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Urban land use mix and AI: A systematic review

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ABSTRACT

This paper provides a comprehensive systematic review of Artificial Intelligence (AI) applications in urban land use mix at the granular level, a critical aspect of urban planning and sustainability. After screening 654 documents published between 2014 and 2024, 66 relevant studies are analyzed in detail. AI technologies are scrutinized for their potential to refine land use mix assessments and enhance the accuracy of urban functional planning tasks. Which could improve urban sustainability and foster spatial synergy by adeptly navigating the complexities of managing land use mix with AI-driven solutions. The review assesses these studies through three core dimensions: (1) AI techniques for urban land use classification and spatial interaction analysis, (2) AI-driven enhancement and optimization strategies for sustainable mixed-use development and management, and (3) AI tools enhancing participatory planning systems and decision-making processes. The review finds that, despite noteworthy progress and potential applicability, substantial challenges remain in fully integrating AI into the adaptive frameworks required by rapidly evolving urban contexts. The review identifies a diversity of research gaps that need to be addressed in future work, with the aim of refining AI techniques to better account for land use mix complexities and support more responsive socio-technical urban development initiatives.

1. Introduction

A diverse mix of land uses is fundamental to urban sustainability, standing in contrast to functional segregation and zoning policies. Built environments that integrate a diverse array of functions foster proximity, short distances and active mobility, encouraging healthier lifestyles, and enhancing the usability of public spaces. Despite this, urban planners continue to need tools to promote and safeguard functional diversity. The integration of Artificial Intelligence (AI) into urban design and planning is heralding a new era for cities, promising smarter, more sustainable environments that better respond to the needs of their inhabitants. As urban areas continue to expand and evolve, the complexity of managing urban systems escalates, making traditional methods insufficient. AI emerges as a powerful tool in addressing these challenges, potentially contributing to the enhancement of planning processes, and ultimately urban sustainability, efficiency, and livability. Integral to mixed-use development, the concept of urban vitality promotes dynamic, balanced neighborhoods that prioritize diverse functions within accessible, walkable distances. AI's role in operationalizing mixed-use environments aligns with these principles, providing urban planners with data-driven tools to achieve vibrant built environments through enhanced land use mix. After screening 654 documents published between 2014 and 2024, this systematic review explores the expanding role of AI in urban planning, emphasizing its potential to profoundly support urban planning and address one of the most pressing challenges of contemporary urbanism: functional diversity. Especially so at a moment when urban planning must react to rapid changes, and digest vast amounts of urban data.

AI applications in urban planning are recently yet diverse and integral to advancing urban intelligence by leveraging digital and informational assets to improve compactness, density, and efficient land use distribution and mix (Allam et al., 2022). Machine learning techniques in urban land-use classification have brought promising advances in the detailed categorization of urban areas. In a study by Liu, Song, et al. (2023), while providing a broad analysis of machine learning-based classification methods (e.g., threshold-based, model-based) for regional-scale land cover change detection, their review lacks a comprehensive exploration of AI approaches, failing to consider neural networks, evolutionary algorithms, and optimization techniques, and does not address granular-level urban land use mix complexities, such as functional diversity, spatial compatibility, and dynamic mixed-use zoning. Chaturvedi and de Vries (2021), provide a machine learning-focused review of land use classification methods at a closer scale, yet their study remains limited to machine learning techniques, without

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exploring broader AI techniques beyond classification. The application of artificial intelligence (AI) in urban land-use planning has also focused on optimizing expansive land-use categories such as agricultural, brownfield, and environmental zones which are usually designated on the Land Cover/Change (LCLC). Research by Castro et al. (2022) and Ding et al. (2021) primarily examine genetic algorithms (GA) and particle swarm optimization (PSO) in land use optimization, focusing on broad-scale land allocation strategies such as agricultural zoning, brownfield redevelopment, and environmental land management, yet their reviews remain limited to specific AI optimization techniques, and failing to address granular-level urban land use mix intricacies, crucial for proximity and public space livability (Carpio-Pinedo et al., 2021). For instance, Utami et al. (2024) focus on AI-based land use prediction modeling, applying machine learning and cellular automata to forecast large-scale land use transitions, but their review lacks a broader exploration of AI methodologies such as deep learning, evolutionary algorithms, and multi-agent systems. Wagner and de Vries (2019) examine AI in decision-support systems for urban development and land management, focusing on cellular automata and multi-criteria decision analysis, yet their work does not address AI applications for urban land use mix adaptation, functional diversity, or spatial compatibility in mixed-use environments.

However, systematic reviews have yet to critically scrutinize how AI methodologies—such as deep learning, evolutionary algorithms, neural networks, and advanced machine learning—are applied to model fine-grained land use mix complexities, including urban density, functional diversity, and the spatial classification/distribution of mixed-use developments. Key gaps persist in synthesizing AI's capacity to resolve operational challenges such as spatial compatibility in mixed-use zoning, and balancing competing demands in dense, multifunctional urban systems. This review systematically explores and synthesizes how AI can support urban planning and design to address the persistent challenges of functional diversity arising from fragmented geospatial datasets, competing sustainability and equity demands in mixed-use zoning, and divergent stakeholder priorities shaping equitable access to urban resources through the lens of three pivotal research questions:

1. How do AI-driven models leverage multisource data to improve urban land use classification and adapt to spatial interactions in evolving urban environments?
2. What are the potential applications of AI-driven strategies on enhancing sustainable urban environments, with a focus on integrated development and balancing diverse urban objectives?
3. In what ways can advanced AI tools enhance participatory planning processes, stakeholder engagement, and the adaptability of decision-making frameworks in urban development?

By addressing these three questions, the review aims to underscore the great potential of AI to assist urban planners and decision-makers to more efficiently develop and manage more sustainable, balanced and vibrant built environments. This review also points to the need to shift AI applications in urban planning from macro-scale frameworks, which are rooted in broad categories and large homogeneous zoning, and regional land cover/change (LCLC) assessments, to fine-grained approaches that navigate the intricate interplay of mixed-use dynamics at the scale of walkable distances. By leveraging AI, a new approach integrating both geospatial data and land use interaction models emerges as a promising path to simulate and inform mixed-use environments, along with considering community priorities into AI-driven conflict-solving participation frameworks.

2. Methodology

2.1. Search approach

This systematic review examines how artificial intelligence (AI) navigates fine-grained land use mix complexities in urban planning. The PRISMA protocol ensured a transparent and rigorous process for identifying, selecting, and synthesizing studies with defined criteria, database selection, and comprehensive documentation (Page et al., 2021). A structured and thorough search was conducted across four prominent academic databases: Scopus, Springer Link, Google Scholar, and Semantic Scholar. These databases were chosen for their relevance to urban planning and AI-related fields, and semantic queries were employed to ensure that relevant studies were captured comprehensively. The search strategy involved the use of a combination of targeted keywords such as, "ai AND urban AND land AND use AND analysis", "deep AND learning AND urban AND spatial AND function," "artificial AND intelligence AND urban AND diversity," "ai AND land AND use AND spatial AND planning," "machine AND learning AND urban AND function" and "artificial AND intelligence AND urban AND land AND use AND classification." To ensure the focus remained on granular land use patterns rather than broader regional-level analyses, synonym searches were conducted for terms like "land use mix," "urban diversity," "spatial function," and "urban zoning." Advanced search techniques, including Boolean operators (such as "AND" and "OR") were employed to refine the search results and ensure that the search captured the most relevant studies. The time frame for the search was limited to publications from 2014 to 2024, which allowed for a focus on the latest advancements in AI technologies as applied to urban planning. Only peer-reviewed journal articles, conference papers, and a select few relevant trial studies were included. Studies that were not published in English were excluded to ensure consistency in the focus on international literature.

2.2. Screening and selection process

The initial search yielded 2107 articles. Duplicate studies, particularly those retrieved from multiple databases were identified and removed using Mendeley reference management software, and irrelevant studies such as those focusing on land cover/change (LCLC), and land use at the regional level were excluded, this narrowed these results down to 654 papers. Studies were required to meet specific inclusion criteria to ensure relevance. The inclusion criteria focused on studies that applied AI frameworks or AI-based tools to urban land use mix at the granular level, considering a wide range of applications including classification, simulation, optimization, and decision-making. This encompassed research on land use mix management, as well as studies examining urban function classification, spatial interactions analysis, and functional land use patterns. Additionally, studies exploring AI-driven strategies for urban growth, mixed-use and sustainable land use development were included, along with those addressing AI's role in participatory planning, stakeholder engagement, and decision-support systems. Studies published outside the 2014–2024 window were excluded. In the first phase, the initial screening of the articles is based on their relevance to inclusion/exclusion criteria, reducing the pool to 187 articles. After the initial screening of the articles, both manual review and an AI large language model (LLM) were employed to enhance the accuracy of the selection process. The LLM tool was used to ensure strict adherence to the inclusion criteria, while manual review helped verify the findings. The LLMs can accurately summarize text and effectively retrieve information to analyze and categorize complex academic texts (Ito et al., 2024). We employed a customized ChatGPT to manage the inclusion and exclusion of papers as per the relevance of AI and land use mix. This process resulted in the identification of 66 relevant papers that were subsequently included in the systematic review. The various stages of the selection process were documented using a PRISMA flowchart Fig. 1, which provided transparency and clarity regarding the number of studies reviewed at each stage and the reasons for exclusion.

2.3. Data extraction

Data extraction followed a systematic and structured approach to

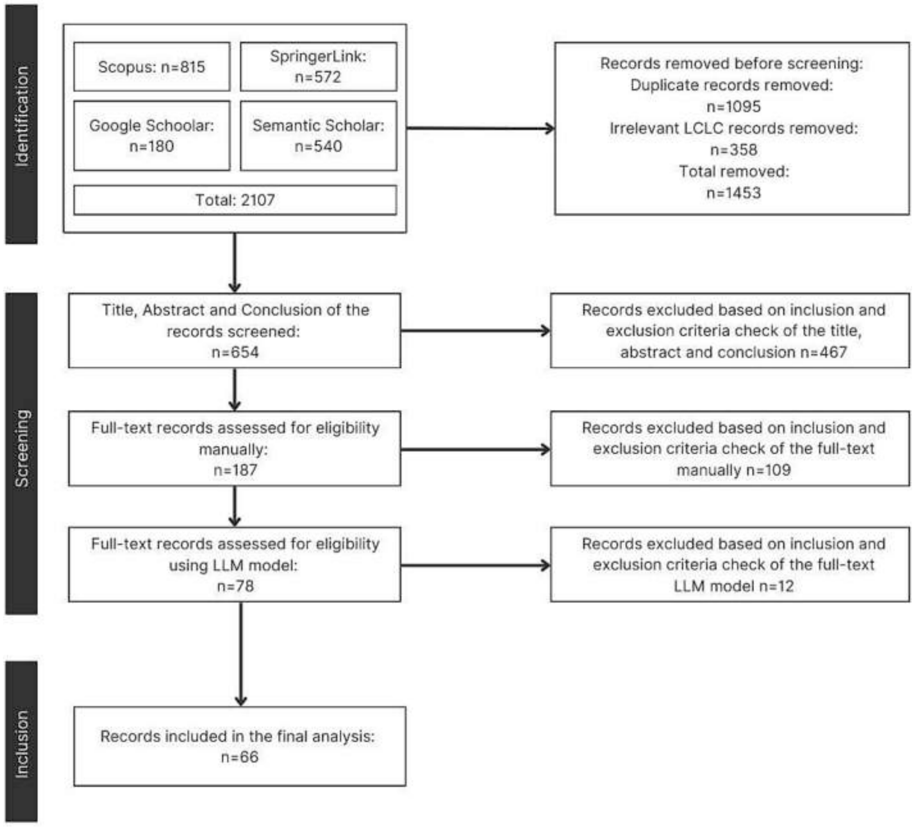

Fig. 1. PRISMA flowchart for the systematic review for urban land use mix and AI.

ensure consistency across all selected studies. Key information extracted from each study included details about the study's objectives, the specific AI methods employed, the data sources used, the outcomes related to the land use mix, and the geographical focus of the research. The AI methods were categorized based on their specific applications in urban land use analysis, evaluating their effectiveness in handling complex tasks such as classifying urban functions, integrating multisource spatial data, and assessing functional diversity. The extracted methods were examined for their potential role in optimizing and enhancing land use mix, improving sustainability-driven urban planning, generating urban layouts, predicting spatial transitions, evaluating existing land use configurations, and supporting stakeholder-informed decision-making. Emphasis was placed on AI models' ability to enhance spatial intelligence, facilitate adaptive urban growth strategies, and integrate diverse urban datasets to provide more evidence-based planning solutions. To ensure the methodological rigor of the selected studies, the Critical Appraisal Skills Program (CASP) checklist was used to assess the quality of the research. The checklist evaluated key aspects of each study, including the clarity of its research aims, the appropriateness of the research design for answering the research questions, the robustness of data collection and the reliability of the data sources used, the validity of the results, and the justification of the conclusions drawn (Shaheen et al., 2023). Studies that did not meet the required standards of methodological rigor were excluded from the final analysis. The extracted data was organized in a structured format to ensure uniformity in the analysis phase. Each study's extracted information was meticulously documented, allowing for comprehensive comparisons between studies and a clear understanding of the methodologies and results achieved.

