatiotemporal patterns of human activity; Visual features of facades (e.g., storefronts).	(Gong et al. 2025; Zheng et al. 2024)
	Building Age	Urban texture, block morphological layout; Architectural styles in street views; Temporal changes in remote sensing imagery.	(Dionelis et al. 2025; Zhuo et al. 2024)
	Building Style	Visual features such as texture, composition, and ornamentation of facades in images; Plan layout and spatial organization.	(Cantemir and Kandemir 2024; Xu et al. 2023)
	Quality / Vacancy	Wall cracks and damage in street views; Absence of night-time lights or low utility (water/electricity) consumption.	(Li and Long 2024; Lodge et al. 2023)
Dynamic Attributes	Renovation	Building age, function, energy consumption level, ownership; The decision to renovate or demolish is a trade-off between cost and benefit.	(Iarkov et al. 2025; Beneito 2024)
	Demolition	Signals of "building" changing to "non-building" on remote sensing imagery; Abandonment status of buildings in street views.	(Rashidian et al. 2021)
	Construction	Signals of "non-building" changing to "building" on remote sensing imagery.	(Zhuo et al. 2024; Huuhka and Kolkwitz 2021)
	Recovery	Issuance volume of building permits acts as a spatiotemporal proxy for recovery activities; Visual damage in post-disaster imagery (e.g., blue tarps).	(Wang and van de Lindt 2021)

	Deterioration	A function of building age and environmental exposure; Service life predicted based on material degradation curves and defect observations.	(Zheng et al. 2021)

The implementation of the aforementioned data-driven cognitive frameworks relies heavily on the availability of multi-source heterogeneous data. As summarized in Table S5, these data sources can be broadly classified into four categories: (1) Remote sensing data, which provides top-down physical observations—such as various optical images, LiDAR point clouds, SAR data, and nighttime lights—serving as the foundation for extracting height, morphology, and coverage (Chen et al. 2024; Wu et al. 2023); (2) Street view and image data, which offers a human-centric perspective of facades—including commercial street view imagery (SVI), crowdsourced imagery (MSI), and UAV imagery—crucial for identifying style, quality, and function (e.g., storefronts) (Zou and Wang 2021; Li et al. 2025b); (3) Social sensing and activity data, which reflects the socio-economic functions of buildings—primarily comprising Points of Interest (POI), mobile signaling, and LBS trajectory data—serving as key inputs for inferring building function (Gong et al. 2025; Nie et al. 2022); (4) Administrative and survey data, which provides accurate but less accessible samples—such as government statistics, building permits, utility data, and field surveys (Stevenson et al. 2010; Nachtigall et al. 2023).

Table S5. Data Sources for Building Attribute Extraction

Data Source	Common Data	Temporal Resolution	Spatial Resolution	Acquisition Cost	Used for Attributes
Remote Sensing	Nighttime Light (NTL)(e.g., SDGSAT-1, JILIN-01)	Low (Monthly/Yearly)	10m ~ 0.94m (Grid)	High	Function, Vacancy
	High-res Imagery(e.g., Maxar)	Low (Yearly)	< 1m (Grid)	High	Height, Function, Age, Demolition, New Construction
	LiDAR / DSM(e.g., Airborne LiDAR, ALOS)	Low (Yearly)	> 1m (Grid)	High	Height, Morphology
Street View	Commercial SVI(e.g., Google, Baidu, Tencent)	Low (Yearly)	Building Facade	Medium	Style, Age, Function, Quality/Vacancy
	Crowdsourced / Mobile Sensing(e.g., Mapillary)	High (Customizable)	Building Facade	High	Quality, Vacancy
Social Media	Human Activity(e.g., Mobile Signaling, LBS, Trajectories)	High (Minute-level)	Base Station / Grid / Trajectory	High	Function
	Social Media Posts(e.g., Twitter, Weibo)	High (Real-time)	Point Location	Medium	Function, Perception
GIS Data	Crowdsourced VGI(e.g., OpenStreetMap, OSM)	Medium	Point / Line / Polygon	Low	Morphology, Height, Function

	POI/AOI (e.g., Amap/Gaode, Baidu)	Medium (Monthly)	Point / Polygon	Medium	Function
Admin. Data	e.g., Building Permits, Census, Utilities, Complaints	Low (Yearly)	Parcel / Building / Household	High	Age, Quality, Vacancy, Renovation, Demolition, Recovery
Surveys	Field Surveys / Questionnaires	High (Customizable)	Specific Building	High	Quality, Style, Comfort

Each data source possesses distinct advantages and limitations regarding temporal precision, spatial resolution, scalability, and acquisition cost; thus, research often necessitates the fusion of these sources to achieve a comprehensive characterization of building attributes.

