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TECHNICAL ARTICLE

AI-driven urban well-being: a conceptual framework for human-centered smart cities and sustainable livability

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ABSTRACT

Artificial Intelligence (AI) is increasingly used to inform urban planning. Machine learning and other AI methods can process data from sources like urban sensors and street-level imagery to support city monitoring and guide planning decisions. Urban planning has traditionally focused on infrastructure and operational performance, with giving less attention to social inclusion, psychological well-being, and urban equity. AI adoption is often based on technological advancements without a systematic approach towards sustainable and livable cities. This leaves a critical gap in how AI can contribute to making cities more resilient, inclusive and adaptive to environmental changes. This paper presents a conceptual framework for AI-driven urban well-being that analyzes the role of AI in public space optimization, sustainable mobility, green infrastructure, and digital governance. In this study, the connections between AI usage in urban planning and people's well-being have been examined through systematic literature review in accordance with the guidelines for PRISMA 2020. In addition, this research includes a thematic synthesis that uses 34 peer-reviewed articles. The data from this process has been coded with the help of the application fields and with the help of the subcodes created in the process of extraction. Reviewed literature shows that AI can be used for urban monitoring, alternatives for planning modeling, and summarizing the public's views. However, evidence that acting on these outputs improves post-implementation resident outcomes or outperforms conventional planning methods remains limited. The proposed model gives policy suggestions, connects the output of AI to planning decisions/services changes, indicators of measuring residents' outcomes regardless of their demographic characteristics, and feedback mechanisms that help make further decisions. The research scope was limited to scientific publications in English language available on the Scopus and Web of Science databases. No risk of bias evaluation was conducted formally. As the framework was not validated empirically, its testing in practical planning settings is needed.

KEYWORDS AI-driven urban planning, Human-centered AI, Smart cities, Sustainable cities, Urban well-being

1. Introduction

Urbanization is rapidly transforming local and global landscapes while exacerbating urban issues, including population density, overcrowding, inadequate infrastructure, environmental degradation, and socio-economic disparities (Oyeleye and Bigon 2025; Moulay and Ujang 2021). This resulted in the emergence of smart cities with the promise of technology-based solutions to achieve efficiency, sustainability, and enhanced urban livability (Yigitcanlar *et al.* 2020a). However, traditional urban planning is still facing some limitations regarding its reliance mainly on an infrastructure approach. This strategy often neglects essential human-centered considerations, such as psychological well-being, social inclusiveness, equity, and accessibility (Oyeleye and Bigon 2025; Stecuła *et al.* 2023). Consequently, these urban contexts become increasingly less resilient and responsive in terms of

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promoting well-being, while also unintentionally promoting inequities and marginalization (Moulay *et al.* 2024).

While these challenges are immense, Artificial Intelligence (AI) is increasingly seen as a key technology in the transformation of urban planning, offering evidence-based solutions to many aspects of the urban challenge through applications of predictive analytics, spatial optimization, and automated responsive governance (Stecuła *et al.* 2023). The use of AI in managing big data using real-time analytics is improving the complex task of monitoring all aspects of cities like traffic management, environmental monitoring, optimization of public spaces, and promoting active civic engagement platforms (Sanchez *et al.* 2023). However, despite such progress, the AI's role in urban planning remains biased, as it is still focused on technological developments instead of emphasizing strategies aligned with human needs (Yigitcanlar *et al.* 2020a). This disjointed approach undermines the full potential of AI to improve urban livability in an integrated and equitable manner.

This study looks at how AI solutions can be harnessed to help in developing sustainable and human-centered cities. In particular, the paper provides a critical evaluation of the practical effects of artificial intelligence on urban well-being and whether existing AI practices support human-centered objectives, like inclusivity, equity, psychological health, and participatory governance. Through assessment of current practices and the development of a more robust conceptual framework, this paper aims to help close the gap between technological implementation and comprehensive urban well-being, thus, advancing the academic debate on how to promote sustainable and equitable urban futures.

2. Methods

This study combines the systematic literature review with the qualitative thematic synthesis in order to examine the connection between the AI use in urban planning and urban well-being. The review was carried out following the PRISMA 2020 guidelines (Page *et al.* 2021). The subsequent sections will describe the criteria for inclusion/exclusion of studies, the search strategy, as well as the methodology used in the thematic synthesis.

2.1. Eligibility Criteria

The selection of studies as direct evidence for urban AI applications was based on the following two criteria: (1) the paper mentioned AI and the role it played in the context of urban planning or smart cities, and (2) it mentioned how the AI application concerned with a particular aspect of human well-being in the city. Both criteria had to be met for inclusion. In the present review, a paper was defined as the direct evidence of an urban AI application if it mentioned some specific AI technology, the output generated by this technology from certain data and input and their use in making urban planning or service decisions. The use of sensors, cameras, dashboards, and platforms for public participation was counted as the supporting infrastructure unless the paper mentioned some specific AI technology used in these tools. Also, technologies that did not use any AI component and only worked according to fixed rules and/or thresholds could not be regarded as the direct evidence of the use of AI in urban planning. Additionally, papers that evaluated public perceptions about AI, proposed purely hypothetical uses of AI, and did not mention the techniques used were tracked separately and were not used as evidence of how a particular AI technique performs. The specific rules for applying these criteria are outlined in Table 1.