3. Results overview

The review aims to capture the progression and application of AI techniques ranging from basic machine learning to advanced deep learning and geospatial analyses, emphasizing their significant role in enhancing urban land use classification, managing urban dynamics, and fostering participatory planning. This overview sets the stage for a structured analysis, which categorizes the studies according to their objectives, methodologies, and outcomes, thus offering insights into the predominant trends and methodological innovations within the field. The studies were synthesized by grouping them into three distinct categories based on their core objectives and outcomes. These categories included: (1) AI applications in urban land use and spatial analysis (29 Papers), (2) AI Strategies for urban mixed-use development and management (30 Papers), and (3) AI in urban land use decision-making (7 Papers). Grouping the studies in this manner allowed for a structured comparison of the various AI methods and their applications in different contexts of urban planning. To ensure the methodological rigor of the selected studies. Geographical distribution forms the crux of our analysis, as highlighted by Fig. 2 which show that nearly half of the AI research in land use is concentrated in China, with the USA and Iran also contributing significantly also the growing interest in research field of AI and urban systems in the last decade and special in post-pandemic era where urban mixed-use spaces got more attention in also achieving AI-driven urban planning and design solutions Fig. 3. This concentration underscores the need for broader international collaboration to address research disparities and ensure global access to AI advancements and sustainable applications. Fig. 4. & Fig. 5 demonstrate how various AI approaches are utilized across different urban planning objectives, including classification, prediction, and sustainability, also temporal evolution of AI research trends in land use mix field, showing an increasing trend towards more integrated applications such as negotiation, prediction, and layout generation. This trend underscores enhancements in AI capabilities and conforms to enduring urban development goals, heralding a transition towards more dynamic and responsive urban planning methodologies. The findings indicate

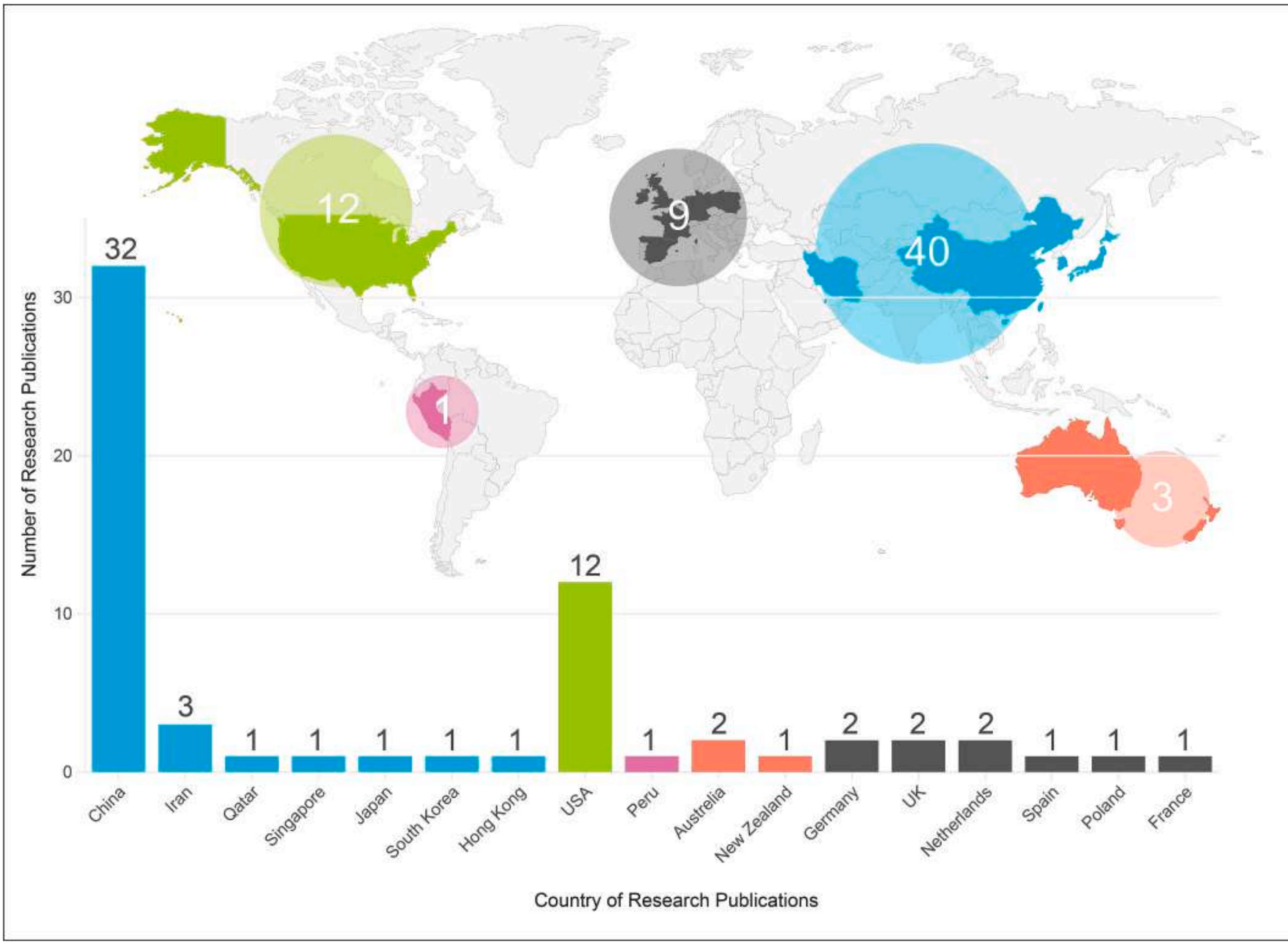

Fig. 2. Geographical distribution of reviewed studies.

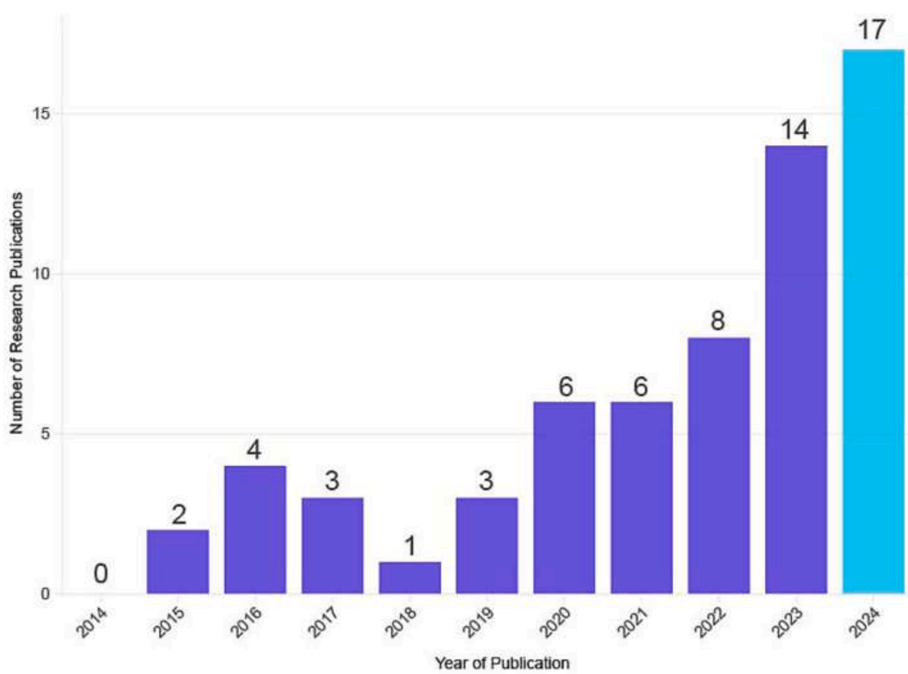

Fig. 3. Published date distribution of reviewed papers.

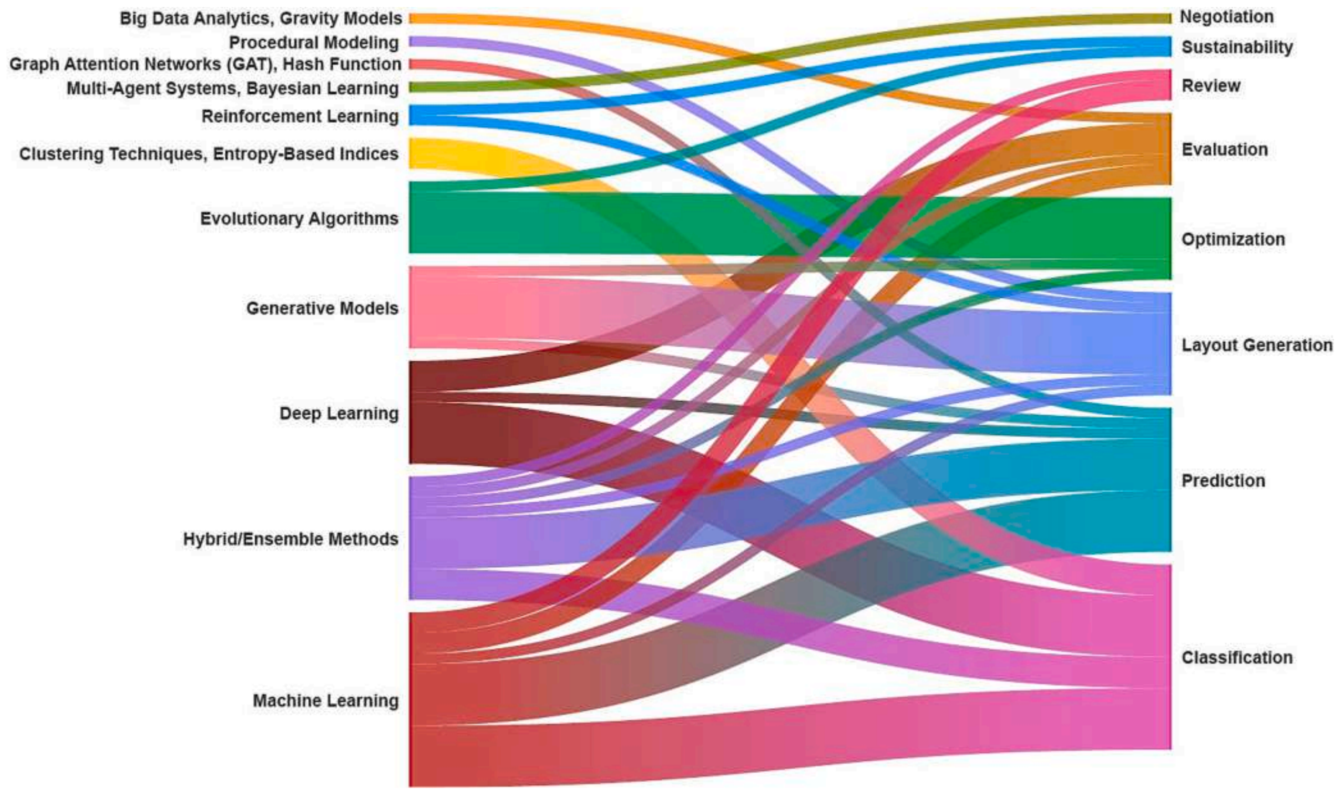

Fig. 4. AI approaches and their applications in urban land use planning objectives.