S2.6 Typical Building Datasets

The dilemma of traditional governance lies in the lack of micro-level data. Building-scale urban studies aims to address this "data foundation" issue for fine-grained governance, a capability largely facilitated by the emergence of high-resolution, large-scale building datasets (Table S6). The development of these datasets (e.g., CMAB, GABLE) signifies that the infrastructure for constructing large-scale, building-level "urban physical examination" databases is gradually falling into place.

Regarding building footprint (2D) extraction, research primarily relies on remote sensing imagery and deep learning techniques (Li et al. 2024). With improvements in data precision and computing power, the spatiotemporal accuracy and coverage of building footprint data have significantly improved (Hui et al. 2019; Chen et al. 2023b). A landmark achievement in this trend is the emergence of large-scale open-source building footprint datasets. For instance, teams at Google (Sirko et al. 2021) and Microsoft used very high-resolution (VHR) imagery to release vector building footprint data covering continents or even the globe. Addressing gaps or insufficient accuracy in these global datasets for specific regions (e.g., East Asia), local scholars have utilized domestic high-resolution satellite imagery to publish high-precision national building datasets (Shi et al. 2024; Sun et al. 2024; Zhang et al. 2025b).

Beyond 2D footprints, acquiring building height to achieve 3D reconstruction is a current focus and challenge. Traditional methods rely on LiDAR point clouds or SAR data; while highly accurate, they entail high temporal and economic costs (Zhu et al. 2025). Consequently, a more scalable approach involves estimating height from multi-source Earth observation data using machine learning or deep learning. These methods rely on diverse "cognitive" logics, such as using building shadows in optical imagery (Kadhim and Mourshed 2018; Lee, Kim 2013), or fusing building footprints, urban morphology (e.g., block density), and multi-source remote sensing features to train models (Milojevic-Dupont et al. 2020; Chen et al. 2024; Wu et al. 2023). Some studies even explore estimating building floors from single street view images (Yan and Huang 2022; Li et al. 2023).

Advancements in these technologies have catalyzed a new generation of global 3D building datasets, which provide estimated building height and volume information alongside building footprints

(Zhang et al. 2025a; Zhu et al. 2025; Che et al. 2024; Papini et al. 2025). Going further, the latest datasets (e.g., CMAB, GHS-OBAT) are attempting to integrate remote sensing, street view, and crowd-sourced data to provide building datasets at national or even global scales that include multi-dimensional attributes such as height, function, age, and style (Zhang et al. 2025b; Florio et al. 2025), thereby advancing the depth and breadth of building-scale research.

Table S6. Existing Typical Building Datasets of the World and China

Dataset Name	Data Source	Spatiotemporal coverage	Method	Resolution	Attributes
Microsoft BRA	Bing Maps, N/A	Global (Excluding China), single year	DNN	Vector	Building Footprints
Google BRA (Sirko et al. 2021)	Google Maps, N/A	Global (Excluding China), single year	U-net	Vector	Building Footprints
3D-GloBFP (Che et al. 2024)	East Asian buildings, 2020	Global, single year	Machine Learning	Vector	Building Footprints & Height
GBA (Zhu et al. 2025)	PlanetScope, 2014-2021	Global, single year	Machine Learning	Vector	Building Footprints & Height
(Liu et al. 2021)	LUOJIA1-01, Population data, N/A	China, single year	Machine Learning	130m	Urban Floor Area
(Wu et al. 2023)	Sentinel 1-2, LUOJIA1-01, 2020	China, single year	Machine Learning	10m	Building Height
CBRA (Liu et al. 2023)	Sentinel 2, 2016-2021	China, 2016-2021	STSR-Seg	2.5m	Building Footprints
90-cities-BRA (Zhang et al. 2022)	Google Earth Satellite (GES), 2020	90 Cities in China, single year	Deeplab-V3	Vector	Building Footprints
East Asian buildings (Shi et al. 2024)	Google Earth Satellite (GES), 2022	China, Japan, R.O. Korea, D.P.R. Korea, Mongolia, single year	CLSM	Vector	Building Footprints
GABLE (Sun et al. 2024)	Beijing-3 satellite imagery, 2021	China, single year	RPN	Vector	Building Footprints & Height
Zhang et al. 2025	Landsat, Sentinel-1/2, etc., 1990-2019	China, 1990-2019	Machine Learning	30m	Building Height & Age
Papini et al. 2025	Sentinel-1/2, etc., 2018-2023	106 Cities in China, 2018-2023	Machine Learning	Vector	Building Footprints & Height
CMAB (Zhang et al. 2025)	Google Earth Satellite, 2022-2023	China	Ensemble Method	Vector	Footprints, Height, Function, Quality, Style, Structure, Age, etc.

