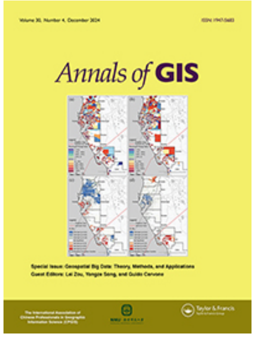

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REVIEW

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Artificial intelligence in urban science: why does it matter?

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ABSTRACT

Urban science aims to explain, discover, understand, and generalize (EDUG) complex, human-centric systems, emphasizing societal context and sustainability. However, integrating artificial intelligence (AI) into urban science presents challenges, including data availability, ethical considerations, and the ‘black-box’ nature of many AI models. Despite these limitations, AI offers significant opportunities for urban management and planning by leveraging vast, multimodal datasets to optimize infrastructure, predict trends, and enhance resilience. Techniques such as explainable AI and knowledge-driven approaches have begun addressing transparency concerns, aligning AI outputs with urban science’s emphasis on interpretability. Urban science reciprocally contributes to AI development by embedding contextual awareness and human-centric insights, enhancing AI’s ability to navigate urban complexities. Examples include digital twins for real-time urban analysis and generative AI for inclusive urban modelling. This opinion piece advocates for fostering a symbiotic relationship between AI and urban science, emphasizing co-learning and ethical collaboration. By integrating technical innovation with societal needs, the convergence of AI and urban science – termed the ‘New Urban Science’ – promises smarter, equitable, and sustainable cities. This paradigm underscores the transformative potential of aligning AI advancements with urban science’s foundational goals.

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Artificial intelligence; urban science; explainable AI; digital twins; human dynamics

Introduction

The rapid rise of artificial intelligence (AI) has led to transformative advancements across numerous scientific fields, as evidenced by AI’s recognition through the 2024 Nobel Prizes in Physics and in Chemistry. While AI is relatively well-developed in the natural sciences, where collaboration is often two-sided (benefiting both AI development and the desire for data-driven scientific discovery), its integration into fields like urban science (which bridges the social and natural sciences) remains more challenging. To fully understand AI’s potential in urban science, we must first address the core question: Why does AI matter for urban science? This requires exploring what urban science aims to achieve and how AI can effectively contribute to advancing those goals.

Urban science is fundamentally about ‘Explanation, Discovery, Understanding and Generalization’ (EDUG) of complex, human-centric systems, with a secondary focus on prediction of future circumstances. It seeks to explain the intricate relationships between social, spatial, and environmental factors in urban contexts and to discover patterns that guide urban management and planning. The advanced computational technologies of our time are revolutionizing urban science, leading to the emergence of the ‘New Urban Science’ (Figure 1). This new field emphasizes the use of urban data analytics and complex modelling to generate deeper insights into how cities operate and evolve (Karvonen et al. 2021). By harnessing vast datasets and employing sophisticated algorithms, the New Urban Science enables a more precise and dynamic understanding of urban systems, allowing researchers and policymakers to uncover patterns, predict future trends, and design more sustainable, equitable cities. This paradigm shift reflects a move towards data-driven, interdisciplinary approaches that redefine urban research and practice.

While AI excels in areas with vast datasets and well-defined parameters, its value to new urban