Table 1. Eligibility criteria used to select studies for the systematic literature review.

Criterion	Include	Exclude
Publication date	Published from 1 January 2015 to 10 November 2026, inclusive	Published outside that period
Language	English-language publications	Publications in other languages
Publication type	Acceptable sources include only those articles that are peer-reviewed and indexed in either Scopus or the Web of Science Core Collection. All sources are evaluated using the same core criteria.	Grey literature, blog posts, editorials, and other non-peer-reviewed sources are excluded
AI application and urban relevance	Included publications must identify a specific AI method or system and explain its role within an urban planning or smart-city setting.	Studies which do not involve any form of AI technology, even if they talk about digitalization, smart city technology, or sustainability in urban areas are excluded.
Human-centered urban well-being	The publications that should be included must have a clear link to the urban application of AI and an outcome, an indicator, or an effect of the technology on residents or communities. The areas include equity, access, inclusion, psychological comfort, exposure, and public participation.	Studies are excluded if they report only technical metrics "such as model accuracy or processing speed" without explaining how those results matter to residents or communities.

2.2. Data Sources and Search Strategy

Records for the updated review were identified through searches conducted in the Scopus and Web of Science Core Collection databases. Both databases were searched on 10 November 2026, covering publications from 1 January 2015 to 10 November 2026. A start date of 2015 was selected to focus the review on recent applications of AI in urban planning and smart cities. During the revision process, the search end date was extended from 2025 to 10 November 2026 so that newer publications could be included. The review was limited to English-language publications to keep the reading, data extraction, and thematic synthesis of findings consistent, especially given the nuanced and context-dependent nature of human-centered urban well-being. While this choice allowed us to apply a uniform coding process across all included studies, we acknowledge that it may have excluded relevant research published in other languages.

Four search blocks were developed and applied in each database. These focused on AI applications related to: (A) public spaces, walkability, and urban perception; (B) sustainable mobility, transport accessibility, and emissions reduction; (C) green infrastructure, thermal comfort, and urban environmental risks; and (D) urban governance and community participation. Within each block, related keywords were combined using the OR operator, while AI-related terms were linked to urban application terms using AND.

Scopus searches were performed using TITLE-ABS-KEY searches within a date range of 2015-2026. In the Web of Science Core Collection database, Topic search (TS) was used, and the date range was specified using publication-date field (DOP). Search strings for both databases are presented in Table 2 and include search fields, date ranges, date of search execution, and number of records. Four Scopus searches resulted in 18,959 records, while four Web of Science searches returned 11,410 records, resulting in a total of 30,369 records before deduplication.

Table 2. Search strategy, execution parameters, and retrieval results.

Database / block	Purpose	Full executable search expression	Search field and date limit	Execution date	Records retrieved (n)
Scopus — A	AI for assessing public space, walkability, and urban perception	TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "semantic segmentation") AND ("public space*" OR "urban park*" OR streetscape* OR "street view" OR "urban perception" OR walkability)) AND PUBYEAR AFT 2014 AND PUBYEAR BEF 2027	Title, abstract, and keywords (TITLE-ABS-KEY); Publication years 2015–2026; English only	10 Nov 2026	4,320
Scopus — B	AI for sustainable mobility, transport accessibility, and emissions reduction	TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network*") AND ("urban mobility" OR "public transport" OR "public transit" OR "bus route*" OR "ride-hailing" OR "traffic signal*" OR "mobility-as-a-service")) AND PUBYEAR AFT 2014 AND PUBYEAR BEF 2027	Same as Scopus A	10 Nov 2026	9,084
Scopus — C	AI for assessing green infrastructure, thermal comfort, and urban environmental risk	TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "random forest*" OR "neural network*" OR "statistical learning") AND ("green infrastructure" OR "urban greenness" OR "urban tree canopy" OR "street shad*" OR "urban heat" OR "outdoor thermal comfort" OR "urban flood*")) AND PUBYEAR AFT 2014 AND PUBYEAR BEF 2027	Same as Scopus A	10 Nov 2026	3,544
Scopus — D	AI in urban governance and community participation	TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "natural language processing" OR "topic model*" OR "large language model*" OR "generative AI" OR ChatGPT OR "algorithmic decision-making") AND ("urban governance" OR "local government*" OR (("public participation" OR "citizen participation" OR "public consultation" OR "community engagement" OR "public feedback") AND (urban OR city OR cities OR municipal*)))) AND PUBYEAR AFT 2014 AND PUBYEAR BEF 2027	Same as Scopus A	10 Nov 2026	2,011
Scopus subtotal					**18,959**