However, despite the expanding volume and spatial coverage of these datasets, a critical gap remains in the availability of long-term, vector-based longitudinal data. Most existing large-scale datasets provide only a static snapshot of the built environment. Building age is predominantly inferred indirectly from other coarse remote sensing products (e.g., CMAB) rather than derived from continuous historical observation. While a few studies have attempted to capture temporal dynamics, they face significant limitations: for instance, Zhang et al. (2025) provide a long time series (1990-2019) but rely on coarse 30m raster data, losing the precision of individual building entities; conversely, while Papini et al. (2025) provide vector-based change detection, the scope is limited to a short timeframe (5 years) and partial geographic coverage (106 cities). Furthermore, with the exception of CMAB, the vast majority of current large-scale datasets (e.g., GBA, 3D-GloBFP) are limited to geometric extraction (footprint and height), lacking the rich semantic attributes necessary for deep historical analysis.

S2.7 Research Methodologies

The 291 reviewed studies employ a highly diverse range of methodologies, reflecting the interdisciplinary nature of this field. Before deepening the analysis, it is necessary to classify and define these methods. Qualitative Methods primarily refer to the use of case studies, interviews, literature reviews, and expert assessments for conceptual definition or decision analysis (Ma et al. 2026; Ruokamo et al. 2024). Deep Learning is almost exclusively used for the automatic extraction of features and recognition of attributes from unstructured data such as images, text, or point clouds (Gong et al. 2025; Xu et al. 2023). Statistics and Machine Learning (e.g., Random Forest, SVM) are employed to process structured data for regression prediction or explanatory analysis (Nachtigall et al. 2023; Klika et al. 2025). Spatial Analysis relies on GIS technology to investigate the geographic distribution patterns of attributes (Du et al. 2024). Furthermore, three distinct modeling approaches are identified: Simulation Modeling refers to system dynamics models, such as Agent-Based Modeling (ABM) or Cellular Automata (CA), which focus on simulating system behavior and evolution driven by human decisions, interactions, or rules (Burke et al. 2025; Yin et al. 2024). Physics-based Modeling applies physical laws (thermodynamics, fluid dynamics) to derive results; this includes not only internal Building Performance Simulation (BPS) or CFD (Egerlid et al. 2025) but also physical models for macro-scale urban climate analysis (e.g., Urban Canopy Models, UCMs), which calculate the physical response of building forms to thermal or wind environments (Guo et al. 2025; Cao et al. 2021). Probabilistic Modeling is dedicated to processing and quantifying uncertainty, aiming to assess risks and failure probabilities (Ye and Liu 2025).

Based on this classification, the quantitative analysis of method frequency (Fig. S5a) reveals a methodological landscape that directly responds to the needs of fine-grained governance. The prominent position of Qualitative Methods (113 mentions) reflects that complex governance goals such as "quality" and "livability" must first be defined through interviews and case studies. The surge in Deep Learning (89 mentions) provides a viable technical path for automatically extracting building attributes from massive, unstructured urban imagery. Secondly, Statistics (52), Machine Learning (47), and Spatial Analysis (46) collectively constitute a robust core for data analysis. Simulation Modeling (34), Literature Review (22), and Physics-based Modeling (10) also occupy specific proportions as specialized analytical paths, while Probabilistic Modeling (5) remains the least applied method.