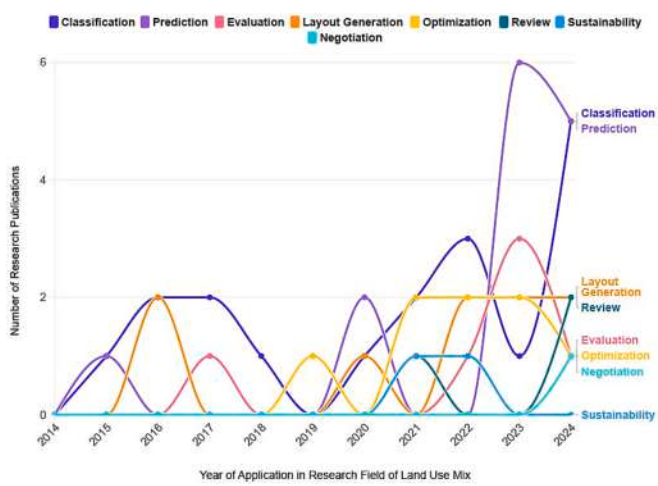

Fig. 5. Evolution of AI research focus areas in urban land use planning objectives.

different trend interests towards adaptive AI systems in urban planning, where responsive AI-driven tools address both technical and social dimensions of sustainable city development. These advanced systems integrate diverse data sources enabling models to capture complex urban dynamics at a finer granularity. As illustrated in Fig. 6, clusters of keywords co-occurrence reveal how integrated AI methodologies are being employed to analyze urban land use mix challenges, reinforcing the consolidation of conceptual frameworks within the literature. By moving beyond traditional, static models, AI might facilitate proactive urban planning, allowing cities to adapt to fluctuations in population density, environmental changes, and mobility patterns. Moreover, as depicted in Fig. 7, regional heterogeneity in the exploration and application of AI techniques reveals that certain countries, such as China and the USA, employ a broader methodological repertoire—ranging from Machine Learning and Deep Learning to Graph Attention Networks and Hybrid/Ensemble Methods. In contrast, regions like Japan, Qatar, and Spain demonstrate a more limited repertoire, primarily focused on Machine Learning. This variation may reflect differences in national urbanization policies, data infrastructure, and institutional focus on diverse AI-driven urban planning approaches. This adaptability could support urban planners in addressing rapidly changing urban environments and in optimizing mixed-use spaces to better align with sustainability goals. This evolution reflects AI's potential to advance urban planning towards a more integrated, data-driven socio-technical approach that prioritizes spatially responsive features of adaptability, usability, and accessibility. AI's predictive capabilities may allow for real-time adjustments and informed decision-making, with simulations that can anticipate the impact of zoning policies or infrastructure changes on various social groups. This transition fosters a participatory model where community inputs and localized factors are integral, enabling the development of cities that are not only efficient but also socially responsive and inclusive. Table 1 presents a structured synthesis of findings from the systematic review, categorizing AI techniques into 11 key techniques and their associated models and algorithms. The table maps these tools to their potential applications in addressing urban challenges such as land-use classification, land-use mix allocation optimization, automating layout regeneration via text descriptions, Simulating stakeholder negotiations, and zoning prediction. This taxonomy highlights how AI bridges fragmented geospatial data and stakeholder priorities, offering planners scalable, data-driven strategies to advance urban sustainability and livability.

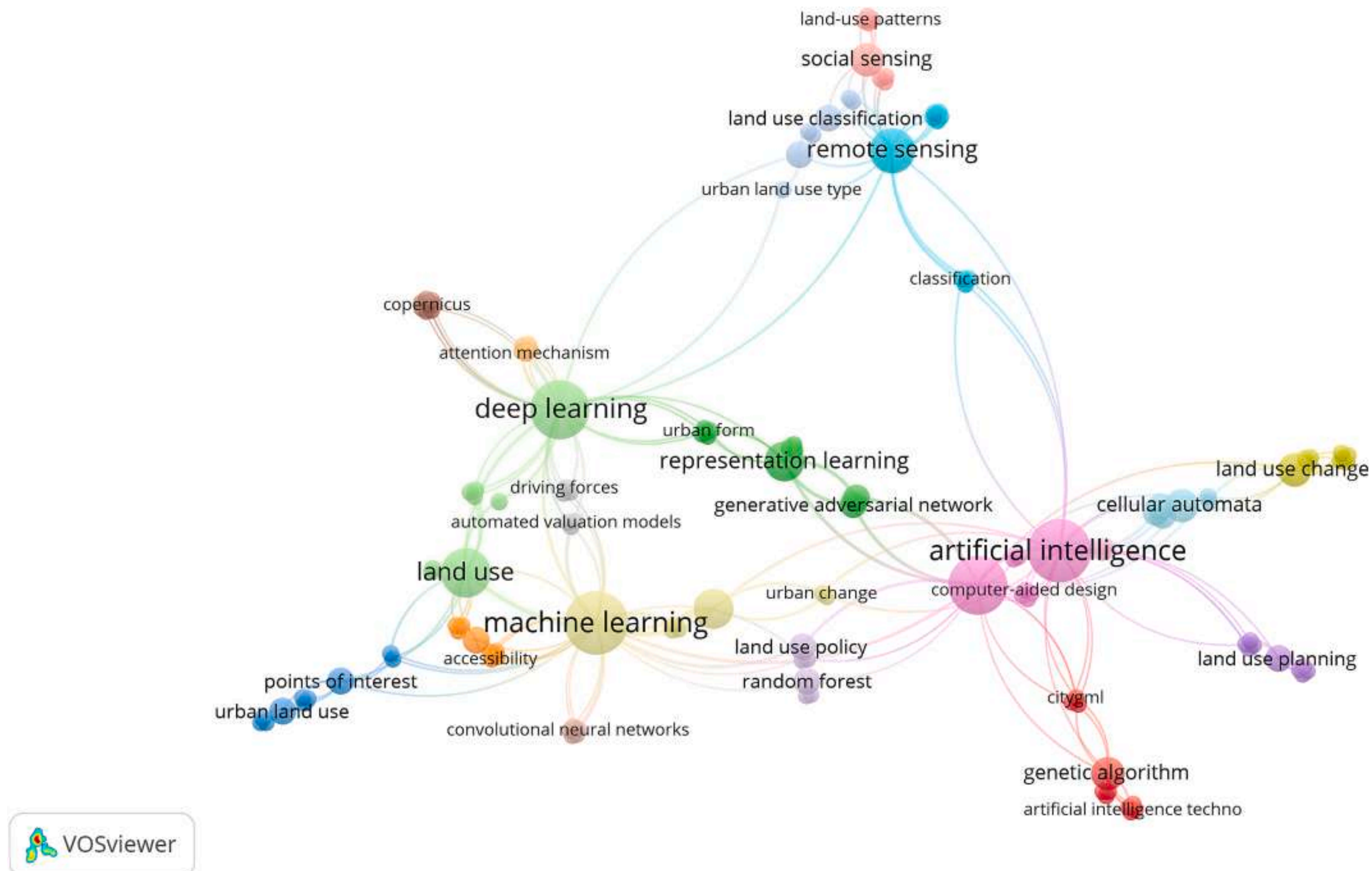

Fig. 6. Keywords Co-occurence.

4. Results

4.1. AI in urban land use and spatial analysis

4.1.1. AI techniques for classifying urban land use

AI techniques showed potential in improving the classification of urban land use, offering urban planners more precise and nuanced insights into the spatial complexities of modern development strategies. Traditional classification methods, which rely heavily on remote sensing and static datasets, often struggle to capture the dynamic nature of evolving urban spaces. In contrast, advanced AI models like Convolutional Neural Networks (CNNs), Random Forests (RFs), and Decision Trees (DTs) have been particularly effective when applied to large-scale, high-dimensional datasets such as satellite imagery and Points of Interest (POI) data, while machine learning ensemble methods show efficient mixed-use patterns classification using unconventional data such as municipal water consumption.

CNNs are especially adept at processing image data, enabling them to distinguish between different land use zones, such as residential, industrial, and commercial areas, with high precision. This has been particularly useful in densely populated cities where land use patterns are complex and hard to discern. RFs, on the other hand, are effective in enhancing spatial resolution, enabling planners to conduct parcel-based classifications. These models allow for more fine-grained control over land use policy implementation at both regional and local scales. One highly notable development is the integration of the Gradient Boosting Decision Tree (GBDT) algorithm, which was applied to POI and urban form data in Yiwu, China (Zhou et al., 2024). This method achieved high accuracy in classifying complex urban functions and detected significant growth in logistics and residential areas over a decade. The use of GBDT outperformed other machine learning models, marking an advancement in AI-based land use classification, particularly for logistics centers and rapidly growing urban hubs. Moreover, innovative AI methods such as Land Value Generative Adversarial Networks (LVGANs) have been deployed to predict changes in land value distributions. These models treat land classification as an image generation task, allowing for the simulation of how public investments, such as infrastructure development, influence land values (F. Jiang et al., 2024). LVGANs have proven particularly effective in simulating urban development scenarios and in promoting equitable urban growth by allowing policymakers to predict the distributional effects of public investments. The rotation forest algorithm, a machine learning ensemble method, has been used to classify socioeconomic functions and mixed land-use patterns by analyzing municipal water consumption time series, demonstrating the potential of non-traditional data sources to enhance urban planning with broad population coverage and long-term temporal granularity (Guan et al., 2020).

Recent advancements in vision-language multimodal learning enhance fine-grained mixed land-use mapping by integrating street view imagery with spatially aware textual prompts, achieving point-level precision in dense urban areas, surpassing single-modal methods, and allowing flexible spatial aggregation, as demonstrated by the CLIP model (Wu et al., 2023). Another interesting approach is the bi-branch neural network (BibNet) model, used for urban functional zone mapping in Shenzhen and Hong Kong Fan et al. (2021), features a dual-branch architecture that processes distinct data types separately. One branch analyzes high-resolution remote sensing imagery, extracting spatial features like building density and land use patterns. The other processes social sensing data, such as points of interest (POI), capturing activity-based characteristics. This dual processing results in more accurate urban land use classification, enhancing the ability to tailor urban development strategies to the unique dynamics of different city areas.

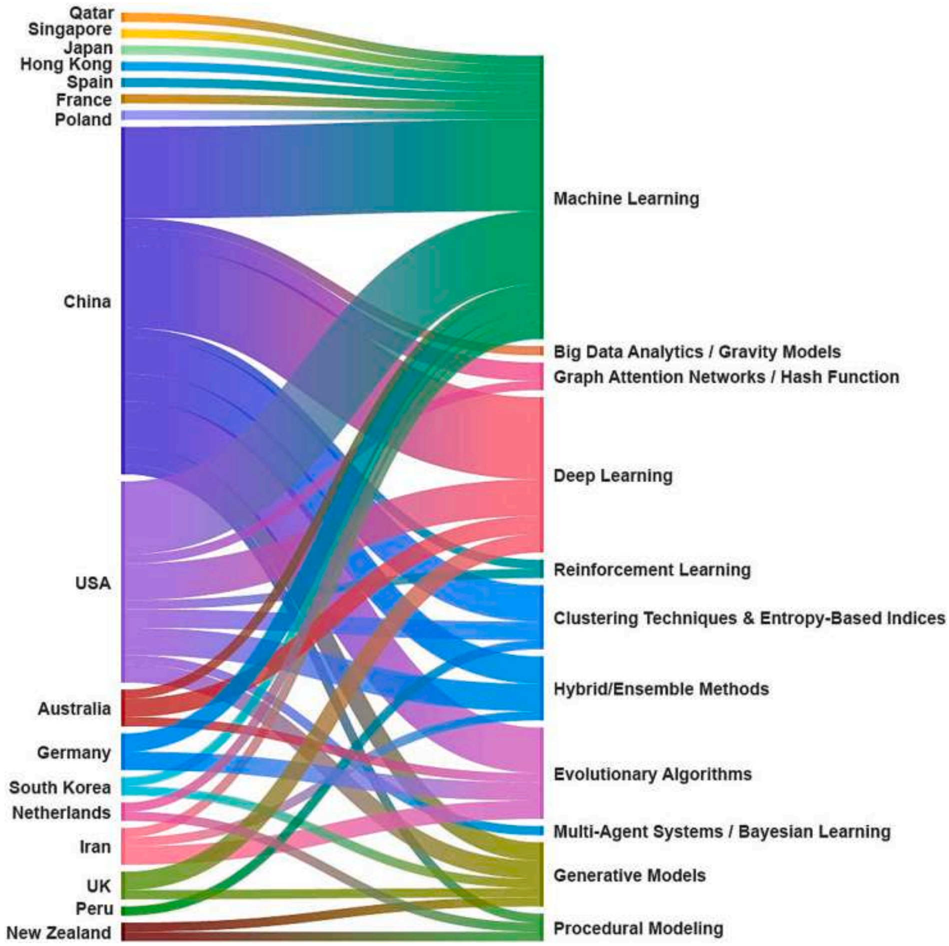

Fig. 7. Distribution of AI approaches by geographic context.

However, some limitations persist. AI techniques like CNNs and RFs might improve urban land use classification, but they could struggle to capture the full complexity of urban environments, as CNNs show high potential with image data but may not accurately represent the intricate relationships between different land uses and their spatial configurations. Furthermore, multimodal approaches, while promising, may encounter difficulties in integrating diverse data sources, which could limit their scalability and practical application in urban planning (Y. Xu et al., 2022). Moreover, these AI models often act as black boxes, hindering the clear interpretation of how classification outcomes are derived, and thus challenging urban planners' ability to validate and trust their insights. This inherent opacity, coupled with sensitivity to the quality and context of input data, further restricts the adoption of AI techniques as reliable decision-making tools for comprehensively understanding urban landscapes.

4.1.2. Integration of multisource data for enhanced classification

A potential advantage of AI lies in its ability to integrate diverse datasets, which is essential for effectively mapping the complexities of urban land use. The fusion of multiple sources of data—such as satellite imagery, social media activity, transportation networks, and demographic statistics—enables AI models to deliver more holistic and evidence-based urban planning solutions. The incorporation of high-resolution satellite imagery from sources like Gaofen satellites, when combined with crowdsourced information from platforms such as OpenStreetMap and social sensing data, has led to remarkable improvements in the granularity and accuracy of land use classification. For instance, Wang, Chen, et al. (2022) raised their accuracy from 72.37 % to 81.17 % classification accuracy by using a grid-based method instead of parcel-based method, by combination of the Random Forest algorithm, the Moore neighborhood correction technique. Similarly, Li et al. (2024) raised their accuracy from 75 % to 82 % using traditional methods like Random Forests to 92 % to 94 % classification accuracy by using Transformer models that integrate multimodal data sources. These integrated datasets provide urban planners with real-time insights into the dynamic in land use patterns over both time and space. Social media data adds yet another dimension, capturing human activities and interactions that static datasets typically overlook.