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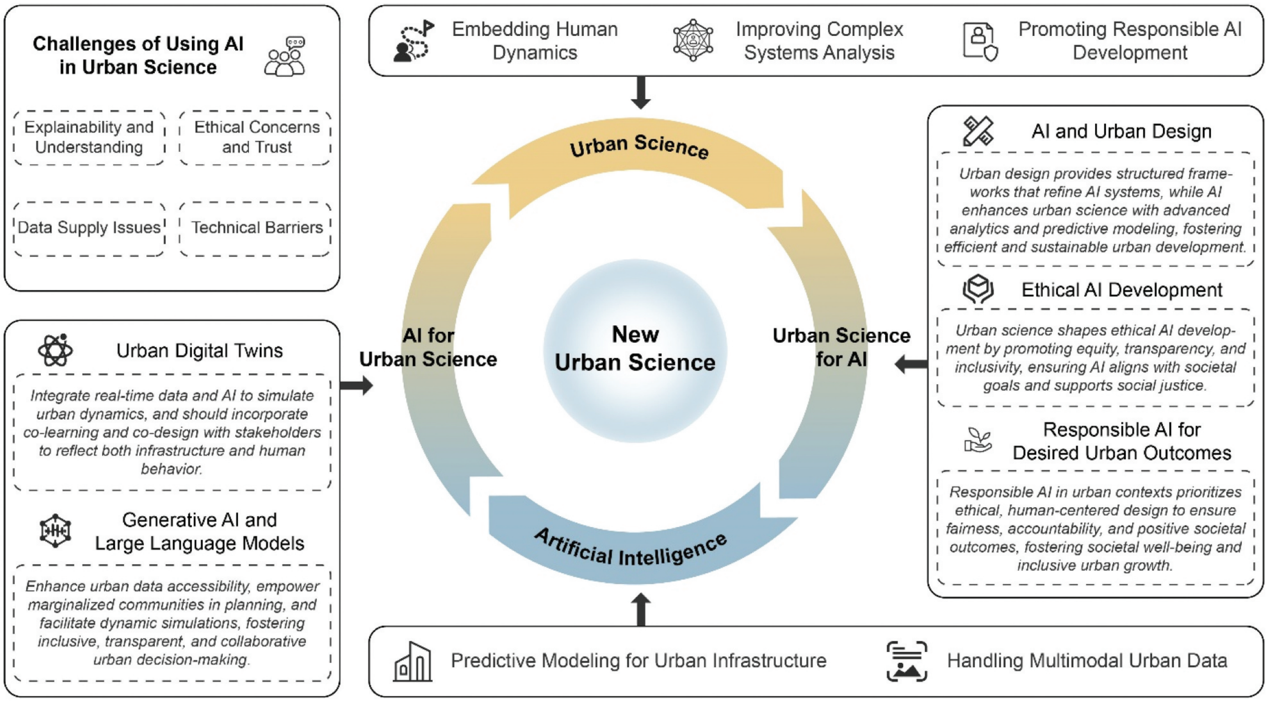

Figure 1. Conceptual framework of new urban science.

science has been less clear due to its inherent limitations in explainability, replicability, and transparency. However, AI has the high potential to make significant contributions to new urban science, even it may fall short in some aspects of traditional scientific inquiry (Long 2019). By emphasizing its application in urban management and planning, rather than focusing exclusively on urban science at large, AI can be more effectively integrated to particularly address practical challenges and optimize decision-making processes.

The New Urban Science also possesses the potential to make AI more robust and context-aware by leveraging its expertise in modelling complex socio-spatial interactions (Ye and Andris 2021). By integrating insights from urban science, AI can develop models that are not only technically advanced but also deeply attuned to human behaviours and societal dynamics (Huang 2024). This reciprocal relationship can help address the limitations of current AI systems, enabling them to understand the context of urban environments more effectively. The current moment presents a critical opportunity to foster a more balanced collaboration and convergence between AI scientists and urban researchers. By leveraging the technical capabilities of AI and the societal insights of urban science, this partnership has the potential to significantly amplify the impact of both fields, leading to more comprehensive and effective solutions for urban challenges.