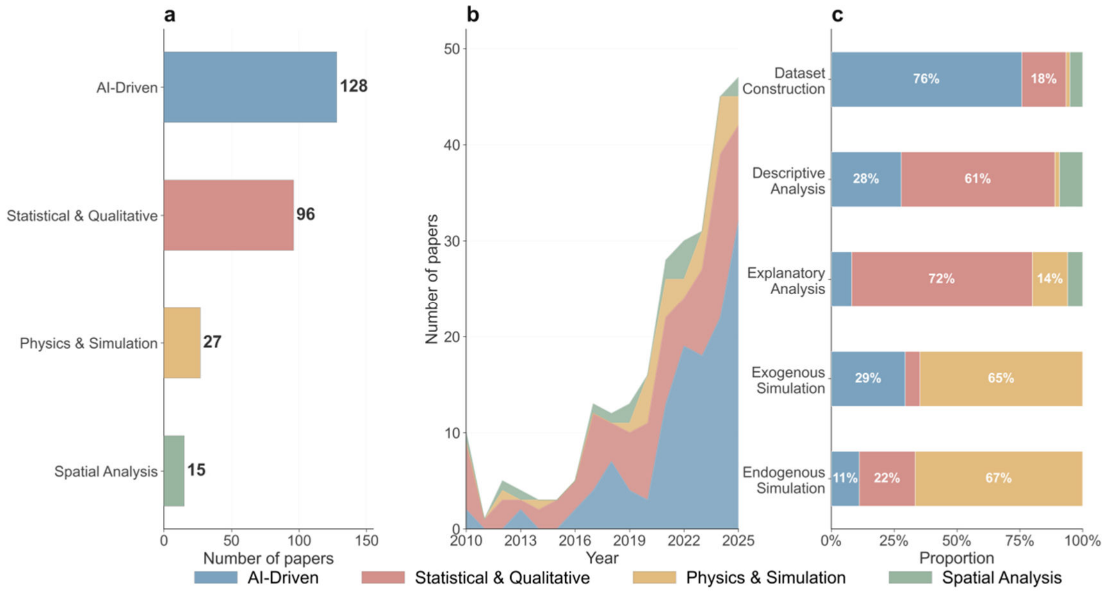


Fig. S5. *Methodological landscape of building-scale urban analytics and simulation. Methods are grouped into four categories: AI-Driven (Deep Learning, Machine Learning), Statistical & Qualitative (Statistics, Qualitative Methods, Literature Review), Physics & Simulation (Simulation Modeling, Physics-based Modeling, Probabilistic Modeling), and Spatial Analysis. (a) Frequency distribution of methodological categories; (b) Annual evolution of methodological applications from 2010 to 2025; (c) Proportional distribution of methodologies across different research types.*

Temporally (Fig. S5b), the field has experienced rapid growth since 2017, largely driven by two distinct methodologies. First, the application of Deep Learning has shown explosive growth; virtually non-existent before 2017, it has expanded rapidly to become a significant component of recent research volume. Second, Qualitative Methods, serving as the foundation of research, have consistently occupied the largest proportion throughout the timeline and also surged between 2023 and 2025. This indicates that as data-driven methods mature, the demand for deep interpretation and conceptual framework construction is growing concurrently. Meanwhile, traditional Statistics, Machine Learning, and Spatial Analysis have shown steady growth commensurate with the field's expansion, whereas Simulation Modeling and Physics-based Modeling constitute relatively stable but smaller specialized niches.

Fig. S5c further reveals specific methodological preferences across different research types. Dataset Construction exhibits the greatest methodological diversity, dominated by Deep Learning (approximately 40%) and Qualitative Methods (approximately 25%). This reflects its complex mandate: utilizing Deep Learning (particularly CNNs and GANs) to automatically recognize visual attributes or generate missing data (Cantemir and Kandemir 2024; Sun et al. 2022), while employing Qualitative Methods (e.g., literature reviews, case analyses) to "define" new attributes or indicators (Liang et al. 2023; Biljecki and Chow 2022). In contrast, Descriptive Analysis and Explanatory Analysis rely heavily on traditional quantitative methods. The former is primarily driven by Spatial Analysis (for mapping geographic patterns) and Statistics (for quantifying distributions) (Du et al. 2024). The latter is dominated by Statistics and Machine Learning (e.g., Random Forest) to mine correlations between variables (Nachtigall et al. 2023; Klika et al. 2025; Qin et al. 2025).