Database / block	Purpose	Full executable search expression	Search field and date limit	Execution date	Records retrieved (n)
Web of Science Core Collection — A	AI for assessing public space, walkability, and urban perception	TS=(("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "semantic segmentation") AND ("public space*" OR "urban park*" OR streetscape* OR "street view" OR "urban perception" OR walkability)) AND DOP=2015-01-01/2026-11-10	Topic (TS: title, abstract, author keywords, and Keywords Plus); Publication years 2015-2026; English only	10 Nov 2026	2,896
Web of Science Core Collection — B	AI for sustainable mobility, transport accessibility, and emissions reduction	TS=(("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "neural network*") AND ("urban mobility" OR "public transport" OR "public transit" OR "bus route*" OR "ride-hailing" OR "traffic signal*" OR "mobility-as-a-service")) AND DOP=2015-01-01/2026-11-10	Same as Web of Science A	10 Nov 2026	4,500
Web of Science Core Collection — C	AI for assessing green infrastructure, thermal comfort, and urban environmental risk	TS=(("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "random forest*" OR "neural network*" OR "statistical learning") AND ("green infrastructure" OR "urban greenness" OR "urban tree canopy" OR "street shad*" OR "urban heat" OR "outdoor thermal comfort" OR "urban flood*")) AND DOP=2015-01-01/2026-11-10	Same as Web of Science A	10 Nov 2026	2,933
Web of Science Core Collection — D	AI in urban governance and community participation	TS=(("artificial intelligence" OR "machine learning" OR "natural language processing" OR "topic model*" OR "large language model*" OR "generative AI" OR ChatGPT OR "algorithmic decision-making") AND ("urban governance" OR "local government*" OR (("public participation" OR "citizen participation" OR "public consultation" OR "community engagement" OR "public feedback") AND (urban OR city OR cities OR municipal*)))) AND DOP=2015-01-01/2026-11-10	Same as Web of Science A	10 Nov 2026	1,081
Web of Science Core Collection subtotal					**11,410**

Database / block	Purpose	Full executable search expression	Search field and date limit	Execution date	Records retrieved (n)
Total search hits					**30,369**

Note. *The reported counts reflect all records retrieved from the eight searches across two databases before deduplication. All 30,369 records were imported into Rayyan prior to removing duplicates. The identified duplicate records were removed during the study selection process in section 2.3.*

2.3. Study Selection and PRISMA 2020 Reporting

All 30,369 records that were found through the eight database searches were imported to Rayyan. After eliminating 12,148 duplicate records, 18,221 unique records were left for screening their titles and abstracts according to the inclusion criteria outlined in Table 1. Screening resulted in exclusion of 17,310 records, leaving 911 reports for full-text review. All 911 full-text reports were accessed and screened for inclusion. The author then screened the 911 full texts based on the pre-defined inclusion criteria outlined in Table 1. To avoid selection bias and increase the consistency of the screening, an independent reviewer experienced in systematic literature reviews screened all full-text reports based on the same criteria. All screening decisions were made using Rayyan, and disagreements were resolved by discussion and re-reviewing the corresponding studies.

Out of the 911 reports whose full text was examined, 877 were excluded. The most important reasons for exclusion were low relevance of technical research on AI to urban planning applications (n = 312), no link to human well-being in urban environments (n = 235), focus on smart city technologies and not on an eligible AI application (n = 187), and lack of methodological rigor, empirical evidence, and reporting quality (n = 143). Each of the excluded reports had one main reason from the above. Therefore, only 34 reports were selected for qualitative thematic synthesis. The entire process of report selection is shown in Figure 1 below.