In an important study by Guo, Tang, et al. (2024) deep learning models like Inception V3 and BERT were used to combine visual and semantic features from multisource geospatial data in Wuhan, China. This integration of human activity data with high-resolution satellite imagery enabled the AI model to achieve high accuracy in identifying mixed land-use patterns, providing planners with detailed insights into complex urban environments. The combination of Inception V3 for visual feature extraction and BERT for semantic data analysis represents a significant leap in urban land use classification, offering a novel way to integrate diverse data sources for more comprehensive urban analysis. Yao et al. (2017) developed an AI-driven framework for sensing urban land use distribution by integrating Baidu POI data, road networks, and traffic analysis zones (TAZs) with the Word2Vec machine learning model. By converting spatial POI distributions into high-dimensional semantic vectors and applying K-Means clustering alongside Random Forest classification, the study achieved 87.28 % accuracy in classifying urban land use types, demonstrating the effectiveness of multisource data fusion in urban land use analysis.

Moreover, methodologies like Geographically Weighted Regression (GWR) and entropy-based measures, when paired with multisource

Table 1
Taxonomy of AI approaches and methodologies in urban land use mix.

AI Techniques	AI Models/Algorithms	Potential Applications
Deep Learning	CNNs, GANs, GNNs, Transformers, U-Net, Text-to-Attribute Networks, GANs, Denoising Diffusion Models, Vision-language multimodal learning, LLMs.	Analytical: Urban land use classification, automated layout generation, predicting urban form/function, mixed use mapping, semantic extraction from human activity data. Generative: Generating urban layouts, simulating land use configurations, automating layout regeneration via text descriptions.
Machine Learning	Random Forest, SVM, XGBoost, k-means clustering, Word2Vec, BERT	Land use classification, zoning prediction, urban vitality analysis, text mining from crowdsourced data (e.g., social media), socio-economic land use pattern detection.
Reinforcement Learning	Hierarchical RL, Multi-Agent RL, Monte Carlo Tree Search	Optimizing land use allocation, resolving stakeholder conflicts, negotiation process simulation.
Genetic Algorithms (GA)	Genetic Algorithms, Particle Swarm Optimization, Multi-Objective Evolutionary Algorithms	Optimizing multi-objective land use allocation, urban heat mitigation, balancing competing demands (e.g., density vs. sustainability).
Graph-Based Methods	Graph Convolutional Networks (GCNs), Graph Attention Networks	Modeling spatial interactions (e.g., traffic networks), simulating land use relationships, enhancing vibrancy.
Ensemble Learning	Stacking, LightGBM, CatBoost	High-accuracy land-use classification, integrating multisource data (remote sensing + social sensing).
Hybrid Models	ANN + LR, RF-CA, CNN-VCA	Urban growth prediction, improving simulation accuracy by combining complementary AI approaches.
Clustering & Entropy Methods	K-means clustering, GW/RSW indices	Assessing land use mix, detecting socio-economic patterns, classifying urban functions.
Big Data Analytics	Gravity Models, Spatial-Temporal Analysis	Analyzing spatial interactions (e.g., metro systems), predicting land use changes, long-term urban dynamics.
Procedural Modeling	Urban Layout Generation (ULG), Multi-state Super-network Model.	Simulating urban layouts for travel behavior, optimizing land-use diversity and mobility.
Agent-Based Models	Multi-Agent Systems (MAS), Bayesian Learning.	Simulating stakeholder negotiations, modeling urban sprawl, participatory planning.

data, have provided a more nuanced analysis of urban land use (Chen & Song, 2020). These approaches allow for finer-scale interpretations of land use patterns, particularly in identifying the mix of residential, commercial, and recreational spaces that are key to fostering sustainable, socially inclusive built environments. By capturing this mix at both larger and smaller scales, AI models help planners maintain the diversity and balance necessary for vibrant urban life. One novel study applied an AI-driven spatial classification approach to urban land in Peru, integrating Sentinel-2 MSI satellite imagery, road networks, and direct observation data with K-Means clustering. The findings revealed significant discrepancies between speculative land values and official urban planning, highlighting the potential of unsupervised learning for refining urban classification and supporting more data-driven land use policies (Zamalloa, 2021).

Despite AI's potential to enhance urban land use classification through multisource data integration, its reliance on crowdsourced and social media inputs systematically excludes marginalized communities lacking digital access, skewing planning insights towards privileged populations. Technical challenges in harmonizing inconsistent datasets further undermine the reliability and scalability of these tools, limiting their ability to deliver equitable, context-sensitive solutions for sustainable mixed-use zoning (Liu et al., 2017; Yao et al., 2017). Moreover, the integration process can amplify inherent biases in data availability and quality, resulting in models that favor areas with robust digital footprints over those with sparse information. This limitation may ultimately narrow the contextual scope of the analysis, impeding the development of truly comprehensive urban zoning strategies.

4.1.3. Spatial relationships and urban functional diversity analysis

AI techniques have been valuable in analyzing spatial relationships within different urban areas, offering planners unprecedented insights into how different land uses interact across the urban fabric. Models such as spatial graphs, clustering algorithms, Moore Neighborhood correction method, and Hierarchical Random Forest algorithm have enabled more sophisticated analyses of urban vibrancy, land use interactions, and population density distributions.

For instance, multi-view spatial graphs have proven particularly useful in analyzing community structures, allowing planners to assess urban vibrancy by examining the diversity of land uses and the movement of people within and between urban zones (Wang et al., 2018). These AI-driven models allow for the identification of high-vibrancy areas, which are crucial for maintaining economic vitality and social cohesion. The incorporation of temporal data and mobility connectivity further enhances these models, providing a more dynamic view of urban evolution. This allows urban planners to model current configurations of urban space, providing tools for managing long-term urban development. In addition to understanding current urban configurations, AI models have been employed to predict future urban growth trends. Temporal data, when combined with mobility patterns, enables planners to simulate how cities might evolve. This predictive capability is essential for long-term planning, particularly when addressing the challenges of rapid urbanization and evolving land use demands and aiming at the mitigation or correction of undesired trends. A Hierarchical Random Forest algorithm was applied to analyze spatial patterns in zoning, achieving ~99 % accuracy within counties and variable accuracy (19 %–90 %) between counties. The model's ability to predict land use interactions highlights AI's role in understanding urban spatial dynamics and supporting planning decisions (Lawrimore et al., 2024). The integration of smart card data from metro systems, combined with land-use function complementarity indices, is also instrumental in predicting spatial interactions and understanding the synergies between land use and transportation networks (Ren et al., 2020). These analyses promote less car-dependent environments, where sustainable mobility means –i.e. walking and public transit— are real options. By capturing the complementarity between different land uses, AI models allow urban planners to design transport systems that align with more balanced and sustainable urban growth Fig. 8.

Furthermore, AI models have been applied to study transitions in urban form, particularly concerning land use intensity and the development of mixed-use areas. Deep neural networks, such as Long Short-Term Memory (LSTM) networks and Multilayer Perceptron (MLP) models, have shown a clear correlation between transportation infrastructure and changes in land use intensity (Almansoub et al., 2022). These models are critical for promoting higher-density, mixed-use developments that reduce reliance on personal vehicles and encourage walkability, aligning with broader goals of sustainable urban development.

AI techniques could advance spatial analysis of land use diversity by modeling urban vibrancy, mobility patterns, and mixed-use synergies,

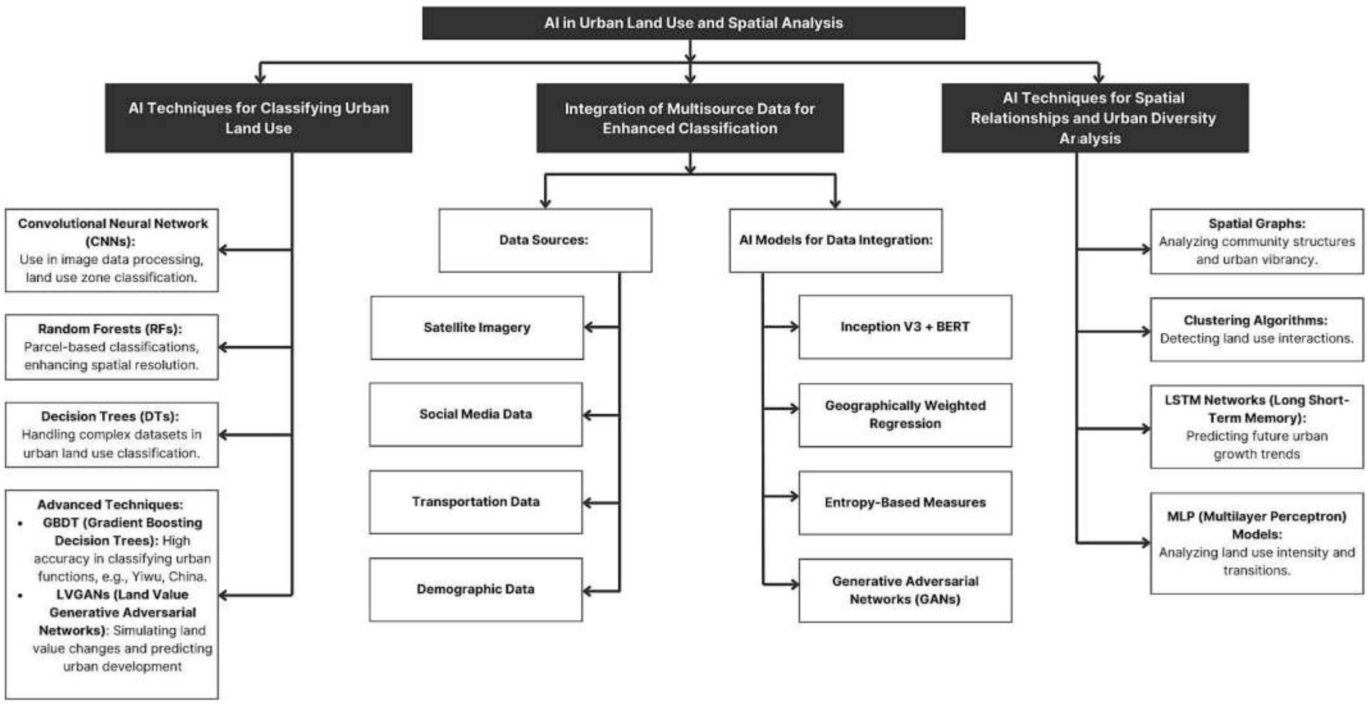

Fig. 8. AI Approaches and multisource data integration for urban planning analysis.

yet their reliance on infrastructure-centric datasets overlooks informal settlements and other underrepresented areas in datasets. This narrow focus risks prioritizing quantifiable metrics over equitable community needs, perpetuating gaps in addressing underdeveloped urban areas. Moreover, these AI models frequently reduce the complex socio-spatial interactions of urban environments to simplified numerical proxies, potentially obscuring vital qualitative factors such as social resilience and local cultural practices. Their overdependence on data-rich infrastructures may also misrepresent the true diversity of urban landscapes, particularly in regions where informal, yet significant, community interactions are poorly documented.

4.2. AI strategies for urban development and management

4.2.1. AI strategies for urban growth management

AI-powered simulation models have potentially enhanced urban planners' ability to predict and manage urban growth by integrating complex datasets, such as population density, land-use mix, transportation networks, and socio-economic factors. By simulating urban growth at both macro and micro levels, AI tools provide nuanced insights into the long-term impacts of different planning policies. These simulations effectively manage urban sprawl, optimize layouts, and help to potentially provide sustainable growth that balances commercial development, residential needs, and green space preservation.

Starting with the deep learning models, the Back Propagation (BP) Neural Network was applied to evaluate urban land use intensity, identifying a gradient of decreasing intensity from urban cores to peripheral areas. The model recommended increasing building density in newly developed residential zones, relocating industrial areas to designated parks, and enhancing commercial land use through higher density and regional centers, aligning with strategies for efficient and balanced urban expansion (Qiao et al., 2017). Moreover, within this technique, generative techniques are exemplified using Generative Adversarial Networks (GANs) in land use mix layout generation. The study of Wang et al. (2020) demonstrates how Generative Adversarial Networks GANs dynamically generate realistic land-use configurations based historical land use configuration data on socio-economic data, such as income levels, housing density, and employment rates, to enable planners to design urban spaces that are equitable and responsive to the needs of all community segments, thus enhancing the ability to anticipate and adapt to complex urban dynamics. These models, including frameworks like LUCGAN+, leverage adversarial learning to create land use mix arrangements based on historical data and economic relationships, aiming to suggest potential enhancements in urban layouts. They allow for future adaptability, enabling cities to evolve in response to changing needs and pressures, ensuring both functional diversity and long-term resilience (Wang, Fu, et al., 2023). An additional innovative approach is the Text2City model, which allows urban layout regeneration to be guided by textual inputs. This model leverages also deep learning techniques, such as Denoising Diffusion Probabilistic Models (DDPMs), to generate urban designs based on text descriptions, providing a user-friendly, intuitive method for planners to specify urban regeneration tasks (Qin, Zhao, Sheng, & Lau, 2024). Text2City combines the precision of machine learning with the flexibility of natural language processing to create urban layouts that adhere to functional and contextual constraints, offering a more interactive and adaptive planning tool for city planners.