Finally, the two Urban Simulation categories demonstrate clear methodological divergence. Exogenous Disturbance Simulation is the primary domain for Physics-based Modeling (e.g., UCM or CFD models) (Guo et al. 2025; Cao et al. 2021) and Probabilistic Modeling (Ye and Liu 2025), used to assess the physical impacts of climate or disasters. Conversely, Endogenous Disturbance Simulation relies most heavily on Simulation Modeling (e.g., ABM) to explore system evolution driven by policy or agent decisions (Burke et al. 2025; Yin et al. 2024).

S2.8 Overview of Simulation-based Research

The reviewed simulation studies exhibit a diverse range of applications, primarily categorized into modeling responses to exogenous disturbances and endogenous system evolution. In the domain of exogenous acute shocks, particularly earthquakes, research has focused on refining risk assessment and recovery modeling. Nie et al. (2024) emphasized the importance of building function types in creating fine-scale spatiotemporal earthquake casualty risk assessments. Significant advances have also been made in post-disaster recovery modeling: Wang and van de Lindt (2021) proposed a quantitative model for residential recovery incorporating dynamic policies, while Opabola and Galasso (2024) introduced a probabilistic framework tailored for developing countries considering socio-economic factors. Further studies have addressed the seismic resilience of regional building functions, the vulnerability analysis of building groups using equivalent individual structure models, and the integration of digital twins to standardize building simulation for emergency evacuation planning (Wang et al. 2024a; Ren et al. 2023).

Regarding exogenous chronic stresses, research has concentrated on climate interaction, energy performance, and urban environmental quality. To address climate challenges, Huo et al. (2021) utilized dynamic scenario simulations to forecast carbon emission peaks in the urban residential sector, while Schiefelbein et al. (2019) developed automated methods to model urban energy systems based on OpenStreetMap data. Microclimate and environmental interactions are also key focus areas; Shen et al. (2021) generated microclimate weather data to simulate building performance under heat island effects, and Deng et al. (2023) quantified the impact of urban densification on thermal environments. More recently, Yap et al. (2025) introduced a physics-informed graph framework to reveal building operating carbon dynamics across multiple cities. Additionally, the broader social impacts of physical changes were explored by Jay et al. (2022), who used deep learning to analyze how demolishing abandoned buildings moderates firearm violence.

Research on endogenous system evolution models the internal dynamics of the building stock driven by human behavior, policy, and economic factors. Several studies focus on urban regeneration and development processes: Burke et al. (2025) employed an agent-based model (ABM) to simulate future urban densification in Toronto, while Yin et al. (2024) used ABM to evaluate demolition plans for neighborhood revitalization in shrinking cities. Policy and planning simulations are also prominent, such as Stermieri et al. (2020) linking dynamic building simulation with long-term energy planning, and Jeong and Kim (2024) analyzing the effectiveness of building energy efficiency certificates. Other contributions include modeling street-level urban changes using cellular automata, examining the decision-making of long-term recovery groups, and developing financial models for urban regeneration option pricing (Jia et al. 2020; Landaeta and Richman 2023; Zhong and Hui 2020). Theoretically, Simmonds et al. (2013) have provided foundational discussions on the distinction between equilibrium and dynamic models in urban simulation.

S3 Conclusion

S3.1 Progress and Gaps

Global urban development has shifted from a phase of rapid expansion to one centered on stock optimization and fine-grained governance. This quantitative review confirms that building-scale analytics and simulation are critical scientific domains responding to this era's demand. They occupy a vital emerging niche, serving as a crucial link between traditional coarse-grained urban models (Simmonds et al. 2013) and highly detailed, physics-based building performance simulations (Benz et al. 2023). While urban models have long operated at regional or block levels, this building-scale approach provides the necessary high-resolution data and systemic perspective to analyze the entire city as a complex, interconnected system of individual buildings. Such granularity is a fundamental prerequisite for modern governance strategies, necessitating a comprehensive, building-by-building diagnosis of urban health, including age, quality, function, and potential vulnerabilities.