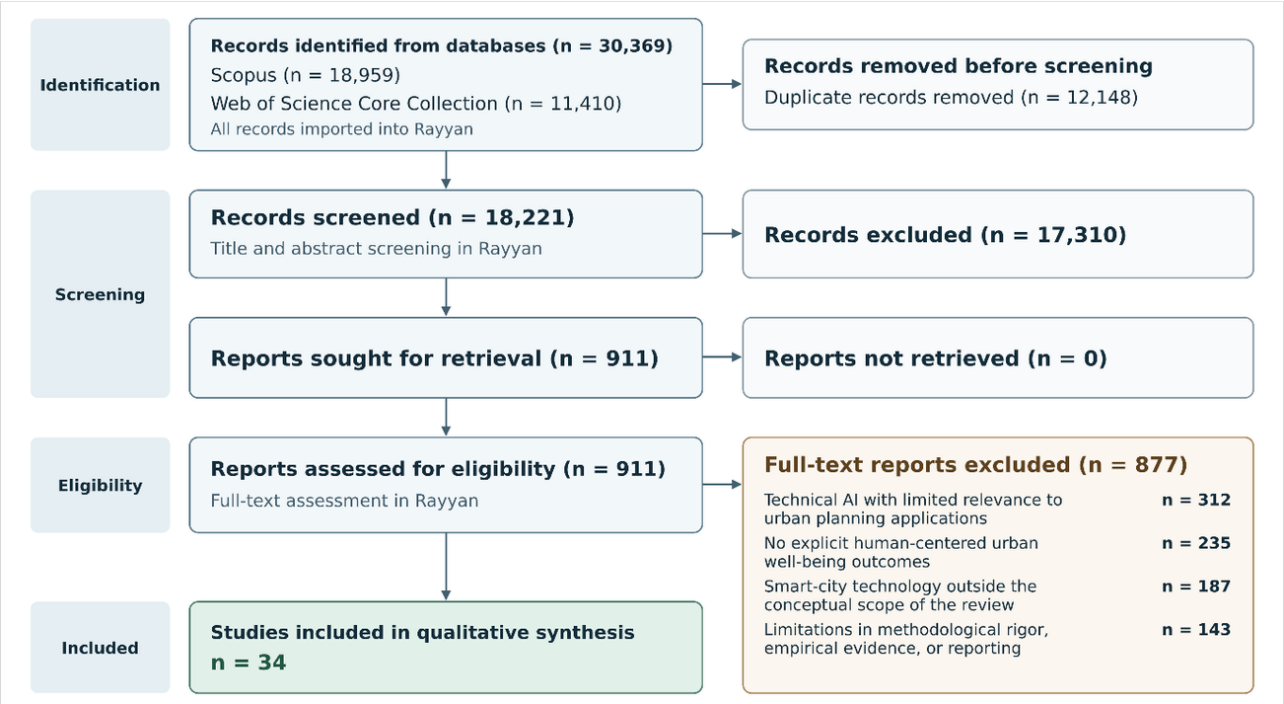


Figure 1. PRISMA 2020 flow diagram of study selection. Values (n) represent the counts of records, reports, or studies labeled at each stage, with each excluded full-text report assigned a single primary reason for exclusion. Adapted from Page et al. (2021).

2.4. Data Extraction and Thematic Synthesis

The data collected from the 34 sources included authors, publication years, urban setting, research methods, artificial intelligence techniques employed, indicators of well-being, main results and methodological limitations. All of these variables were systematically structured in an Evidence Extraction Table. Thematic analysis was done in NVivo by coding the study findings extracted in accordance with their meaning as units of analysis. The four search domains introduced in Section 2.2 served as the basis for deductive framework, while descriptive subcodes were created based on the extracted findings. The codes were then grouped into four major themes: optimization of public space, sustainable mobility, green infrastructure, and digital governance. Related findings were compared in order to define boundaries between themes and understand the meaning of each theme. When a study covered multiple domains, connections between these domains were taken into account; however, each study was eventually assigned to one main theme according to its research goal and results. With the completion of the coding structure, the author reviewed all of the coded data again to ensure that the application of codes and thematic categorizations had been done in a consistent fashion. The thematic structure that has been formed along with the major themes and the supportive evidence are shown in Table 3. Apart from all the information related to the studies and their results in the Evidence Extraction Table, the appendices contain the coding framework (Appendix A1), sample coded evidence (Appendix A2), and a thematic matrix of studies (Appendix A3). The thematic coding was done solely by the author, without any independent duplicate coding as the independent researcher discussed in Section 2.3 helped only in the full-text eligibility screening process. To differentiate between the true AI-based interventions and the digital infrastructure and contextual evidence, the data extraction process differentiated between the analysis approaches employed, their output, and their relationship to particular decisions about urban planning and governance.

Since there were various research designs in the included literature, covering different topics such as simulations, observations, concepts, and comparisons, no single quality assessment scale or design-specific evaluation was used. Rather, the Evidence Extraction Table contains the design and limitations of each paper. During the synthesis, the evidence was evaluated based on the type of evidence it presented: results gave information about possible outcomes under certain assumptions; observations gave information about conditions or relationships that were observed in a particular context; and concepts or comparison papers were helpful in theoretical interpretation without proving the actual impact of an AI intervention. For instance, the Penrith bus route paper helped in discussing modeled transit accessibility under different routes without proving that people actually experienced better access once implemented.

Table 3. Thematic coding table – AI-driven urban well-being.

Main themes	Categories	Short justification	Included publications and comparators
Public Space Optimization	Spatial analytics and assessment	The field of computer vision is applied in describing park use, street environment features, and city perception qualities. These investigations contribute to spatial analysis and design but do not prove that artificial intelligence can automatically reshape public spaces.	Dubey et al. (2016); Gravitz-Sela et al. (2025); Li et al. (2023); Luo et al. (2025)

