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Urban AI for a sustainable built environment: Progress and future directions

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Introduction

Urban areas stand at the forefront of the climate crisis, facing escalating environmental pressures, growing social inequalities, and heightened risks to human health and well-being. These challenges are especially pronounced in rapidly expanding cities across the Global South, where informal settlements, resource constraints, and inadequate infrastructure amplify vulnerabilities. Conventional urban planning and management approaches, developed prior to recent advances in data-intensive urban analysis, are increasingly unable to address the complexity, scale, and dynamism of these issues.

In this context, the convergence of artificial intelligence (AI) and urban science, commonly termed UrbanAI (Caprotti et al., 2024), offers transformative potential for data-driven urban sustainability design and modeling. UrbanAI broadly refers to the application of AI techniques to understand, design, and govern urban systems. Recent breakthroughs in remote sensing, computer vision, and machine learning enable the extraction of meaningful patterns from vast, heterogeneous data sources, including satellite and drone imagery, street-level imagery, environmental sensor networks, and crowdsourcing datasets (Li and Hsu, 2022). These advances facilitate high-resolution and fine-granularity monitoring and modeling of urban processes at unprecedented spatial and temporal scales. For instance, UrbanAI methods can map heat resilience at the resolution of individual households, model the risk of mosquito bites potentially carrying pathogens (Knoblauch et al., 2024, 2025a, 2025b), or predict residents' perceptions of safety (Knoblauch et al., 2025c;

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Zhang et al., 2021). By linking physical urban form, environmental conditions, and human experience, UrbanAI reshapes how cities are represented and understood. Importantly, AI is not only enhancing data acquisition but also transforming analytical paradigms, enabling scalable, adaptive, and equitable urban interventions. When integrated into planning and policy frameworks, these tools can inform targeted solutions tailored to local contexts, ultimately fostering resilient and inclusive urban futures (Ye et al., 2025).

This special issue showcases a diverse collection of pioneering research contributions that exemplify the current progress and future directions of UrbanAI for a sustainable built environment. Together, they demonstrate how geospatial technologies, AI-driven analytics, and human-centered modeling approaches are expanding the frontiers of urban observation, understanding, and adaptation in the face of climate change and social challenges.

Urban sensing as a foundation for UrbanAI

Urban sensing constitutes a critical foundation for UrbanAI, encompassing the diverse methods and technologies used to observe, measure, and interpret both the physical fabric and dynamic activities of urban environments. Broadly defined, urban sensing refers to the collection and management of data on static elements such as buildings and infrastructure, as well as dynamic phenomena including traffic patterns, social media activity, environmental conditions, and human mobility (Shi, 2021). As a major pillar of urban analytics, it underpins data-driven decision-making across a wide array of domains, from transportation, disaster response, and public health to tourism, food systems, and social equity (Abirami and Chitra, 2023; Biljecki, 2023; Calabrese et al., 2013; Shin et al., 2015; Xu et al., 2022; Yang et al., 2023).

In recent years, urban sensing has undergone rapid evolution, driven by several converging trends. These include the proliferation of sensing platforms (e.g., sensor-equipped vehicles, drones, and smartphones), improved spatial and temporal resolution of data (e.g., high-resolution satellite imagery and LiDAR), and the emergence of new data sources such as street-level imagery, social media, wearables, and crowdsourced contributions (Huang et al., 2024; Lei et al., 2026; Liu et al., 2025b). The rise of citizen science platforms such as OpenStreetMap and crowdsourcing tools has further democratized data collection, enabling residents themselves to become active participants in sensing and mapping their urban environments. The dramatic growth in data availability has been matched by advances in computational power and analytical techniques (Gao et al., 2023a).

In particular, geospatial artificial intelligence, commonly referred to as GeoAI, has become a transformative force in urban sensing. GeoAI leverages machine learning, computer vision, and natural language processing to extract meaningful patterns from vast and heterogeneous urban datasets (Das et al., 2022; Gao et al., 2023b; Li, 2020; Liu and Biljecki, 2022). These tools enable the fusion of multimodal inputs, from satellite and drone imagery to location and text data, producing holistic representations of urban systems at unprecedented resolution and scale. In this special issue, we expand this research landscape into two directions: the first focuses on modeling of physical environment, and the second focuses on sensing of social environment.

Yuan et al. (2025) propose a deep learning-based approach for large-scale, detailed assessment of street transparency, defined as the proportion of ground-level openings (windows and doors), utilizing open-source street view imagery. They find that that street-level penetration rate in first-tier Chinese cities (i.e., Beijing, Shanghai, and Guangzhou) is affected only by economic construction but also the layout of street with significant spatial heterogeneity observed.