The importance of building-scale urban studies has become a consensus. The quantitative review indicates that Urban Analytics is currently the dominant research category. A primary achievement in this domain is the creation of foundational, city-wide, building-level attribute datasets (Zhang et al. 2025b; Florio et al. 2025). The widespread application of deep learning in this task—whether using satellite imagery to map geometric attributes (Shi et al. 2024; Chen et al. 2023b) or street view imagery to identify quality and style (Aravena Pelizari et al. 2021; Han and Yin 2023), or employing generative AI (e.g., GANs) to synthesize missing semantic data (Sun et al. 2022)—has effectively constructed the data infrastructure required for precision urban management, planning, and renewal policies.

Building upon the diagnosis of the current urban state, Urban Simulation enables the exploration of future "what-if" scenarios. The review confirms this as a nascent yet critical sub-field, addressing the historical difficulty of linking macro-policies with dynamic changes at the individual building level (Jia et al. 2020). Two primary simulation foci are identified: dynamics simulation and urban generation. The former utilizes models like Agent-Based Modeling (ABM) to assess complex policy scenarios, such as the impact of demolition plans on shrinking cities (Yin et al. 2024). The latter is modeling socio-economic lifecycle dynamics like renovation or demolition (Bittner et al. 2018; Ikeno et al. 2021).

Despite these advancements, this review reveals three critical scientific gaps hindering the realization of fine-grained spatial governance. (1) The Data Gap ("What is"): Existing datasets are predominantly single-period cross-sections or rely heavily on street-level observations, resulting in "data islands." There is a distinct lack of a fine-grained data foundation covering the entire urban domain with multi-dimensional attributes and long time-series. (2) The Analysis-Simulation Gap ("How it evolves"): Traditional paradigms prioritize static indicator diagnosis while neglecting dynamic risk disturbances during the renewal process. Consequently, "urban diagnosis" problems cannot be synthesized into core driving forces for "urban regeneration" prognosis. (3) The Behavior-Modeling Gap ("Why it evolves"): Existing simulation models largely rely on predefined rules, struggling to replicate authentic human decision-making within complex strategic games. There is a marked deficiency in the deep characterization of behavioral driving mechanisms involving multiple stakeholders, such as governments and residents.

To address these triple requirements and systematically resolve the aforementioned scientific problems, this paper proposes two complementary conceptual frameworks (Sections 3.2 and 3.3).

S3.2 Conceptual Framework for Building-Scale Urban Analytics

To systematically address the aforementioned scientific problems, this study proposes a conceptual framework for building-scale urban analytics. This framework aims to simultaneously resolve the "Data Gap" (Problem 1) and the "Analysis-Simulation Gap" (Problem 2). Its core mission is to extract static and dynamic building attributes and synthesize the risk disturbance factors driving their evolution, thereby providing high-quality data and rule inputs for subsequent simulations. Operationally, the framework is divided into two modules: Building Attribute Extraction and Building Attribute Analysis (see Fig. 1 in the main text).

In the Building Attribute Extraction module, the priority is to overcome the limitations of "cross-sectional data" and "data silos," directly responding to the "Data Gap." This requires a unified spatial intelligence framework that integrates multi-source data—including remote sensing imagery, street view imagery (SVI), and Points of Interest (POI). The objective is not only to extract geometric and semantic attributes (e.g., function, age, style) but also to focus on critical attributes that are difficult to observe through manual surveys yet vital for fine-grained governance, such as building quality and vacancy rates (Lin et al. 2021; Mohajer and Aksamija 2021; Wang and van de Lindt 2021; Häberle et al. 2022), as well as the dynamic measurement of building lifecycles (e.g., deterioration, renovation, demolition).

In the Building Attribute Analysis module, the core objective is to address the evolution of urban buildings, responding to the "Analysis-Simulation Gap." On one hand, it employs spatial analysis to calculate and visualize how changes in the spatial patterns of 2D and 3D buildings affect other environmental variables (Liu et al. 2020; Deng et al. 2023; Cao et al. 2021), while also analyzing the deep-seated policy mechanisms behind urban regeneration. On the other hand, it involves constructing a micro-scale risk disturbance database. By introducing dynamic analysis and risk attribution, this module systematically synthesizes how disturbance factors—such as disaster shocks, policy interventions, and market pressures—act upon different static building attributes to ultimately drive dynamic evolution.

The comprehensive extraction of static attributes and the systematic synthesis of dynamic processes and their disturbance laws lay a solid data and rule foundation for building-scale urban simulation (Zhao 2018; Wang 2023).