	Use patterns, perceptions, and well-being	The use of image-based measures allows for studying relationships between the characteristics of neighborhoods and physical activity, perceived safety, mental health, and inequalities in visual walkability. These findings were dependent on the technique used to assess the exposure: Helbich et al. (2019) found relationships with depressive symptoms using the street-level green and blue space data, but not with satellite-based measures.	Helbich et al. (2019); Suel et al. (2019); Wang, Liu, et al. (2019a); Wang, Yuan, et al. (2019b); Zhou et al. (2019)
Sustainable Mobility	Traffic control, emissions, and safety	Signal-control research focuses on the significance of timing in dealing with pollution and needs of different road users. The safety research involving adaptive signals is similar in this respect and needs to be distinguished from those using deep learning techniques for signal control.	Lv et al. (2025); L. Wang et al. (2023b); Khattak et al. (2018)
	Equitable mobility access	Route planning, forecasting the demand for ride hailing, and analyzing mobility services help determine whether there are any access gaps or any biases in planning for the services. A contrast of how pedestrians use infrastructure against walking is helpful in identifying shortcomings in planning.	He and He (2024); Liu et al. (2024); Yoo et al. (2023); Zheng et al. (2023)
Green Infrastructure	Environmental sensing and prediction	Imaging analysis and machine learning are used to create maps for thermal comfort, heat exposure, and flood exposure. The maps will guide planning decisions but will not, on their own, prove that an intervention decreased exposure.	X. Wang et al. (2023a); Yang et al. (2025); X. Zhu et al. (2024); S. Zhu et al. (2025)
	Localized sustainability responses	Analysis of the tree canopy, access to street shade, and differential flooding highlights that green and adaptive efforts have to be congruent with local conditions and identity of those who are more vulnerable.	Wilson et al. (2024); Zhong et al. (2025); Zhou et al. (2025)
Digital Governance	AI-enabled participatory tools	Natural language processing, machine learning, and generative imagery can help organize public input, identify concerns raised in consultations, or illustrate proposals for discussion.	Arana-Catania et al. (2021); Fu, Brinkley, et al. (2025b); Preussner et al. (2025)
	Algorithmic accountability and public acceptance	These researches entail the use of residents and city managers in understanding how citizens perceive AI in their municipality in terms of control, willingness to use AI-based services, and possible barriers to adopting such systems. This does not prove the effectiveness of any form of transparency.	Oleksy et al. (2023); Yigitcanlar, Agdas, et al. (2023b); Yigitcanlar, Li, et al. (2023a)
	Cross-domain framework comparators	These papers provide substantial insight in understanding the four themes in relation to citizen agency, autonomy of urban AI systems, sustainability, algorithmic planning, and the uses of large language models. The role of these papers in the above context is to contextualize the framework and not measure the outcomes of any intervention.	Cardullo and Kitchin (2019); Cugurullo (2020); Fu, Li, et al. (2025a); Son et al. (2023); Yigitcanlar and Cugurullo (2020b)

Note. Every study is included just once based on its thematic contribution. This results in a total number of 34 references organized according to four themes: Optimization of Public Space (9 studies), Sustainable Mobility (7 studies), Green

Infrastructure (7 studies), and Digital Governance (11 studies) including 5 studies that can be classified into Digital Governance and one other theme. This count considers the categorization provided in Table 3 but not the number of studies demonstrating a positive effect. Furthermore, the Evidence Extraction Table highlights empirical findings/outcomes and concepts/ideas/theory.

Of the 34 publications reviewed, 23 were assigned to a single geographic region based on their recorded study settings: East Asia (12), North America (4), Southeast Asia (2), Europe (2), Oceania (2), and Western Asia (1). Six studies with multinational, simulated, hypothetical, or geographically unspecified settings—along with five cross-domain comparators—were retained in the review but excluded from these regional counts. East Asia alone accounts for more than half of the single-region studies, whereas none of the publications in this group examined a Gulf, African, or Latin American context. Furthermore, because several studies focused on individual parks, intersections, or local service areas, their findings offer limited evidence regarding citywide deployment or transferability to smaller, resource-constrained municipalities.

3. Theoretical foundations

Human-centered urbanism has developed in the past decades in response to decades of planning discourse that gave priority to infrastructure, efficiency, and system optimization to the detriment of lived experience and community well-being (Mao 2025). In contrast, human-centered urbanism puts people instead of infrastructure at the center of design. It focuses on psychological comfort, inclusivity, and responsiveness to a range of lifestyles (Galdini and De Nardis 2023).

Urban well-being encompasses both the physical conditions residents encounter and how they experience those environments. For example, the number of destinations reachable within a set travel time captures one dimension of accessibility (Pereira 2019), whereas residents' self-reported feelings of safety reflect their lived experience of public space (Pérez-Tejera *et al.* 2022). Equity introduces a distinct set of questions: who receives the benefits, who can influence the decision-making process, and whose needs are formally recognized (Schlosberg 2004). Accordingly, the framework separates objective physical conditions, subjective resident experiences, and how outcomes are distributed across different population groups.

However, Artificial Intelligence is adding more complexity to these limitations. Despite being seen as a means for improved efficiency in the urban systems, AI changes the ways that cities are governed, experienced, and contested (Wolniak and Stecuła 2024). It determines which data should be gathered and how it is interpreted, and prioritizes the values used for the urban decision-making, which is rarely neutral (Sanchez *et al.* 2023). AI systems also mimic existing biases of institutions and socio-political dynamics that, if unchecked, can perpetuate inequities. Its reach is greater than logistics or analytics to also constitute inquiries into agency, representation, and control (Wolniak and Stecuła 2024; Stecuła *et al.* 2023).

The use of digital technology can allow civic engagement without affecting the power of decision making. In a case study of an urban regeneration scheme in Morocco, Moufid et al. (2025) have studied the role of the digital twin as a collaboration tool, while Cardullo and Kitchin (2019) have analyzed the roles played by citizens in European smart cities and the limitations of their influence. Both are useful in evaluating civic engagement, although neither is cited here in order to claim that AI contributes to it.