The challenges of using AI in urban science

Explainability and understanding

One of the main reasons AI has not yet fully realized its potential in urban science is the difficulty of aligning its output with the core scientific goals of EDUG. Traditional science values models that are transparent, interpretable, and replicable, allowing researchers to explain phenomena clearly. In contrast, many AI models, particularly deep learning models, are often seen as 'black boxes' with poor interpretability, making it difficult to explain the mechanisms behind their predictions. This limits their utility in urban science, where understanding the underlying causes of urban issues is often more important than simply predicting outcomes. However, it is important to point out that there exist various AI approaches and some AI approaches are knowledge-driven rather than data driven. For example, expert system was a popular AI approach in late 1990s and early 2000s (Fox 1990; Liao 2005; Rolston 1988). Expert systems normally build a knowledge base derived from knowledge of experts in a particular domain and then use an inference engine to emulate the decision-making process of the experts (Tripathi 2011). The knowledge-based AI approaches therefore offer better explainability and understanding. Recently, various data-driven AI tools have emerged to address AI interpretability challenges, gradually 'unboxing' black-box models. Techniques like Shapley Additive Explanations (SHAP) reveal feature contributions, and neuron visualization clarifies how models process information. Recent advances even enable precise explanations of complex graph neural networks, bridging AI models with the interpretability needs of urban science. These tools enhance AI transparency, empowering researchers to gain actionable, human-centred insights that align with empirical findings in urban contexts. Yet, despite these advancements, data-driven AI's black-box nature remains only partially unravelled. This remaining gap highlights the need for 'Explainable New Urban Science', which focuses on developing AI systems that provide not only accurate predictions but also insights into the underlying processes shaping urban dynamics. This would ensure that AI tools contribute meaningfully to urban research and decision-making, by balancing technical innovation with the scientific need for clarity and transparency.

Data supply issues

AI's success in fields like weather forecasting and protein unfolding can be attributed to the availability of vast, high-quality datasets. These fields have a consistent and abundant flow of structured data that supports accurate, scalable AI applications. Urban science, on the other hand, can be limited by fragmented, incomplete, or proprietary data sources. Privacy concerns, data ownership issues, and the high cost of data collection in urban environments limit the quality and availability of datasets. These constraints hinder the scalability of AI and raise ethical questions about the use of AI in data-limited urban contexts. This raises the question of whether AI will ever be as useful for urban science as it is for data-rich fields like weather forecasting. To address these challenges, it is critical to develop approaches that can use unique properties of data (e.g. spatial autocorrelation in geospatial data) to reduce the training data size needed to achieve the same accuracy level (Chen et al. 2024). In addition, it is essential to establish ethical frameworks for data collection that respect privacy, promote transparency, and ensure equitable access to data for researchers and policymakers, thereby fostering a more responsible and inclusive application of AI in urban environments.

Ethical concerns and trust

The ethical and trust implications of AI in urban contexts go beyond privacy and bias. Uncertainty in predictions, lack of transferability across different urban settings, and the challenge of presenting results transparently can all undermine the trustworthiness of AI systems. For AI to be valuable in urban science, it must meet the traditional norms of scientific publication – results should be presented with sufficient transparency and detail to allow replication. Without this transparency, AI risks exacerbating distrust, particularly in public policy and urban management, where decisions based on opaque models could deepen inequalities. Therefore, to build trust and ensure fairness, it is essential to embed ethical guidelines in 'Responsible AI' development that prioritize transparency, accountability, and inclusivity, ensuring that AI-driven decisions foster equity and public trust in diverse urban contexts.

Technical barriers

Urban scientists often lack training not only in big data methods but also in coding and intensive programming skills, which are more commonly found in the natural sciences (Ye and Rey 2013). Without proficiency in these technical areas, urban scientists may struggle to fully engage with advanced computational methods or to develop sophisticated AI models. Additionally, the absence of access to high-performance computing resources or specialized AI expertise further limits their ability to apply cutting-edge approaches to urban research. This skill gap impedes the adoption of AI's full potential in addressing complex urban challenges. To overcome this barrier, it is crucial to foster interdisciplinary collaboration, where urban scientists partner with data scientists and AI experts, while also incorporating targeted training programmes that bridge technical knowledge gaps and expand computational literacy within urban research communities.

AI's contributions to urban science

While AI's contribution to EDUG in urban science remains somewhat limited, particularly it holds considerable promise for urban management and planning, where the primary objective is to optimize systems for efficiency and performance, even if it means not fully comprehending all the underlying complexities. AI's ability to process and analyse vast amounts of multimodal data – varying from transportation flows to social media interactions – can help urban planners and policymakers make more informed decisions (Huang et al. 2022). To clarify these points, the following examples illustrate AI's transformative impact on urban science.