Additionally, Procedural modeling and Multi-Objective Evolutionary Algorithms (MOEAs) such as, Non-dominated Sorting Genetic Algorithm II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D) are widely employed to address multi-scale complexities within urban systems, including compatibility, dependency, suitability, and compactness (Masoumi & van Genderen, 2023). MOEAs enable planners to simulate scenarios that optimize various objectives, such as maximizing residential density while preserving green spaces. Furthermore, the integration of Genetic Algorithms (GA) and Game Theory in land-use allocation allows for the simulation of negotiations between competing land-use demands—such as urban expansion versus agricultural preservation—leading to more socially balanced urban development strategies (Liu et al., 2015). In terms of large-scale planning, reinforcement learning-based hierarchical models have also gained prominence. These models simulate interdependencies between macro urban functions, such as transportation networks, and localized urban parcels and blocks. By doing so, they could facilitate the alignment of development goals with granular zoning decisions, creating a more integrated and dynamic urban framework (Wang, Wang, et al., 2023).

Moreover, AI-driven strategies for urban growth management often replicate historical inequities by training on datasets embedded with past land use biases—such as prioritizing high-income zones in density optimization or neglecting informal settlements in generative models like GANs. This heavy reliance on historically shaped data and rigid algorithmic frameworks risks reinforcing outdated planning paradigms, limiting the capacity of these models to detect emerging trends, model for new goals and criteria, and adapt to rapidly evolving environmental, social, and spatial challenges.

4.2.2. AI-based tools for urban diversity exploration and enhancement

AI tools are being rapidly used to simulate urban functional diversity, focusing on the balanced distribution of land uses—residential, commercial, recreational, and public—across urban spaces. These tools enhance the planners' ability to simulate interactions between different land uses, optimizing urban layouts that promote accessibility, economic vibrancy, and sustainability.

Models such as Graph Neural Networks (GNNs) and Generative Adversarial Networks (GANs) have proven particularly effective in capturing the complexities of urban systems. These models incorporate a wide range of data, from population distribution and environmental conditions to socio-economic factors, to simulate both present and future urban mixed-use configurations. A GAN-based AI advisor was developed to generate conceptual land use plans by translating GIS and land-use data into RGB-encoded images, visualizing building density and land coverage across different urban density scenarios while identifying limitations in extreme density conditions (Park et al., 2023). By analyzing the interactions between land uses, GNNs, and GANs allows planners to anticipate how changes in zoning will influence overall urban functionality, helping to design mixed-use developments that foster economic vitality and social well-being. Another development is the MIT Media Lab's Generative Land Use project, which utilizes genetic algorithms and particle swarm optimization techniques to model land-use distribution. This project focuses on generating more integrated urban environments by considering social, economic, environmental, and cultural factors, creating layouts that prioritize community well-being (Overview ‹ Generative Land Use for Human-Centric Communities — MIT Media Lab, n.d.). Similarly, the Interactive Design System-AI (IDS-AI) leverages Geographic Information Systems (GIS) and Fuzzy Analytical Hierarchy Process (FAHP) to create 3D simulations of urban landscapes (Safabakhshpachehkenari & Tonooka, 2023).

The integration of deep learning and reinforcement learning within these AI-based tools enable planners to dynamically adjust urban layouts based on evolving conditions. For instance, models that incorporate reinforcement learning provide adaptive solutions that respond to changes in urban patterns, ensuring that cities remain resilient and capable of supporting sustainable development even in the face of shifting socio-economic landscapes.

However, AI tools for land use mix improvement assume static quantitative definitions of balance ignoring how human behavior and practices dynamically reshape urban spaces. This rigidity limits their capacity to model less rigid or clear land use categories, like in self-organizing neighborhoods where informal or hybrid land uses evolve organically over time. Moreover, reliance on predetermined metrics tends to obscure the unpredictable nature of urban change, leaving these tools ill-equipped to adapt to unforeseen shifts. Their focus on fixed data parameters also restricts possible serendipities and the ability to acknowledge emerging spatial configurations that defy traditional classification.

4.2.3. Strategic impacts of AI on urban policy and planning

The integration of AI into urban development processes is promising and showing more potential for larger contributions in the field of urban land use mix, offering planners more data-driven and precise tools for optimizing land-use configurations and promoting sustainable development. AI-driven models facilitate analysis of socio-economic, environmental, and operational factors, while also enabling planners to predict the long-term impacts of policy decisions and urban growth strategies in a parallel process. This dual capability may result that urban environments are designed for balanced usability, accessibility, and sustainability.

Tools such as IHPlanner by Wang, Wang, et al. (2023) combine human input with AI-generated designs, allowing urban planners to guide AI outputs in alignment with specific goals or regulatory frameworks. This hybrid approach can help planners retain control over essential urban design elements while benefiting from AI's capacity to process large datasets and generate comprehensive urban configurations. AI has also become increasingly important in integrating functional diversity with economic considerations. For example, the use of machine learning techniques, such as XGBoost and Deep Neural Networks (DNNs), allows planners to predict land values and evaluate the economic implications of different land-use strategies (Jafary et al., 2024). The amalgamation of economic models with functional diversity simulations guarantees that urban expansion is sustainable, functional, and economically feasible. Moreover, AI has made significant contributions to the development of mixed-use density integration AlKhereibi et al. (2023) demonstrate that by using machine learning models, such as Random Forest and XGBoost, to predict metro ridership based on urban land use policies, this can help planners to refine transportation strategies and enhance the spatial synergy between land use distribution and metro accessibility. This helps cities enhance public transportation accessibility, reduce reliance on personal vehicles, and promote more sustainable forms of mobility. AI-based simulations are thus transforming urban planning into a more dynamic and responsive process. By integrating real-time data, advanced AI models, and human expertise, urban planners are equipped with tools to design resilient, diverse, and economically prosperous cities that meet the evolving needs of their populations while promoting sustainability and economic prosperity.

Despite AI's potential to refine land use policy, its reliance on historical datasets entrenches path dependency, stifling the innovation process. Fixed variables like ridership and land value prioritize incremental adjustments, which leads to neglecting novel mixed-use solutions beyond the training data. Furthermore, anchoring predictive models to established metrics risks overlooking emerging urban indicators that could redefine planning paradigms. As a result, policy strategies may remain constrained to traditional models, limiting the pursuit of innovative approaches essential for addressing future urban challenges.

4.2.4. AI in advancing sustainable urban land use mix development

Artificial intelligence (AI) plays a considerable role in sustainable urban design, particularly in mixed-use developments, by optimizing land use configurations to balance sustainability objectives. These applications allow AI to enhance urban spaces while aligning with environmental strategies, utilizing models like Geographic Information Systems (GIS), Convolutional Neural Networks (CNNs), and Random Forests (RF) for land use optimization. In Liu, Qin, et al. (2023) study, GIS and Genetic Algorithms (GA) were applied to optimize urban street spaces, achieving a 53.43 % utilization rate of available land, which supports both vehicular and pedestrian traffic flows, aligning with the broader goals of urban vibrancy and functionality. Similarly, CNN-based models have been employed to forecast urban expansion, ensuring that new developments promote efficient resource management while minimizing environmental degradation (Koumetio Tekouabou et al., 2023). Furthermore, AI-driven simulations play a crucial role in designing urban layouts that promote efficient, integrated urban spaces, integrated, sustainability-focused urban frameworks. These tools enable urban planners to test various land use configurations and make informed decisions, ultimately enhancing urban livability and accessibility.

Advanced tools like UNet CNNs identified specific land-use patterns—such as industrial zones contributing 37 % higher PM2.5 emissions than residential areas—enabling targeted zoning reforms to mitigate pollution (Zhao et al., 2023). Meanwhile, Land Use Random Forest (LURF) models improved PM2.5 prediction accuracy by 22 % over regression-based approaches, though interpretability challenges emerged when modeling intricate interactions within land use mix variables—such as the co-location of residential, commercial, and recreational zones (Brokamp et al., 2017). These insights could potentially support policymakers in aligning urban growth with environmental preservation, leveraging AI-driven analysis of pollution patterns and land-use mix interactions to advance sustainable urban development. AI's predictive capacity could allow cities to implement zoning regulations and strategies that promote sustainability while enhancing urban livability. However, LURF models face interpretability gaps when analyzing mixed-use variables like conflicting, adjacent land uses, which may limit actionable policy insights.

However, LURF models face interpretability gaps when analyzing mixed-use variables like conflicting, adjacent land uses, which may limit actionable policy insights. Their narrow focus on metrics like PM2.5 reduction could overlook broader sustainability trade-offs, such as how land use mix decisions might impact resource efficiency. Furthermore, an exclusive emphasis on specific pollutant metrics may sideline other critical environmental factors like energy usage and water conservation. This constrained perspective risks generating policy recommendations that address only parts of the sustainability challenge rather than fostering truly holistic urban design strategies.

4.3. AI in participatory planning systems

4.3.1. AI contributions to stakeholder engagement in urban planning

AI technologies have shown promising potential for stakeholder engagement in urban planning by making decision-making processes more inclusive and adaptable. Tools like Multi-Agent Reinforcement Learning (MARL) are particularly effective in simulating the interactions between diverse stakeholders—residents, businesses, developers, and government entities—allowing for a more collaborative planning process. MARL models simulate the dynamics of urban scenarios, providing quick feedback on trade-offs between different interests, such as economic growth, environmental sustainability, and social impacts. For instance, these models enable the visualization of potential outcomes from decisions like increasing residential density or preserving green spaces, allowing stakeholders to see how their contributions influence long-term outcomes (Qian et al., 2023). In complex urban environments, where multiple interests often conflict, AI-based models act as mediators.

By capturing the priorities of different groups, these tools promote a consensus-driven approach, where each stakeholder's perspective is integrated into the decision-making process. This enhances transparency and helps urban plans reflect the needs of a diverse community. Unlike static models, MARL adapts to real-time changes in stakeholder input, allowing for iterative adjustments based on updated simulations. This continuous feedback loop assists in keeping stakeholders actively engaged, contributing to dynamic, data-driven urban plans that are both inclusive and responsive. For instance, Ghavami et al. (2022) developed a web-based Intelligent Group Decision Support System (IGDSS) that employs Multi-Agent Systems (MAS) and Bayesian Binary Logit Models to model opponents' preferences during participatory land-use negotiations. Their system uses software agents to learn stakeholders' Social Value Orientations (SVO)—such as prioritizing equity, self-interest, or collective benefit—through iterative Bayesian inference, reducing negotiation time and enhancing equity in land-use allocations. Moreover, AI-driven tools facilitate a more interactive planning process by allowing stakeholders to directly experiment with different planning scenarios. This hands-on involvement helps participants understand the implications of their choices and fosters a more democratic planning environment. As a result, AI may help urban planners design projects that better balance social, economic, and environmental objectives, aligning long-term planning goals with the immediate needs of the community.

Furthermore, AI tools for participatory planning risk centralizing decision-making authority, as planners' and tech experts' control over algorithmic frameworks—such as defining negotiation rules or input categories—can subtly prioritize institutional priorities over grassroots stakeholder autonomy. This centralized control may inadvertently sideline less dominant perspectives and inhibit the spontaneous exchange of ideas that is critical for authentic stakeholder engagement. Additionally, the lack of transparent methodologies in these systems can erode trust, leaving participants uncertain about the fairness and inclusivity of the decision-making process.

4.3.2. AI-based participatory planning tools

AI-based tools are enhancing regulatory integration and land-use optimization in urban planning, offering advanced methods to translate complex zoning codes into actionable guidance. By leveraging Large Language Models (LLMs), these tools automate the interpretation of regulatory texts, converting zoning documents into computational algorithms. This allows stakeholders in cities like Oakland and Auckland to visualize how zoning decisions impact urban development, fostering more informed and collaborative planning processes. With predictive insights into the effects of legislative changes, planners can anticipate outcomes before implementation, supporting a proactive approach to mixed-use urban development (*Generative AI for Zoning Acquisition | by* Urban AI, 2024). Beyond regulatory interpretation, AI tools that combine Machine Learning with Cellular Automata (CA) provide robust simulations of urban growth patterns and land-use transitions.