4. Critical analysis of AI's role in enhancing urban well-being

This section discusses AI implementation in the four main areas, identified via thematic coding analysis: public spaces optimization, sustainable transportation, green infrastructure, and digital governance. While there are numerous positive views about AI, many issues emerge with regard to inclusiveness, responsibility, and real-life benefits that benefits the citizens from data-based technologies. In each of the four areas, the AI technologies play different roles in planning: computer

vision park-use patterns from video to inform site assessments (Gravitz-Sela *et al.* 2025); neural networks forecast ride-hailing demand while reinforcement learning evaluates alternative bus routes (Zheng *et al.* 2023; Yoo and Lee 2023); machine learning combines sensor and spatial data to map heat exposure and prioritize areas for review (Wang *et al.* 2023a); and natural language processing organizes public comments while generative image tools help residents visualize proposed changes (Arana-Catania *et al.* 2021; Preussner *et al.* 2025). From the realm of observation to prediction and optimization, all the way through to content creation, most systems provide insight or alternatives that are subject to human inspection, while those that change services are considered automated control.

4.1. Public space optimization

The use of image and video analysis can help urban planners assess public spaces at different levels. For example, Gravitz-Sela et al. (2025) used videos to examine the time and location of individuals using parks. At the street level, Dubey et al. (2016) estimated public perceptions of streetscapes using crowdsourced image ratings, Li et al. (2023) combined imagery, sensor data, and geographic information systems (GIS) to assess walkability, and Luo et al. (2025) used a digital twin to compare perceived streetscape quality across design options. At the broader neighborhood scale, Suel et al. (2019) used street imagery to predict local inequalities, while Zhou et al. (2019) mapped how visual walkability varied across different neighborhoods. However, despite these tools capture specific physical conditions or general perceptions, they cannot explain why an individual resident chooses to avoid a place.

Related health studies also highlight why the choice of measurement matters. Wang, Liu, et al. (2019a) explored links between neighborhood perceptions and physical activity, while Wang, Yuan, et al. (2019b) examined how perceived safety relates to mental health. Notably, Helbich et al. (2019) found associations with depressive symptoms using street-level green and blue space data that did not appear when using satellite imagery. Even so, these findings do not prove that redesigning a public space based on AI outputs will directly improve resident health. When planners need to understand why people avoid a space, direct site observations and interviews with non-users should complement image analysis.

4.2. Sustainable mobility solutions

Mobility research analyzes a number of outcomes at various stages of the planning process. For example, Yoo et al. (2023) conducted a comparison of bus-route designs with and without a measure of transit need, and Zheng et al. (2023) examined the ability of a ride-hailing algorithm to reduce forecast error disparities in demand. In the same vein, Liu et al. (2024) used stated travel preferences to estimate equity trade-offs in mobility as a service settings, and He and He (2024) found inconsistencies between walkability assessments and actual walking based on mobile phone data. While these studies can be helpful in terms of route design, demand forecasting, or analyzing mobility measures, they do not prove that the use of AI increases access of residents after implementation.

Lv et al. (2025) studied modeled vehicle emissions under various traffic signal strategies at the intersection level, while L. Wang et al. (2023b) assessed multimodal signal control in a simulation setting. As a field-level safety comparison study, Khattak et al. (2018) studied crash records after the implementation of adaptive signals through Empirical Bayes analysis. Since the three studies have different research questions in terms of modeled emissions, simulated travel delays, and crash records, they cannot be considered comparable proof of AI's effectiveness in the real world.

4.3. Green infrastructure and environmental risk

The reviewed research show how different environmental measures are linked to planning processes. For example, Wang et al. (2023a) combined sensors on the ground with satellite imagery to produce

maps of the heat exposure outside buildings, Yang et al. (2025) focused on visual perception related to thermal comfort, and Zhu et al. (2025) explored how geometric layout of the streets is connected to temperature. Another research trend in this area included Wilson et al. (2024), who analyzed the effect of tree coverage and landscaping patterns on land surface temperatures and Zhong et al. (2025), who mapped uneven street shading in Shanghai. Nevertheless, even if this analysis makes it possible to determine areas requiring special consideration, it does not address the heat stress of pedestrians directly.

This is also evident from the literature on floods. X. Zhu et al. (2024) used remote sensing as well as social sensing to develop a flood susceptibility map, whereas Zhou et al. (2025) investigated differences in model-based flood risk assessment. While these maps can be helpful for planners to decide where to undertake field verification, they cannot prove that their use has indeed redirected adaptation priorities or reduced vulnerability.

4.4. Digital governance & community engagement

The digital governance studies draw a clear line between what AI can do to process public input and whether it actually makes civic participation more representative. In Madrid, Arana-Catania et al. (2021) tested methods for organizing and summarizing public proposals and comments, while in Hamilton, Fu, Brinkley, et al. (2025b) applied text mining to analyze community submissions on urban densification. Using a more visual strategy, Preussner et al. (2025) investigated the role of generative images in helping people visualize the planning proposals. While these studies provide examples of how people can work with the consultation materials, the assessment of the comments submitted or the testing of prototypes do not tell us whose voice was not heard and whether residents made an impact on the choices made.