S3.3 Conceptual Framework for Building-Scale Urban Simulation

Building upon the unified data and analytical foundation provided by the framework in Section 3.2, this study proposes a novel conceptual framework for building-scale urban simulation to address the third challenge: the "Behavior-Modeling Gap" (i.e., how to simulate complex human decision-making). This framework is termed the Government and Resident Participation Graph Lingual Network Model for Buildings (GPGLB). Distinct from traditional Agent-Based Models (ABM) that rely on predefined rules or calculated utility functions, GPGLB operates as a dynamic spatiotemporal graph where each building constitutes a node. Crucially, each node is treated as an autonomous "Owner Agent," whose behavior is inferred by a Large Language Model (LLM) through contextual reasoning. This agent-based graph network integrates two levels of participation: a global "Government Agent" that defines policy scenarios (e.g., subsidies), and "Resident/Public Participation," modeled as dynamic environmental features perceived by the owner agent (e.g., street footfall or "public vitality") (see Fig. 2 in the main text).

Specifically, the simulation path in GPGLB follows a "Perception-Reasoning-Action" loop for each owner agent at every time step. First, the model programmatically generates a structured prompt to perceive its environment. This prompt synthesizes the agent's internal state (e.g., current building quality, owner type) with its local context, including neighborhood influences (derived from graph neighbors, e.g., "broken windows" effect) and public vitality (dynamic features). Next, this prompt is dynamically modified based on proactive policy scenarios from the government agency (e.g., "50% subsidy available for CBD locations"). The LLM receives this rich contextual prompt, performs situational reasoning, and returns a discrete structured decision (e.g., "Renovate," "Maintain," "Deteriorate"). This decision is then executed through state transition rules to update the building attributes for the next time step.

Model calibration is achieved by refining prompt templates. The goal is to adjust the "personality" and "sensitivity" of the LLM agents (e.g., their sensitivity to neighborhood decay) until the macro-spatial patterns generated by the simulation (e.g., spatial autocorrelation of building quality) align with patterns observed in real-world validation data. Once calibrated, the framework allows for robust policy "what-if" analyses, such as comparing a "baseline trend" against scenarios like "CBD-based renovation" or "TOD-based upgrading" by altering the policy text injected by the government agency.

S4 Discussion

This systematic review reveals a critical structural bottleneck in current urban studies characterized by a massive over-concentration on static analytics juxtaposed with a scarcity of dynamic simulation. While the community has achieved high proficiency in extracting geometric and functional attributes, as evidenced by the surge in dataset construction literature, this static urban physical examination often fails to translate into actionable urban regeneration strategies. The gap between analysis and simulation implies that the field effectively diagnoses the current health of the city but lacks the prognostic tools required to predict its future evolution under stress. The conceptual frameworks proposed in this study directly address this disconnect. By treating building attributes as evolving variables within a risk disturbance database rather than fixed labels, this study provides a theoretical pathway to transform static datasets into dynamic input parameters for simulation, effectively linking the current state to potential future scenarios.

A key theoretical contribution of this study is the proposal of the Government and Resident Participation Graph Lingual Network Model, which addresses the existing gap in behavior modeling. Traditional urban simulations, such as Cellular Automata or standard Agent-Based Models, rely heavily on predefined and fixed rules. However, real-world urban regeneration involves complex interactions including policy incentives, economic trade-offs, and subjective human desires. The integration of Large Language Models into the simulation loop represents a paradigm shift from rule-based to reasoning-based modeling. Unlike traditional agents that strictly follow utility functions, the agents in our framework can interpret semantic context, such as the nuance of a new government subsidy policy or neighborhood effects, and make probabilistic decisions. This capability significantly enhances the fidelity of simulating endogenous disturbances and offers a more realistic representation of how micro-level interactions drive macro-level urban evolution.

The transition from extensive expansion to stock optimization requires governance tools that are both fine-grained and forward-looking. The proposed workflow supports this integration by creating a closed loop that begins with diagnosis and extends to prognosis. Specifically, the analytics framework fuses multi-source data for a comprehensive health check to address the data gap, while the simulation framework allows for testing various policy scenarios. This approach moves beyond the passive monitoring of building indicators to the active management of urban resilience, providing policymakers with a scientific basis for precise interventions in urban regeneration and disaster mitigation.

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