These models enable planners to predict how different policy decisions may shape the cityscape over time (T. Xu et al., 2019). By integrating data from various sources, including geographic information systems (GIS) and satellite imagery, AI models provide a holistic view of how urban functions evolve, ensuring that planning decisions align with both short-term needs and long-term sustainability policies at both local and national levels. These AI-driven platforms also enhance stakeholder collaboration by allowing them to interact directly with planning models. For example, stakeholders can explore scenarios involving green space allocation, transportation networks, or changes in residential density, seeing how their inputs influence projected outcomes. This interactive approach makes planning processes more transparent and inclusive, ensuring that diverse social, economic, and environmental factors are considered in land-use mix decisions. As a result, planners can design cities that are more resilient and responsive to the needs of their communities, balancing growth with environmental conservation.

AI's automation of zoning code interpretation could risk codifying existing regulatory biases, prioritizing technical compliance over reimagining policies that hinder equitable, sustainable land use mix innovation. Furthermore, an over-reliance on algorithmic readings of zoning codes may inadvertently reinforce outdated legal frameworks, limiting the scope for progressive reform. This approach can constrain urban development by discouraging critical reassessment of established norms and thus impede the adoption of innovative, forward-looking planning strategies.

4.3.3. Decision-support systems in participatory planning

AI-driven decision-support systems (DSS) play an interesting role in urban planning by integrating advanced computational techniques that allow for nuanced decision-making. These systems utilize machine learning models, including reinforcement learning and multi-objective optimization, to simulate land use mix scenarios, enabling planners to assess trade-offs between goals like economic growth, environmental sustainability, and social equity. By automating scenario analysis, AI-DSS can rapidly adapt to new datasets, making the planning process more responsive to changing urban conditions and stakeholder needs. A distinct advantage of AI-based DSS like Goal-Reasoning Monte Carlo

Tree Search (G-MCTS) AI agent lies in their ability to solve complex multi-criteria optimization problems, such as optimizing the spatial distribution of land uses based on criteria like transportation efficiency, thermal comfort, and economic viability (Wagner & de Vries, 2019). For example, DSS models can adjust urban layouts in real time, using geospatial data to reduce urban heat islands and optimize traffic flows throughout land use mix configurations. This enables planners to align urban design with sustainability goals more effectively, ensuring that land-use decisions are data-driven and precise (Chen et al., 2020). Real-time integration of data streams, such as sensor networks and satellite imagery, further enhances the capabilities of AI-DSS. This allows stakeholders to interact with continuously updated planning scenarios, offering immediate feedback on the impact of their input. The iterative nature of these models supports collaborative adjustments, where stakeholders can explore the effects of different decisions on development outcomes. By combining predictive modeling with real-time geospatial analysis, AI-DSS provides a dynamic framework for managing complex urban planning challenges, enabling sustainable growth that adapts to the evolving needs of urban communities.

AI-driven decision support systems (DSS), while potentially optimizing land use scenarios, could exclude resource-constrained cities by relying on costly computational resources and high-quality data inputs. This reliance might limit their accessibility for equitable urban planning. Moreover, the ongoing need for advanced technical maintenance and specialized expertise can further widen the gap between cities with robust technological infrastructure and those with limited resources. Such disparities risk reinforcing the digital divide, where only well-funded regions reap the full benefits of advanced AI-DSS tools, potentially leaving behind areas that might benefit most from innovative planning solutions.

5. Discussion

The rapid integration of AI enhances the precision and scope of urban data analysis, managing large, complex datasets and merging varied data sources to address modern cities' intricate complexities effectively (Koumetio Tekouabou et al., 2023; Zhao et al., 2023). Research is predominantly concentrated in technologically forward regions such as Chinese cities—Beijing, Nanjing, and Guangzhou—leveraging extensive, high-quality datasets like satellite imagery to perform sophisticated urban analyses (Wang, Wang, et al., 2024). In contrast, regions such as the United States and Europe face different pace of AI adoption due to stricter privacy regulations, historical urbanization theories, and fragmented urban data landscapes, which limit access to the granular, real-time data crucial for effective AI applications (*Generative AI for Zoning Acquisition | by* Urban AI, 2024). In areas where high-quality datasets are scarce, urban planners and policymakers can adopt collaborative data-sharing models, allowing the pooling of anonymized data from multiple regions while adhering to privacy regulations. By establishing data-sharing frameworks that promote the use of open-source datasets, cities can enhance access to AI-driven urban planning tools globally.

A central challenge, as illustrated in Fig. 9, involves bridging the gap in how data are collected, standardized, and shared across institutions. This observation underscores an urgent need to develop consistent methodologies and governance protocols that not only enhance data quality and address disparities in data availability but also mitigate the detrimental effects of fragmented data acquisition and isolated silos, emphasizing a more integrative approach to data stewardship and cross-sector collaboration.

GeoAI, as demonstrated by Mortaheb and Jankowski (2023), enhances participatory urban planning by enabling more dynamic interactions among residents, planners, and policymakers. This facilitates a deeply democratic approach to urban development by ensuring that all stakeholder voices are actively incorporated into the decision-making

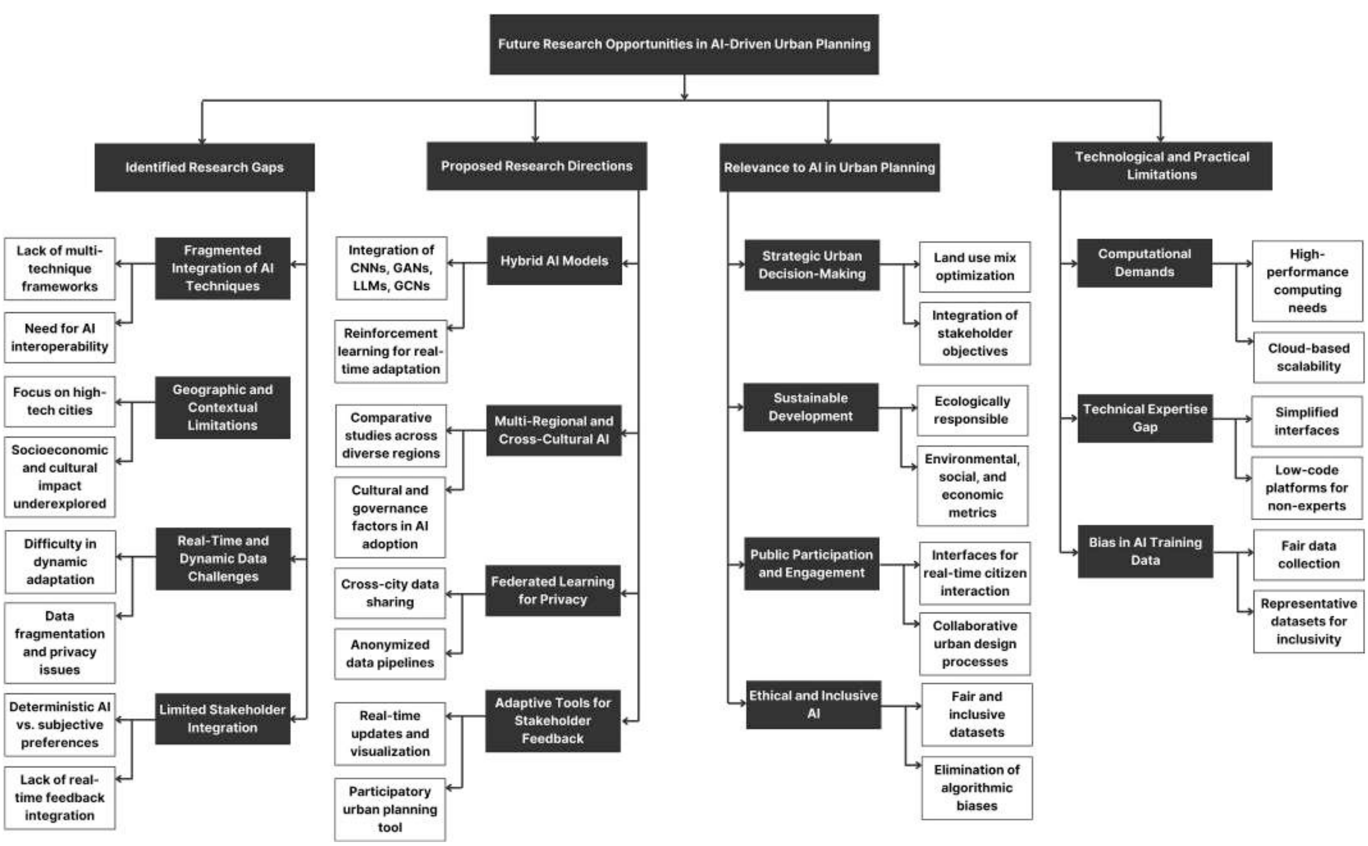

Fig. 9. Mapping future research opportunities in AI-driven urban land use mix planning.

process. Additionally, Qian et al. (2023) highlight the use of Multi-Agent RL and GNN to effectively balance diverse stakeholder interests. AI-driven insights hold high potential for developing land use policies, empowering policymakers to create adaptable and inclusive urban governance frameworks. By embedding AI models into these frameworks, cities can achieve more transparent, data-informed decision-making that balances stakeholder interests, enhances participatory planning, and fosters sustainable urban development tailored to diverse community needs. Developing criteria and adaptive AI tools that integrate real-time feedback from stakeholders to address these issues will be an exciting challenge soon. However, the application of AI in decision-making for land use mix and sustainable development is still emerging. AI tools primarily serve technical assessments and have not been fully utilized to shape urban policies directly. These AI-driven approaches advocate proximity-based, mixed-use developments that decrease dependence on cars and cultivate accessible and livable urban environments. By measuring and scrutinizing the diversity of urban functions, AI offers practical insights that make the smart and evidence-based urban design strategies that balance functional distribution, accessibility, and sustainable mobility more applicable and effective across various urban settings. Despite their potential, AI models encounter significant limitations, including the requirement for advanced programming expertise, substantial computational requirements, biases in data training present a significant challenge, as models trained on datasets with limited diversity or geographic variability may produce outputs that overlook the complexities and specific needs of diverse urban contexts.

In this context, and as further illustrated in Fig. 9, there is a critical need for research that examines how AI can more adeptly address the socioeconomic, environmental, and cultural nuances intrinsic to diverse urban landscapes. The illustration indirectly highlights that overcoming these challenges demands not only technological improvements but also innovative research strategies that harmonize technical capabilities with the diverse demands of heterogeneous urban realities. This approach can help mitigate the risks of one-size-fits-all solutions and promote truly inclusive urban development.

To help advance addressing AI limitations in urban planning, future research should integrate federated learning, lightweight models like fine-tuned BERT and LLMs, and multi-objective optimization algorithms to balance precision with participatory governance. Federated learning trains model locally, sharing only insights—not raw data—to protect privacy, thereby offering a nuanced pathway for further academic investigations. This approach could facilitate collaboration by allowing multiple entities to contribute to a comprehensive AI model while ensuring their data remains decentralized. Associated datasets, such as residential mobility patterns, commercial activity data, utility usage, and public transportation flows, often contain sensitive information. Federated learning securely aggregates insights from these datasets, ensuring models accurately represent diverse urban contexts multi-source data without compromising data sovereignty (Kaleem et al., 2023). Computational barriers could be mitigated via fine-tuned BERT for policy-text analysis (e.g., decoding zoning amendments) and GNNs for spatial tasks like land use synergy. These models prioritize critical planning workflows (e.g., zoning conflicts, density simulations) while minimizing resource use. Furthermore, distilled or fine-tuned LLMs can potentially interpret regulatory and community inputs, extracting contextual knowledge to support participatory planning by analyzing stakeholder preferences, and summarizing feedback. Scalability can be enhanced through modular AI pipelines embedding NSGA-II to resolve tradeoffs such as functional complementarity and compatibility of land use mix allocation, while RL agents refining scenarios with stakeholder feedback (e.g., equity-driven adjustments). Collectively, these considerations provide a potential framework for future research, emphasizing the possibilities for advanced AI-driven methodologies to harmonize with the evolving complexities of urban land use mix.

Despite challenges like cross-disciplinary expertise and data infrastructure demands, planners can tailor general-purpose AI tools into a specialized assistant, effectively adapting these tools to the complexities of urban diversity and transforming AI into a flexible partner. This adaptability enhances scalability and allows for tailored applications across varied urban contexts and interests, making urban planning more dynamic and responsive to evolving challenges. Future research should focus on creating AI methodologies that integrate seamlessly into decision-making processes, particularly in sustainable development and land use mix, to provide data-driven tools that align with technological advances and support proximity, mixed-use intensity, and spatial fluidity (Wagner & de Vries, 2019; Wang et al., 2020). Exploring predictive modeling for real-time urban adaptability and AI's role in citizen-led urban planning for dynamic land use offers new frontiers for research, particularly in understanding and responding to rapidly changing urban needs.