Predictive modeling for urban infrastructure

AI is fundamentally reshaping how cities manage their resources by optimizing traffic systems, improving the efficiency of critical infrastructure, and enhancing environmental monitoring. With the ability to process vast, multi-source datasets – including satellite imagery, transportation flows, sensor data, and social media activity – AI enables urban scientists and planners to uncover patterns and predict trends that were previously difficult to detect. This deeper level of insight helps cities forecast and respond to emerging issues, ranging from managing traffic congestion during peak hours to anticipating the impacts of extreme weather events (Ye et al. 2024). By enabling real-time data analysis, AI enhances cities' adaptability and resilience, empowering them to respond more effectively to rapid urbanization, climate change, and other evolving urban challenges. As a result, urban systems become not only more efficient and sustainable but also more proactive in mitigating risks and enhancing quality of life for residents (Fu et al. 2024; Wang et al. 2020).

Handling multimodal urban data

Data and models are two essential components of AI. The commonly used data for constructing AI are tabular data, images, and texts. However, urban environments produce complex, heterogeneous data combining geospatial, social, and infrastructural dimensions. AI's ability to integrate these different data streams into a coherent model can facilitate faster, more effective decision-making in areas like disaster response, public health, and urban mobility. For instance, in the event of a natural disaster, AI can integrate geospatial data to evaluate damaged areas, social data to identify individuals requiring assistance, and infrastructural data to pinpoint disrupted services, facilitating more efficient allocation of resources (Ye et al. 2023). Integrating urban data into AI models helps AI systems evolve beyond their current limitations, developing more robust multimodal capabilities that account for the intricacies of urban life (Zhang et al. 2024). In sum, multimodal urban data practices can develop the fundamental capabilities of relational and collective machine learning of pattern regularity from heterogeneous and irregular data (Liang, Zadeh, and Morency 2024).

Nevertheless, an important question remains concerning whether AI's contributions to urban management and planning ever be as profound as they are in fields like protein folding or weather forecasting? The answer lies in addressing the limitations of current AI systems, particularly around the issues of data quality, interpretability, and ethical use.

How urban science can shape AI development

Despite the challenges, urban science offers an essential contribution to AI—i.e. 'contextual awareness'. Urban science provides AI with deep insights into the socio-cultural and economic fabrics of cities. Incorporating this contextual information allows AI models to better understand and interpret human behaviours and urban phenomena (Augusto 2022). This leads to more accurate predictions and recommendations in areas like public health, urban mobility, and social services, as AI becomes attuned to the unique characteristics of different urban communities (Jiang et al. 2023). Additionally, urban science's ability to seamlessly navigate between different scales – from the broader city context to specific sites – enables AI models to assess and integrate data across multiple levels. This multiscale approach ensures that AI can provide solutions that are both locally relevant and globally informed, enhancing its capacity to address complex urban challenges with precision and adaptability (Li et al. 2024). Urban scientists have a deep understanding of the socio-cultural, economic, and environmental complexities that shape urban life. By embedding this contextual knowledge into AI models, urban science can make AI more robust, adaptable, and socially responsive (Chander et al. 2024).

Embedding human dynamics

Urban science's focus on human behaviour is crucial for making AI systems more attuned to how people interact with urban infrastructures. For example, on the one hand AI models that incorporate insights from human dynamics research can create more accurate and socially relevant simulations (Shaw, Tsou, and Ye 2016). This helps improve public health outcomes, urban mobility, and social service provision. On the other hand, investigating AI systems under human dynamics can provide foundational insights into developing continual learning and adaptive learning capabilities to navigate unexpected variances and strengthen the robustness of AI systems (Hadsell et al. 2020; Wu et al. 2024). More importantly, we need to move from a techno-centric AI to a human-centric AI to better serve social sciences including urban science. Shaw and Sui (2019) present a new GIScience framework which places humans at the centre as dynamic and living entities who interact with the world through four interrelated concepts of place and space (i.e. location in absolute space, locale in relative space, identity in relational space, and sense in mental space). Mortaheb and Jankowski (2023) argue for a GeoAI-enabled, human-centred city planning framework for smart city. These human-centric frameworks have great potential of integrating human dynamics and making AI more useful to urban science.