Wang et al. (2025) examine the feasibility of fine-tuning natural language processing (NLP) models to classify POI data into manufacturing industry categorizes and correlating their spatial concentration with carbon emission intensity. As a result, more than 90% of manufacturing land can be accurately identified in a Chinese city, namely, Hefei, to support high-resolution carbon emission mapping tasks.

In Chen et al. (2025), the authors explore the spatiotemporal patterns of activities and violence associated with unrest events by analyzing social media data with Biterm Topic Modeling (BTM) approaches. Using the 2013 Brazil Protest as a case study, they found that locations where groups expressing concern about violence gather are more likely to become sites of actual violence, providing a promising approach to capture changes in the social environment.

Modeling human perception and behavior

A particularly vibrant area of UrbanAI research investigates the links between environmental characteristics and human perception, experience, and behavior. Traditionally reliant on field surveys and observational studies, such insights are increasingly being derived from large-scale, digital datasets. Crowdsourcing platforms such as MapSwipe (Ullah et al., 2023) or Place Pulse (Dubey et al., 2016) enable the annotation of street-level imagery to capture subjective perceptions such as safety, walkability, or esthetic appeal. UrbanAI models can then be trained to identify latent visual features predictive of these perceptions without requiring explicit feature engineering. These AI models provide scalable tools for mapping urban experience across entire cities, although care must be taken to validate them against spatial, socioeconomic, and cultural biases to ensure fairness and reliability (Quintana et al., 2025). In parallel, wearable sensors and personal mobility data are increasingly being used to capture real-time physiological and behavioral responses to urban form (Cheng et al., 2026). Explainable machine learning techniques reveal how features such as intersection density, green space, exposure to sky, or noise levels relate to perceived stress or active mobility choices. Within our special issue, there is a noticeable share of work dedicated to modeling human perception and behavior in the built environment.

Ma et al. (2025) investigate the impact of perceived distance to greenery on psychological restoration utilizing street view images and explainable AI models. Experiment results in Wuhan, China, show a significant positive causal relationship between urban greenness and psychological restoration, enhancing future evidence-based promotion for the health and well-being of city residents.

Moser et al. (2025) introduce a methodology to assess environmental stressors in urban cycling, addressing stress and safety concerns. Their study in Osnabrück combined wearable electrodermal activity (EDA) sensors with spatial data from OpenStreetMap, Sentinel-2, and Mapillary imagery to analyze stress levels during cycling. Using a random forest model, they found that cycling infrastructure, traffic regulations, and road users were more significant predictors of stress than green space. This approach provides a transferable method for evaluating urban environments, offering valuable insights for designing safer cycling spaces.

Lim and Lee (2025) examine the travel pattern and transportation modes of shared bicycles in the city of Seoul by applying an explainable LightGBM enhanced with a robust SHapley Additive exPlanation (SHAP) method. Their findings reveal distinct difference in travel patterns and associated spatiotemporal influencing factors, shedding lights into clarify personal mobility patterns and inform sustainable transport policy.

As a highlight, Noyman et al. (2025) introduce a novel agentic simulation platform, namely, TravelAgent, to model pedestrian navigation, activity, and human-like decision-making in the built environment, which aim at understanding how different people might experience diverse built environments under varying environmental conditions. Preliminary results based on both interior and exterior spaces confirm the model capacity of simulating complex agent profiles, behaviors, and interactions and provide helpful insights into human decision-making, experience, and emotional responses in urban smart cities.

AI for urban morphology, design, and planning

AI is transforming the practice of urban design and planning by enabling data-driven understanding and generative creation of urban morphology and city forms, enhancing efficiency, sustainability, and inclusivity in urban development. By integrating urban big data with design innovation, AI empowers planners and architects to model, simulate, and optimize urban environments for sustainable, resilient and human-centered cities. Beyond sensing and perception, UrbanAI is employed to reimagine urban morphology and guide data-driven design and planning practices. A final cohort of works in this special issue presents recent progress in applying generative models, graph-based networks, and reinforcement learning to optimize urban forms, allocate resources, and protect cultural heritage, reflecting a future of AI-assisted urban planning that is both responsible and sustainable.

Huang et al. (2025) address the complexity of assessing preservation city boundaries in historic districts by integrating explainable AI and game theory, facilitating a tree-step process of urban morphology assessment. Their preliminary findings show that historical heritage plays a major role in core zone decisions, underscoring the key impact of prioritizing cultural value for heritage conservation.

Zhang et al. (2025) propose a deep reinforcement learning approach to optimize spatial resource allocation for school district division task. The key idea is to leverage the advantages of deep reinforcement learning for real-time response and flexibility, which directly learns behavioral implication based on the input of changing school district states, supporting long-term school districting strategies in urban development.