6. Conclusion

Artificial Intelligence is contributing to the future of urban planning by enhancing the understanding of land use mix with improved analytical and propositional depth. Machine learning and deep learning frameworks synthesize fragmented geospatial, socio-economic, and environmental data, potentially supporting cities to balance competing priorities such as density, sustainability, and equitable resource distribution. Further, these technologies present a high potential for empowering planners to develop strategies that address urban growth, land use spatial interactions, and environmental sustainability. By leveraging data-driven insights, AI may enhance urban governance by integrating technical accuracy with community-focused considerations, making urban environments more adaptable and responsive.

A key aspect of this evolution is AI's ability to democratize decision-making. By integrating participatory tools—such as simulations driven by stakeholder inputs and natural language processing for policy analysis— AI could become a platform to foster more inclusive urban planning. However, this reliance on data-driven systems necessitates rigorous safeguards to mitigate biases, ensure transparency, and prioritize marginalized voices. Ethical frameworks must evolve alongside technical advancements to embed accountability into algorithmic governance, ensuring AI serves as a bridge between innovation and equity rather than a source of exclusion.

The path forward demands interdisciplinary collaboration, uniting strategic planning, urban design, computational science, and social equity. AI's true potential lies not in replacing human judgment but in augmenting it, offering planners dynamic tools to navigate complexity while preserving cultural and contextual nuances. By harmonizing technical rigor with participatory principles, cities can leverage AI to cultivate resilient, inclusive environments where technology amplifies human well-being, ensuring urban landscapes thrive as equitable, sustainable ecosystems for generations to come.

CRediT authorship contribution statement

Haithem Drici: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **José Carpio-Pinedo:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-4/4o in order to check the grammar and improve its clarity and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A

Table 2
Overview of reviewed papers.

Citation	Geographic Context	AI Approach	AI Methodology	Data Inputs	Research Objective	Outputs
Xu et al. (2022)	China (Beijing)	Deep Learning	Graph Convolutional Networks (GCNs), Delaunay Triangulation, Softmax layer, Cross-Entropy Loss	OpenStreetMap Traffic Road Network, AMAP POI data, Beijing Urban Land-Use Map	Urban land-use classification	GCNs outperform traditional methods in urban land-use classification by preserving 2D spatial relationships
Guo, Zhu, et al. (2024)	China (Nanjing)	Machine Learning	K-means clustering, DTW, XGBoost	Nanjing Urban Rail Passenger Flow Data, Commercial Services Data, Closeness Centrality	Passenger flow and station classification	Identified four station types, with key factors such as commercial services and centrality influencing passenger flow.
Safabakhshpachehkenari and Tonooka (2023)	Japan (Tsukuba)	Machine Learning	Logistic Regression (LR), Support Vector Machines (SVM), Decision Forest (DF), Hybrid ANN + LR with fuzzy overlay	Multi-resolution satellite data (ASTER, WorldView-2, GeoEye-1), DEM, LULC maps	Urban growth prediction and model comparison	The hybrid ANN + LR model with fuzzy overlay showed the highest accuracy and kappa values, outperforming other models.
Liu et al. (2017)	China (Guangzhou)	Machine Learning	Probabilistic Topic Models (pLSA, LDA), Support Vector Machines (SVM)	High Spatial Resolution remote sensing images, Gaode POI, Real-Time Tencent User Density (RTUD)	Urban land-use classification	Achieved 86.5 % overall accuracy with a Kappa coefficient of 0.828, improved classification by integrating remote sensing and social media data.
(Lawrimore et al., 2024)	USA (North Carolina)	Machine Learning	Hierarchical Random Forest algorithm	Publicly zoning maps, population data, community characteristics	Predict spatially complete zoning maps	Within-county models achieved ~99 % accuracy, between-county accuracy varied (19 %–90 %). Residential districts performed better than non-residential and mixed-use districts.
Fleischmann and Arribas-Bel (2024)	UK	Deep Learning	Convolutional Neural Networks, Gradient-Boosted Classifiers, Logistic Regression	Sentinel 2 satellite imagery (RGB), British spatial signatures (building footprints, land use data)	Predict urban form and function	Incorporating spatial configuration of images improved predictive performance in decoding urban form and function.
Li et al. (2024)	China (Shenzhen)	Deep Learning	CNNs, RNNs, GANs, Transformers	Remote sensing data and social sensing data.	Urban land use classification	Evaluated deep learning models for land use classification, achieving high accuracy with data integration from remote and social sensing sources.
Wang et al. (2018)	China (Beijing)	Graph Embedding, Autoencoders, Ensemble Learning	Multi-view spatial graphs, Autoencoder-based graph embedding, matrix factorization	POI data, human mobility data	Ranking urban vibrancy in residential communities	Ranked urban vibrancy by embedding spatial graphs and outperformed baseline models, identifying vibrant communities.
Jiang et al. (2024)	USA (New York City)	Generative Adversarial Networks (GANs)	LVGAN, Attention Mechanisms, Feature Polishing Module	NYC PLUTO data, census block data, OpenStreetMap POI data	High-resolution regional land value estimation	The LVGAN model reduced MAE by 36.58 %, improving granularity in land value predictions.

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Table 2 (*continued*)

Citation	Geographic Context	AI Approach	AI Methodology	Data Inputs	Research Objective	Outputs
Qiao et al. (2017)	China (Nanjing City)	Artificial Neural Networks (ANN)	Back Propagation (BP) Neural Network	Remote sensing images, population density, land price, infrastructure data	Urban land use intensity assessment	Evaluated land use intensity, with recommendations for optimizing urban planning and land use efficiency.
Ren et al. (2020)	China (Shenzhen)	Big Data Analytics, Gravity Models	Gravity Models, Land-use Function Complementarity Indices (FCIs)	Shenzhen metro smart card data, Shenzhen 2014 building census data, metro network data	Impact of land-use complementarity on interactions	Incorporating land-use function complementarity improved spatial interaction model accuracy.
Almansoub et al. (2022)	China (Wuhan City)	Deep Learning	Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP)	Transportation data (bus lines, subway stations), parcel-level land-use data, GIS spatial data	Effects of transportation supply on mixed land use	LSTM and MLP models achieved low error rates (3.62 %–4.28 %) in predicting the impact of transportation on mixed land-use.
Chen and Song (2020)	USA (Multiple Cities)	Clustering Techniques, Entropy-Based Indices	K-means clustering, Geographically Weighted (GW) and Regional Structural Weight (RSW) indices	U.S. Census LEHD dataset, ACS, Twitter stream API data	Urban land-use classification using big data	GW and RSW indices, provide more accurate assessments of land use mix and patterns.
Wang, Chen, et al. (2022))	China (Xiamen City)	Random Forest (RF), Moore Neighborhood Correlation	Random Forest algorithm, Moore neighborhood correlation	Gaofen satellite imagery, POI data, Zhihuizuji mobile data, WorldPop population data, OSM building and road data	Grid-based urban land use classification	The grid-based classification achieved 81.17 % accuracy for Level I categories, surpassing traditional parcel-based methods.
Wang, Wang, et al. (2024)	China (Nanjing)	Machine Learning	Gradient-Boosted Regression Trees (GBRT), Random Forest (RF), Support Vector Regression (SVR)	Baidu, Sina Weibo, Earth Observation Group, Gaode POI data, GIS data	Factors influencing urban vitality	Key factors influencing urban vitality include transportation, morphology, and land use diversity.
(Wang, Huang, & Biljecki, 2024)	Singapore, USA (San Francisco), Netherlands (Amsterdam), Spain (Barcelona)	Unsupervised Learning	SimCLR, k-means clustering	OpenStreetMap, Global Building Morphology Indicators (GBMI)	Urban morphology discovery (unsupervised learning)	Identified and clustered urban morphology types, highlighting distinct patterns and uses across cities.
Wang et al. (2016)	China (Beijing)	K-means Clustering, Word2Vec	K-means clustering, Word2Vec for text mining	Geo-tagged Sina-Weibo messages, POI data from Data	Mapping dynamic urban land use patterns	Identified seven urban land use clusters, including residential, commercial, and mixed-use areas.
Chen et al. (2021)	USA (San Francisco, Denver, New Orleans, Chicago, New York City)	Ensemble Learning	Multi-layer stacking, Random Forest, LightGBM, CatBoost, Neural Networks	OSM, Sentinel-1/2, NAIP imagery, Twitter data, WorldPop, VIIRS nightlight,	Urban land use classification using open big data	Urban land use classification across multiple regions using ensemble learning models.
Jiang et al. (2015)	USA (Boston Metropolitan Area)	Machine Learning	Decision Trees, Random Forest, Instance-Based Learners (IBk)	VGI-based POI data from Yahoo!, D&B database, infoUSA database	Urban land use classification and disaggregation	Improved accuracy in disaggregated land use estimates at the census block level using POI data.
Wu et al. (2023)	USA (New York City)	Vision-Language Multimodal Learning	CLIP (Contrastive Language-Image Pre-training)	Google Street View images, OSM (OSM) data	Improve mixed land-use mapping (multimodal learning)	Improvement in fine-grained mixed land use mapping.
Hu et al. (2023)	China (Beijing)	Representation Learning Methods	Temporal Convolutional Networks, node2vec, doc2vec, Fuzzy C-Means Clustering	Taxi OD data (Didi Chuxing), Sina Weibo, Land use data (EULUC-China map)	Analyze mixed urban functions (activity data)	Identified and analyzed mixed urban functions, providing spatial insights into how human activities influence land use and functional diversity.
Guan et al. (2020)	China (Changshu)	Time Series Analysis & Machine Learning	Rotation Forest Classifier, Time Series Feature Extraction	Municipal water consumption data from 405,768 customers	Identify socio-economic land-use types (water data)	Identified residential and non-residential land-use patterns, classified socioeconomic functions, and analyzed long-term urban dynamics.
Yao et al. (2017)	China (Guangdong)	Machine Learning	Word2Vec, K-Means Clustering, Random Forest Algorithm (RFA)	Baidu POIs, Traffic Analysis Zones (TAZ) data	Classify urban land-use patterns using POIs	Achieved 87.28 % accuracy in classifying urban land use types.

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Table 2 (*continued*)

Citation	Geographic Context	AI Approach	AI Methodology	Data Inputs	Research Objective	Outputs
Zamalloa (2021)	Peru (Huancayo)	K-Means Clustering	K-Means Clustering Algorithm	MSI Satellite Imagery (Sentinel-2), Land Value Data, Primary Road Systems	Classify land by value using imagery and clustering	Produced a spatial map classifying urban areas by speculative land value and use patterns, highlighting urban sprawl and informal settlements.
Tepe and Safikhani (2023)	USA (Florida)	Machine Learning	Artificial Neural Networks (ANN), Random Forest (RF),	Florida Parcel Database	Model land use changes (spatio-temporal dynamics)	Achieved up to 92 % prediction accuracy for land-use function change.
Zhang et al. (2021)	China (Shenzhen)	Geo-Semantic Mining and Random Forest	Traj2Vec model, Word2Vec, Random Forest	Mobile phone positioning data, POI datasets	Quantify spatial trajectories of urban land use	High accuracy in mixed land-use classification and urban land-use type estimation.
Zhou et al. (2024)	China (Yiwu City)	Supervised Machine Learning	Decision trees, random forest, Gradient Boosting Decision Tree (GBDT)	POI data, urban form data, building form data	Track urban function evolution using heterogeneity	GBDT outperformed other models, highlighting significant growth in logistics and residential areas from 2012 to 2022.
Guo, Tang, et al. (2024)	China (Wuhan)	Deep Learning Networks	Inception V3 for visual feature extraction, BERT,	satellite images, POIs, AOIs, building footprint data	Identify urban land use patterns using geospatial data	High accuracy in identifying mixed land-use patterns.
Fan et al. (2021)	China (Shenzhen, Hong Kong)	Bi-Branch Neural Network (BibNet)	BibNet, a deep learning model with dual branches	Remote sensing social sensing data	Improve UFZ mapping with remote/social sensing data	High UFZ mapping accuracy: 94.46 % for Shenzhen, 91.90 % for Hong Kong.
Lyu et al. (2022)	Netherlands (Eindhoven)	Procedural Modeling	Urban Layout Generation (ULG) model, Multi-state Supernetwork Model	Dutch national travel survey data	Impact of land-use on travel behavior (layout model)	Increased land-use diversity reduces car use and increases walking and cycling in simulated urban layouts.
Liu et al. (2015)	China (Gaoqiao Town)	Genetic Algorithm, Game Theory	Genetic Algorithm, Game Theory	Second nationwide land survey, yearbooks, suitability evaluation maps, topographic maps, GIS	Optimize developmental land uses	Optimized land-use allocation, minimized conflicts between agricultural and development land, strategic insights for local government decision-making
Masoumi and van Genderen (2023)	Iran (Tehran)	Multi-Objective Optimization Algorithms (MOOAs)	Comparison of NSGA-II, MOPSO, and MOEA/D algorithms	GIS data, municipal plans, population data, and per capita demand statistics	Compare MOOAs for optimizing urban land use allocation	Improved urban land-use arrangements, optimizing land-use efficiency, diversity, and compactness.
Jafary et al. (2024)	Australia (Melbourne)	Machine Learning and Deep Learning Models	XGBoost, Support Vector Regression, Random Forest, Deep Neural Network	GIS data, socio-economic factors, land valuation data for Melbourne Metropolitan Area	Compare ML and DL models for land valuation	XGBoost excelled in large-scale land valuation, offering high accuracy, scalability, and efficiency.
Wang, Fu, et al. (2023)	China (Beijing)	Adversarial Learning and Graph Neural Networks	GANs, GNNs, Representation Learning	Housing price data, POI, taxi trajectories, public transportation data, check-in data	Automate land use configuration using adversarial learning	The LUCGAN+ framework produced superior land-use configurations, surpassing other GAN models in evaluation criteria.
Tong et al. (2024)	China (Wuhan)	Machine Learning and Network Analysis	XGBoost, Bipartite Network, Modified Hungarian Algorithm	Commuting data, built environment data, mobile phone location data, TAZ data	Detect commuting anomalies and optimize planning	Identified overloaded and underloaded commuting patterns, visualized spatial distribution, and quantified nonlinear effects.
Park et al. (2023)	South Korea (Seoul)	GAN-based Image-to-Image Translation	Generative Adversarial Networks (GANs), Modified pix2pix	GIS data, encoded RGB images of land use, FAR, BCR	Develop AI advisor for generating land-use plans	AI-generated land use plans with visualized FAR and BCR, limitations observed in extreme density scenarios.
Mohammadi et al. (2016)	Iran (Isfahan)	Hybrid Meta-heuristics	Genetic Algorithm, GRASP, Simulated Annealing, LLTGRGATS (Low-Level Teamwork GRASP–GA–TS)	Land-use data, planning regulations, GIS maps	Compare algorithms for optimizing land use allocation	LLTGRGATS outperformed SVNS in solution quality and improving urban land-use allocation.
Guan et al. (2024)	China (Shenzhen)	Graph Attention Networks (GAT), Hash Function	VCA, Graph Attention Network (GAT), SHA-512 Hash Function	Land-use data (2009–2014), GIS, spatial data	Improve simulations of land use by integrating spatial heterogeneity	HashGAT-VCA model improved accuracy in land-use change