Other studies focused on the reactions of public and organizations toward municipal AI systems. In Oleksy et al., 2023, the authors evaluated public reaction toward the application of hypothetical scenarios. On the other hand, the study of Yigitcanlar, Agdas, et al. 2023 analyzed opportunities and challenges in city managers' views. Meanwhile, Yigitcanlar, Li, et al. 2023 studied resident reactions on AI application for public services. However, these findings have not been able to demonstrate that any particular use can result in more effective service delivery and public confidence.

The evidence in each of the four domains includes results and consequences, as well as theoretical contributions, as shown in Table 3 and the Evidence Extraction Table. The literature demonstrates the ways artificial intelligence might help urban planners to monitor the environment, model various scenarios and synthesize public opinion. However, the evidence proving that the use of these tools helps to produce better outcomes after implementation or that the method outperforms conventional planning approaches is limited. In case there is a simpler way to achieve similar outcomes, implementation of AI will only lead to increased cost of processing data and will not be of any value. Accordingly, it is important to evaluate not only the tangible benefits that accrue from the implementation of such technologies but also the costs involved, inclusive of privacy issues and possible overlooking of minority groups.

5. Challenges & ethical considerations

The emergence of these technologies in urban settings raises serious ethical and structural questions that go beyond mere functioning. These innovations challenge the very foundations of urban governance, equality, and freedom, creating doubts about who governs the city, on whose behalf the governance is done, and for what purpose.

If outputs of AI are used for informing decisions of local governments, they should state how the model works, how the outputs are used, and how people can apply for human evaluation (Tabassi 2023). The danger caused by differential performance of the model is illustrated by Zheng et al. (2023), who found out that ride-hailing forecasts were systematically underestimating the demand in poor neighborhoods in Chicago. Although their new model improved this problem in terms of

prediction errors, the authors did not look into whether it brought any change in service distribution. Therefore, if the predictions will be used for urban planning, then local governments should examine error rates in different areas and groups of people.

Data collection should be limited for what is necessary to accomplish the clearly defined objective of planning. For instance, in cases where there is a need to gather pedestrian counts in order to identify appropriate places for crosswalk improvements, the footage can be analyzed within the same city and only the aggregates are kept, instead of keeping identifiable video and trips of individuals. In cases where the personal data needs to be kept, it should be made sure that the data is only accessed by those who have been authorized to do so and all the views are recorded along with a set deletion date. Transparency should not mean disclosing the personal data; on the other hand, the municipalities can simply tell about the purposes and decisions made along with their results. Before publishing the data findings, planners must ensure that small sample sizes or specific geographical locations will not lead to re-identification of participants (OECD 2019).

6. Conceptual framework

Existing theoretical models also consider the connection between technology, community, and policy in relation to urban outputs, such as accessibility and well-being (Yigitcanlar *et al.* 2018). Moreover, Yigitcanlar and Cugurullo (2020b) investigate the contribution of artificial intelligence to the creation of smart and sustainable cities. The proposed framework (Figure 2) builds upon this research and focuses on the planning intervention itself in order to demonstrate how the AI output impacts a certain planning decision, how people may change their everyday conditions, and how they may impact future decisions based on their feedback. The four review topics namely optimization of public space, sustainable mobility, green infrastructure, and digital governance, serve as examples of practical contexts for this analysis. In addition, three further sources provide the background necessary to define the scope of the proposed framework. First, Cugurullo (2020) makes a distinction between automation and autonomy in urban systems, which is important when an AI application is no longer an advisor but rather a modifier of a public service. Second, Fu, Li, et al. (2025a) identify the possible use cases of large language models in urban planning. Finally, Son et al. (2023) compile the existing literature on algorithmic planning. As a whole, these researches ask important questions regarding the issue of decision-making power, development of new tools, and execution of interventions, rather than serving as empirical proofs themselves.

In this approach, well-being in cities is concerned not only with conditions and services that city residents experience in urban settings, but also with how those conditions are experienced. Public participation is separately evaluated, considering not only the participants in decision making but also the degree of impact of their contributions. Thus, Table 4 features the measures of participation along with the measures of resident outcomes. In all four areas of application, ethical governance is ensured by the presence of explicit provisions for privacy, transparency, accountability, and human oversight. The abilities of AI, including prediction and optimization, are used to guide decision making on planning or service delivery, e.g. changing a bus route. Resident outcomes are the resulting changes people experience, such as improved service access or greater perceived safety, while well-being indicators are the measures used to assess those changes. Equity is examined by comparing resident outcomes and participation across different neighborhoods and population groups. Table 4 outlines illustrative measures for future evaluations, along with the spatial or population scales at which they can be applied.

Table 4. Proposed indicators and measurement scales for urban well-being.