In Huang and Oki (2025), the authors present generative AI approach leveraging a stable diffusion model with massive public walking preference data in Tokyo, to establish a workflow of generating revitalized street scenes that aimed at enhancing subjective walking preferences. They validate the proposed method in a real-world case study using data collected from Tokyo's Setagaya ward, highlighting the potential of generative AI in equipping urban designers and planners with fast and insightful visual assistance in their early design stages.

Last, Liu et al., 2025a present a contribution in designing a heterogeneous graph autoencoder, called HeteGAE, to jointly embed street and waterway network into a unified, graph-based representation for better urban form understanding. Experimental results in Singapore confirm the capability of HeterGEA in achieving highly competitive prediction accuracy across a range of downstream tasks, including land surface temperature and resale prices of public housing. More importantly, it underscores the value of integrating UrbanAI into evidence-based planning and highlights the potential of graph neural networks to support more nuanced and sustainable urban design.

Future directions

As UrbanAI continues to evolve, several key challenges and opportunities will shape its trajectory toward a sustainable built environment. Inspired by the contributions in this special issue, we have identified three future directions in further advancing UrbanAI research. As an unexhausted list, we hope these directions will guide ongoing research, inspire practical applications, and foster collaborative innovation in UrbanAI and beyond.

The reliability of UrbanAI depends fundamentally on high-quality, diverse urban data. While data availability is expanding rapidly, through sensors, crowdsourcing, and smart city infrastructures, there remains a pressing need for standardized quality assessment and fusion techniques to effectively integrate heterogeneous and multimodal urban datasets. To combine structured and unstructured data such as imagery, mobility traces, and social sensing information, there is a need to advance the spatial representation learning that enables latent alignment of these complex data streams and reveal dynamic patterns across space and time (Mai et al., 2024). Improving temporal resolution and leveraging historical urban data will further enable dynamic, longitudinal studies that capture subtle changes in cities over time (Yue et al., 2025).

Emerging urban analytic data types, from indoor location data to environmental IoT sensors, human mobility data, and social media data, offer unprecedented insights into urban dynamics and human–environment interactions. These novel urban data streams capture both urban build environment and human digital footprints, allowing researchers to model spatial-temporal human behavior across scales, from individual building usage to city-wide mobility flows. Integrating such diverse urban data can reveal how city dwellers interact with urban infrastructure, experience environmental exposure, and perceive urban designs. These novel data streams require tailored UrbanAI analytical methods and raise important concerns around privacy, bias, and ethical usage (Sanchez et al., 2025). Establishing data standards, benchmarks, and privacy safeguards will be essential to responsibly harness these opportunities (Li et al., 2024).

The ability to reproduce or replicate research minimally requires the existence and availability of the provenance of that research, which is an adequate record of how researchers produced a result. Promoting open and interoperable urban datasets and software, via standardized formats, metadata documentation, and FAIR (Findable, Accessible, Interoperable, Reusable) and CARE (Collective Benefit, Authority to Control, Responsibility, and Ethics) principles, can enable researchers and stakeholders to better leverage existing research findings and focus on innovative solutions. To this end, UrbanAI research must embrace open data, transparent workflows, and reproducible methods. Overcoming barriers posed by proprietary data and computational complexity will foster broader collaboration and trust within the community (Kedron et al., 2021).

Conclusion

The research presented in this special issue highlights the transformative potential of UrbanAI to reshape how cities understand, govern, and adapt to environmental and social challenges. By integrating advanced sensing technologies, artificial intelligence, and participatory data practices, UrbanAI enables fine-grained, dynamic insights into the complex relationships between people, infrastructure, and the environment. Importantly, it not only improves scientific understanding but also supports more targeted and efficient interventions, laying the foundation for more sustainable, inclusive, and resilient urban futures.

Realizing this promise, however, demands progress on multiple fronts. As UrbanAI systems increasingly rely on vast, multimodal datasets, such as emerging textual sources, challenges around data quality, interoperability, and privacy become more urgent. The generalizability of models across diverse urban contexts remains limited, and the “black-box” nature of many UrbanAI techniques underscores the growing need for explainability and transparency (Goodchild and Li, 2021). Large language models may enhance interpretation, but ethical frameworks must keep pace with technical capabilities. Equally critical is the gap between research and policy: despite rapid advances, UrbanAI tools are seldom adopted in practice due to limited trust, regulatory constraints, and a lack of institutional capacity. Bridging this divide will require interdisciplinary collaboration, open science, and deliberate efforts to embed UrbanAI within accountable governance frameworks.

As this special issue demonstrates, the future of sustainable urban development lies not only in technological innovation but also in ensuring that these tools are explainable, generalizable, ethically grounded, and actionable. These advances will ultimately serve the diverse needs of urban populations and be guided by human-centered priorities.

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