Improving complex systems analysis

Cities are complex systems with numerous interconnected components. Urban science provides AI with the necessary frameworks to model these systems more effectively. By integrating methodologies from urban science, AI can better manage the intricate interactions within urban environments, improving its capacity to handle real-world complexity (Li, Batty, and Goodchild 2020). While AI systems can struggle with urban complexity due to challenges in capturing dynamic human behaviour and the interconnected nature of urban systems, their strength lies in uncovering patterns within well-structured behavioural data. With high-quality data, AI can effectively identify trends and relationships that may be difficult for humans to discern, providing valuable insights. However, data gaps, biases, and limited adaptability still pose significant challenges to ensuring that AI addresses evolving urban issues equitably (Palmini and Cugurullo 2023). Studying urban science from the perspective of complex systems can provide transformative insights into graph machine-learning capabilities, including graph embedding, reasoning, inference, and community detection (Alexiadis 2024).

Promoting responsible AI development

Urban science can guide the ethical deployment of AI in cities by ensuring that AI models are transparent, accountable, and inclusive. Urban scientists are in a unique position to address issues of data bias, privacy, and fairness, ensuring that AI systems benefit all urban residents, not just the privileged few (Sanchez, Brenman, and Ye 2024). Designing, developing and deploying ethical AI-driven urban systems, such as local government responsible AI systems, serves as a critical platform for implementing practices such as bias detection and mitigation, fair decision-making, transparency, explainability, privacy protection, and inclusivity. These efforts aim to align technological innovations with human values, ensuring that responsible AI constructs are effectively integrated into urban management and planning (Cheng, Varshney, and Liu 2021; Wang, Lu, and Fu 2023; Yigitcanlar et al. 2024).

The new urban science: a symbiotic relationship between AI and urban science

The symbiosis between AI and urban science presents a powerful opportunity to address the complex challenges of modern urban environments (Figure 1). AI's capacity for large-scale data analysis and predictive modelling can accelerate innovation in urban management, while urban science ensures that AI systems remain socially responsive, contextually grounded, and ethically sound. The convergence of these fields, so called the New Urban Science, holds the potential to create smarter, more sustainable, and more equitable cities, capable of adapting to the global challenges of the 21st century.

Urban science, which uniquely bridges the gap between natural and social sciences, occupies a pivotal position to elevate AI's contributions while advancing its own domain. Its interdisciplinary nature enables urban science to not only leverage AI in addressing complex urban challenges but also to drive the evolution of AI by integrating crucial social, spatial, and environmental dimensions into algorithmic frameworks (Goodchild and Li 2021). In an era where cities are becoming increasingly data-driven and technologically sophisticated, urban science has the potential to shape AI's trajectory, making this a great moment to foster deeper collaboration between the two fields. Together, they can unlock innovative approaches to pressing urban issues such as climate resilience, equitable infrastructure and social cohesion (Son et al. 2023).

Nevertheless, for this relationship to thrive, key barriers must be addressed – data supply issues, ethical concerns, and the need for greater transparency in AI development. The reciprocal benefits of this relationship, or perhaps more accurately the symbiosis, are significant. AI offers urban science powerful tools for scaling and enhancing research, particularly through its capacity for big data analysis, predictive modelling, and geo-simulation. By harnessing AI's predictive capabilities, urban science, utilizing various GeoAI and Urban AI applications – can better optimize critical areas such as traffic management, resource distribution, and environmental sustainability (Marasinghe et al. 2024). At the same time, the application of urban science's real-world complexities can inform AI development, making it more socially aware, contextually grounded, responsible and capable of solving multifaceted and complex urban problems. The symbiosis is crucial for building cities that are not only efficient and innovative but also inclusive and sustainable in the face of global challenges. A collaborative approach involving AI is the key to shaping resilient urban environments that address the needs of all communities.