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Table 2 (*continued*)

Citation	Geographic Context	AI Approach	AI Methodology	Data Inputs	Research Objective	Outputs
						predictions compared to traditional VCA models.
Wang, Wang, et al. (2023)	Global	Hierarchical Reinforcement Learning (RL)	Actor-Critic Method, Single-Agent Iterative POI Allocation	Geographical data, mobile data, IoT data	Automate land use configuration using hierarchical RL	Hierarchical RL effectively plans region and block-level configurations, improving planning dependencies
Wang, Wu, et al. (2022)	China (Beijing)	Deep Hierarchical Generative Learning	GANs, CVAE, Multi-head Attention, Semantic Segmentation, Hierarchical Generative Modeling	POIs, taxi trajectories, road networks, housing price, check-ins from social platforms	Automate urban land use planning using hierarchical generative learning	IHPlanner successfully generates urban land-use configurations based on human instructions and geospatial contexts.
Kamrowska-Załuska (2021)	Poland, Germany, China	ANN, Machine Learning, Deep Learning, Agent-Based Models, Fuzzy Logic	Neural networks, machine learning, agent-based models, deep learning, fuzzy logic	Mobile phone data, GPS, VGI, social media data, administrative data	Evaluate AI's impact on urban planning (land use, mobility, sustainability)	Improved urban design, transport systems, land-use simulations, and real-time urban flow analysis
Karakostas (2016)	Generalizable Urban Greenfield	Multi-Objective Evolutionary Algorithms (MOEAs), NSGA-II, UDT-MOEA	NSGA-II, UDT-MOEA	Spatial data for land-use allocation in greenfield projects	Optimize land value and planning in greenfield development	UDT-MOEA outperforms NSGA-II, providing more diverse non-dominated planning solutions with higher land values
Chaturvedi and de Vries (2021)	Global	Machine Learning, Hybrid Models (RF-CA, CA-Markov)	Random Forest, Support Vector Machines, CNN, GANs, CA	EO data, satellite imagery, GIS, remote sensing, VGI	Review ML applications in land-use planning	RF and CNN excel in classification; hybrid models like RF-CA and CA-Markov enhance urban growth simulation
Podrasa et al. (2021)	Germany (Berlin)	Supervised and Unsupervised Learning	Artificial Neural Networks (ANN), k-means clustering	OpenStreetMap, GIS datasets, Berlin city data	Automate land-use scenario generation for urban design	Developed flexible and automated land-use scenarios considering environmental and transportation factors.
Wang, Hijazi, et al. (2024)	Germany (Berlin)	Genetic Algorithms	Multi-objective optimization using genetic algorithms and system dynamics	CityGML, Berlin Property Value Expert Committee data, simulation models	Optimize dormitory allocation in Berlin	Developed optimized spatial configurations for dormitories, improving accessibility, cost efficiency, sustainability.
Overview 〈 Generative Land Use for Human-Centric Communities — MIT Media Lab (n.d.)	Generic	Genetic Algorithms, Particle Swarm Optimization	Multi-objective optimization, genetic algorithms, particle swarm optimization	Social, economic, environmental, cultural metrics	Develop human-centric urban environments for sustainability	Created optimal land-use distributions with a 3D model and agent-based simulations to assess community impacts
AlKhereibi et al. (2023)	Qatar (Doha)	Machine Learning	Elastic Net, k-nearest Neighbors, Support Vector Regression, Decision Trees, Random Forest, Gradient Boosting, XGBoost	Time-series metro ridership data, urban land use data (educational, governmental, mixed-use densities)	Predict metro ridership and support TOD	Identified key contributors to metro ridership, providing insights to optimize land use for transit-oriented development.
Wang et al. (2020)	China (Beijing)	Adversarial Learning	Generative Adversarial Networks (GANs), Graph Neural Networks (GNNs),	land use configuration, POI data, housing prices, taxi trajectories, public transportation	Develop automated city layouts using adversarial learning	LUCGAN model to generate efficient land-use configurations and improve urban planning.
Zhai et al. (2020)	China (Shenzhen)	Convolutional Neural Networks (CNN), Random Forest (RF)	CNN for feature extraction, RF,	Historical land use data, topographic data, transport data, socio-economic data, POI data	Integrate CNN for land-use change simulation	The CNN-VCA model improved simulation accuracy and predicted future land use patterns, supporting urban planning decisions.
Mortaheb and Jankowski (2023)	USA (Phoenix)	GeoAI, Machine Learning, Deep Learning	GeoAI, CNNs, SDSS, GeoDesign	GIS data, PPGIS, VGI, Urban Heat Island data, spatial decision support data	Integrate GeoAI for improving urban services	Showcased AI's role in addressing urban heat islands, participatory planning, and spatial decision-making through SDSS
Qin, Zhao, Sheng, and Lau (2024)	China (Shanghai), Hong Kong, UK, France	Denoising Diffusion Probabilistic Models (DDPMs), CLIP	Denoising Diffusion Probabilistic Models (DDPMs), Text-to-Attribute (T2A) Network, Contrastive Language-Image Pretraining (CLIP)	OpenStreetMap (OSM) layout data, textual descriptions, annotations for road and building layouts	Automate layout regeneration using textual descriptions	Generated precise urban layouts from text descriptions, enhancing efficiency and contextual coherence in planning.

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Table 2 (*continued*)

Citation	Geographic Context	AI Approach	AI Methodology	Data Inputs	Research Objective	Outputs
Wan and Ma (2022)	China	Artificial Neural Networks (ANN), Monte Carlo Tree Search (MCTS)	ANN, MCTS, Random Forest	Baidu Maps, Tencent Maps, Landsat-8 satellite imagery, POI data, OpenStreetMap	Generate optimized urban layouts using AI	AI models efficiently optimized urban layouts, enhancing spatial functionality and accuracy in land-use planning
Zarro et al. (2022)	USA (Phoenix)	Deep Learning	U-Net architecture	Sentinel-1 (SAR) and Sentinel-2 (Optical) satellite imagery, NAIP data	Detect urban sprawl and assess COVID-19 impact	Generated urban sprawl maps and revealed reduced urban expansion during COVID-19
Qin, Zhao, Yang, et al. (2024)	UK	Deep Generative Model	Function-aware deep generative models, CNNs, pixel and vector-level data	OSM data covering 147 K regions, road layouts, building layouts, urban functions	Regenerate layouts based on function/context	Demonstrated that the UrbanEvolver model regenerates urban layouts conditioned on function and context.
Liu, Qin, et al. (2023)	China	GIS and Genetic Algorithm (GA)	GIS for spatial simulation, Genetic Algorithms multi-objective optimization	Geographic and urban planning data including traffic flow and land-use information	Optimize urban street spaces and functions for health and sustainability	Achieved 53.43 % street space utilization, enhancing traffic flow, pedestrian access, sustainability, and public health goals.
Koumetio Tekouabou et al. (2023)	Global	Machine Learning	CNN, RNN, Random Forests, boosting methods	Sensor data, satellite imagery, survey data	Review AI methods in urban planning (land-use, mobility)	Key ML applications in urban planning: deep learning excels in spatial tasks, ensemble methods in environmental issues.
Brokamp et al. (2017)	USA (Ohio)	Random Forest	Land Use Random Forest (LURF), Land Use Regression (LUR)	PM2.5 data, land use variables from CCAAPS, 24 pollution sites, Land Use Data	Compare models predicting pollution and land use	LURF outperforms LUR in predicting PM2.5 concentrations, improving exposure assessment with trade-offs in model interpretability for land use variables.
(Abid et al. (2024)	Global	Convolutional Neural Networks (CNNs) and Spider Monkey Optimization (SMO)	CNNs for spatial data analysis, SMO	Urbanization datasets, GDP, employment in agricultural and urban sectors	Forecast urban expansion and optimize sustainability	Improved urban expansion prediction accuracy, optimized urban planning strategies focusing on sustainability and resource management.
Zhao et al. (2023)	China (Wuhan)	Deep Learning	UNet Convolutional Neural Network (UNet CNN)	Air quality data, land use data, meteorological data from Wuhan metropolitan area	Explore the link between land use and PM2.5	Key land use types affecting PM2.5: green spaces reduce pollution; industrial zones and high FAR areas increase it.
Qian et al. (2023)	USA	Multi-Agent Reinforcement Learning (MARL), Graph Neural Networks (GNN)	MARL, GNN	Real-world urban data from Kendall Square	Enhance urban planning through AI by addressing stakeholder interests.	Balanced urban development, efficient decision-making, and stakeholder consensus in land-use planning.
Ghavami et al. (2022)	Iran (Zanjan)	Multi-Agent Systems, Bayesian Learning	Multi-Agent Systems (MAS), Bayesian Binary Logit Model.	Urban land-use plans, stakeholder preferences	Urban land-use negotiations	MAS and Bayesian learning reduced negotiation time and enhanced land-use decision quality.
Generative AI for Zoning Acquisition | by Urban AI (2024)	USA (Oakland), New Zealand (Auckland)	Large Language Models (LLMs)	Large Language Models (LLMs), Function Generation for Algorithm Creation	Zoning documents for Oakland and Auckland, building data, and polygon data for parcels	Automate capacity computation from zoning constraints	LLMs automate capacity calculations, generate functions for zoning constraints.
Chen et al. (2020)	China (Chongqing)	Machine Learning	Artificial Neural Network (ANN), Markov Chain, Cellular Automata (MC-CA)	National Land Use Survey Database (NLUSD) of China, spatiotemporal land use data	Evaluate land use policies' impact on urbanization	MC-CA and ANN models predicted future land-use changes, preservation with improved policy analysis.
Chen et al. (2020)	China (Yantai)	Reinforcement Learning (RL)	Monte Carlo Tree Search (G-MCTS), Multi-Criteria Decision Analysis (MCDA)	Urban land-use data from Yantai, China, synthetic scenarios	Integrate goal-reasoning AI for democratic urban land use planning	G-MCTS outperforms traditional methods in balancing heterogeneous goals, facilitating democratic decision-making
Wagner and de Vries (2019)	China, USA, Germany	Artificial Intelligence (AI)	Machine Learning (ML), Neural Networks (NN), (CA),	Literature review on AI tools for urban planning	Compare AI, CA, and OR methods for urban planning and land management	AI enhances urban simulations; CA predicts urban growth; OR aids spatial decision-making

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Citation	Geographic Context	AI Approach	AI Methodology	Data Inputs	Research Objective	Outputs
Qi (2024)	Australia (Sydney)	Genetic Algorithms (GA)	Operational Research (OR) Ontology-based Knowledge Representation, Sensitivity Analysis, Multi-Objective Optimization	Real-world case studies from Leppington and Green Square, Sydney	Optimize urban heat mitigation strategies (UHMS) using AI	Improved temperature reduction, mortality rates, and energy costs through automated decision-making in various urban land uses areas.

Data availability

Data will be made available on request.

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