By fostering stronger collaboration between AI scientists and urban researchers, the New Urban Science can unlock transformative insights and generate innovative solutions that benefit urban communities globally. The future of cities will not rely solely on AI's technical prowess, but also on the societal understanding and ethical considerations provided by urban science. The intersection of AI and urban science presents significant opportunities for advancing both fields as elucidated below.

AI for urban science

Urban digital twins

Urban digital twins – virtual replicas of physical urban environments – offer immense potential as a platform for AI-urban science collaboration (National Academies of Sciences, Engineering, and Medicine 2023). By integrating real-time data from sensors, IoT devices, satellite imagery, and social media, digital twins simulate and predict complex urban dynamics, providing critical insights for urban planning, transportation, and public health (Ye et al. 2023). To maximize their impact, these models should embrace co-learning and co-design to reflect not only physical infrastructure but also human behaviour and social processes. The co-design process involves stakeholders – urban planners, AI developers, and communities – ensuring these tools address the needs of diverse populations. Continuous co-learning allows AI embedded in digital twins to evolve, adjusting to new data and urban dynamics, while maintaining ethical standards.

Generative AI and large language models

The integration of Generative AI and large language models (LLMs) is revolutionizing accessibility to urban models, especially for economically disadvantaged and marginalized groups. These AI technologies enhance data comprehension, presenting complex urban data in more intuitive and accessible formats, thus empowering communities to engage in urban planning from ideation to design stages. Generative AI and LLMs also contribute significantly by enriching urban data assimilation and interpretation. By synthesizing vast data streams from sources like satellite imagery, sensors, social media, and historical records, these models facilitate dynamic simulations that capture the fluid nature of urban areas. This capability not only aids in projecting future urban scenarios but also incorporates a more human-centred perspective, addressing uncertainties and environmental variability often overlooked in traditional models. Moreover, the conversational capabilities of LLMs make urban science more participatory, allowing stakeholders to query, analyse, and visualize urban data in natural language. This fosters a more inclusive, transparent, and collaborative urban planning process, where data-informed decisions can be made swiftly, considering diverse perspectives and community needs. By promoting more accurate, inclusive, and sustainable decision-making, these AI innovations help ensure that urban science remains equitable, adaptable, and responsive to the challenges faced by different urban populations (Du et al. 2024).

Urban science for AI

AI and urban design

Urban science, particularly urban design, plays a crucial role in refining AI systems by offering structured frameworks that guide AI algorithm optimization. Real-world urban cases provide valuable data that help enhance AI's predictive models and decision-making processes (De Silva and Alahakoon 2022). For instance, urban design frameworks introduce complex scenarios that allow AI systems to learn and improve through application in real-world contexts. In return, AI supports urban science by offering advanced data analytics and predictive modelling tools, which help urban planners make informed decisions about urban growth, environmental impact, and human behaviour (Batty 2021). This reciprocal relationship fosters the development of urban environments that are both efficient and sustainable, balancing human needs with environmental stewardship (Steinitz 2020).

Ethical AI development

Urban science plays an important role in shaping responsible AI development by addressing ethical concerns like bias, privacy, and unequal access. By prioritizing principles such as equity, sustainability, and public participation, urban science ensures that AI technologies are designed and deployed in ways that promote social justice. Urban scientists advocate for transparency in AI decision-making, the use of inclusive data, and the protection of individual privacy. This ethical framework not only helps build public trust but also ensures that AI systems align with societal goals, such as fairness, inclusivity, and sustainability, making AI a tool for positive transformation (Li, Yigitcanlar, Browne, et al. 2023; Yigitcanlar et al. 2021).

Responsible AI for desired urban outcomes

In urban contexts, responsible AI development goes beyond harm reduction; it focuses on proactively designing AI systems that promote positive societal outcomes. Urban science plays a key role in embedding ethical principles into AI development, ensuring that these systems prioritize human-centred goals over mere technological efficiency. This involves safeguarding against algorithmic bias, ensuring accountability in AI-driven decisions, and tailoring AI systems to meet the diverse needs of urban populations. By placing ethics at the heart of AI innovation, urban science supports equitable urban development and fosters AI technologies that enhance societal well-being (Li, Yigitcanlar, Nili, et al. 2023).

Concluding remarks

As AI continues to transform scientific research, it is crucial for the social sciences – and urban science in particular – to take an active role in shaping its trajectory. Especially the recent advancements in computational power and machine learning are revolutionizing urban science by unlocking new analytical capabilities. These technologies enable more sophisticated modelling, real-time data analysis, and predictive insights, allowing for better understanding and management of complex urban systems. However, before embracing AI wholesale, we must first clearly articulate why and how AI can contribute to urban science's fundamental goals of EDUG. The convergence of responsible AI and urban science – as we call it, the symbiosis of responsible AI and urban science or the New Urban Science – presents a powerful opportunity to address the complex challenges of modern urban environments.

In other words, AI provides transformative tools for urban science, helping cities become smarter, more sustainable, and more equitable by leveraging data-driven insights to tackle urban complexities. Nonetheless, while AI holds great potential for urban management and planning, it is essential to be aware of knowledge-driven vs. data-driven AI approaches and recognize its current limitations, particularly in scientific explanation and transparency. Furthermore, we need to consider both techno-centric AI and human-centric AI to make AI more relevant and useful to social sciences in general and urban science in specific. These challenges underscore the need for careful consideration when applying AI in urban contexts, ensuring that it complements rather than replaces traditional methods of inquiry.

Data availability and quality present significant challenges in this convergence. Collaborative platforms are essential for overcoming barriers between AI and urban science. These platforms facilitate synthetic data sharing, enabling urban scientists and AI researchers to work together. Unlike fields such as weather forecasting where data is abundant, urban science faces unique constraints related to privacy, cost, and proprietary ownership. While AI-generated synthetic data can help urban areas lacking real-time datasets, we must carefully consider the implications for research validity and reproducibility. This fosters co-learning and leads to more accurate urban models for decision-making (Batty 2023).

Co-learning networks are crucial for fostering collaboration between AI and urban science. These networks bring together experts from both fields, equipping future researchers with cross-disciplinary expertise. Training programmes should emphasize not only technical integration but also critical ethical considerations beyond privacy and bias, including the handling of uncertainty, transparency, and trust. Through real-world projects, scholars can learn to integrate AI with urban science, ensuring that collaborations are socially informed and technically advanced. Particular attention should be paid to establishing scientific norms for reproducibility and transparency in AI applications (Yigitcanlar, Agdas, and Degirmenci 2023).

While recognizing that AI may not transform urban science as dramatically as it has fields like protein folding or weather forecasting, the current condition calls for a recalibration of the relationship between AI and the social sciences, advocating for a more integrated and mutually enriching partnership. By advancing AI's theoretical and practical applications within urban science, while remaining mindful of its limitations and ethical implications, we can amplify the impact of both fields. In this context, the New Urban Science offers transformative insights into the dynamics of urban spaces and pave the way for smarter, more sustainable, and more equitable cities.

In this opinion piece, we explore the growing importance of AI in transforming urban science and its applications – in other words, why AI matters for urban science. As cities become increasingly complex and data-driven, AI offers unprecedented opportunities to analyse, predict, and optimize urban systems, from infrastructure and transportation to sustainability and public health. However, realizing AI's full potential in urban science requires more than just technological adoption; it demands a nuanced understanding of how AI can be integrated into urban planning, governance, and societal contexts. We advocate for embracing this symbiotic relationship with thoughtful consideration of ethical, social, and practical implications. By doing so, we can unlock AI's transformative capabilities to create smarter, more sustainable, and resilient cities for the future.

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