Dimension and meaning	Example indicator and measurement approach	Scale
Accessibility: ability to reach valued destinations	Number of essential destinations reachable within a locally justified travel-time threshold, estimated using transport networks and schedules (Pereira 2019).	Service catchment; compare neighborhoods and transport modes.
Environmental quality: physical conditions residents encounter	Percentage of a pedestrian route in shade at a specified time, estimated using street imagery and spatial modelling (Zhong *et al.* 2025).	Street segment or walking route; compare equivalent times and seasons.
Psychological comfort: how safe and at ease people feel in a place	Survey rating of perceived safety at a specified site and time, as one aspect of psychological comfort (Pérez-Tejera *et al.* 2022).	Park or public space; compare resident groups and times of day.
Social inclusion: whether residents feel welcome and that they belong	Survey rating of feeling welcome in the space; seek responses from regular users, infrequent users, and non-users (Powers *et al.* 2022).	Public space and surrounding neighborhood; compare relevant resident groups.
Participation: who takes part and whether their input can influence a decision	Compare participant profiles with the affected population and check decision records for how public input was considered (Rowe and Frewer 2000).	Consultation or project; compare groups and participation channels.
Public trust: confidence in the authority responsible for the decision	Survey residents about the named authority's competence, benevolence, and integrity (Grimmelikhuijsen and Knies 2017).	Affected residents; compare groups where sample sizes permit.

Note. Equity is evaluated by comparing how outcomes and participation differ across population groups and neighborhoods, including whether existing gaps narrow or widen after an intervention (Pereira 2019). Note that these indicators are provided as examples for future evaluations and were neither scored nor combined in this review.

The model examines the notion of fairness based on three criteria: distributive equity (distribution of gains and losses), procedural equity (participation and decision-making capacity), and recognition (consideration of needs and experiences) (Schlosberg 2004). When assessing distributive equity, the planners need to compare citywide averages and group-specific changes in access to services or exposure to the same baseline and check whether the existing gap gets smaller or bigger (Pereira 2019). For instance, a new bus route design will increase average transit accessibility citywide but at the same time decrease the number of vital locations that could be reached from an underprivileged area. As for procedural equity, planners need to compare participation levels among different demographic groups with the demographic makeup of the affected population and document how the feedback was addressed by the authorities (Rowe and Frewer 2000). And lastly, concerning recognition, planners need to compare digital data coverage with that of the overall population and use convenient in-person or telephone consultations to reach people not covered by digital data sets or online consultations, with always mentioning any data deficiency which prevents the evaluation of any specific target audience.

AI results can be used to make planning decisions through showing different options and revealing unfulfilled requirements. In particular, Yoo et al. (2023) used reinforcement learning to test bus route options for disadvantaged travelers, and Zhong et al. (2025) tested gaps in street shade in various communities. While these examples show the potential of AI to produce relevant data for planners, the next step depends on implementation: the redesigned bus route can improve access by increasing the number of accessible destinations for residents, but the modeling of accessibility and mapping of shade do not prove that residents' life conditions have improved after the intervention. The feedback loop is a distinct stage: residents' experience can affect future decisions only if there are

channels for reporting barriers and the responsible authority can react to them. Likewise, even though Arana-Catania et al. (2021) show how AI can help summarize public comments, whether the authorities change their decisions based on this data is still an empirical question. The papers were chosen from the review to show particular stages of Figure 2, including comparing planning options, revealing unequal conditions, and summarizing residents' comments. They are not a part of the comparative case analysis and are presented as concrete examples, not a validation of the whole framework.

There are three testable relationships in the framework. Firstly, the output of an AI can improve or influence residents' well-being if and only if it influences a decision or service through a causal relationship, which affects the lived experience of residents. Secondly, the improvement in technical performance will lead to improvement in daily experience if and only if it eliminates the actual barrier for the residents. For example, having a faster bus ride has no added value when the bus fare is too expensive or the walkway to the bus stop is dangerous or the stop is not accessible for the residents. Similarly, digitizing a municipal service will have no added value for residents who do not know how to use the technology or do not trust the authority with their personal data. Therefore, technical indicators and the experiences of residents should be separately assessed and compared across neighborhoods and populations. Thirdly, resident feedback can influence future decision-making if and only if there is a real channel for contesting an AI output and the authority has the ability to deal with the concerns. This framework is built to ensure that application of artificial intelligence becomes clearly understood and recognized in urban development and services delivery. This framework makes it easy to design interventions, select indicators, and evaluate pilots in varied environments.

Feasibility of implementation is a key first step before implementing an AI output in order to make planning decisions or changes. In situations where the lack of reliable data, technical staff, and funding is present, the framework is still relevant to help identify the needs of residents, assess conventional planning options, and select relevant indicators from Table 4. With medium capabilities available, the city can test the use of AI as a decision-supporting tool for a well-defined task and compare the results with current approaches. Expansion of application should depend on proven added value to residents, review of possible increase in inequalities and data gaps, assignment of a team responsible for managing the system, and funding to maintain it. If the pilot program makes the situation worse for a disadvantaged population group, the city should improve the program and reevaluate it before further expansion.

Figure 2 shows how the convergence of the four fields of application takes place via one single route. In this model, artificial intelligence provides information which assists planners to make planning decisions or modifications in the services offered, while well-being indicators help planners to evaluate the real impact of the plan on the lives of citizens and different groups.

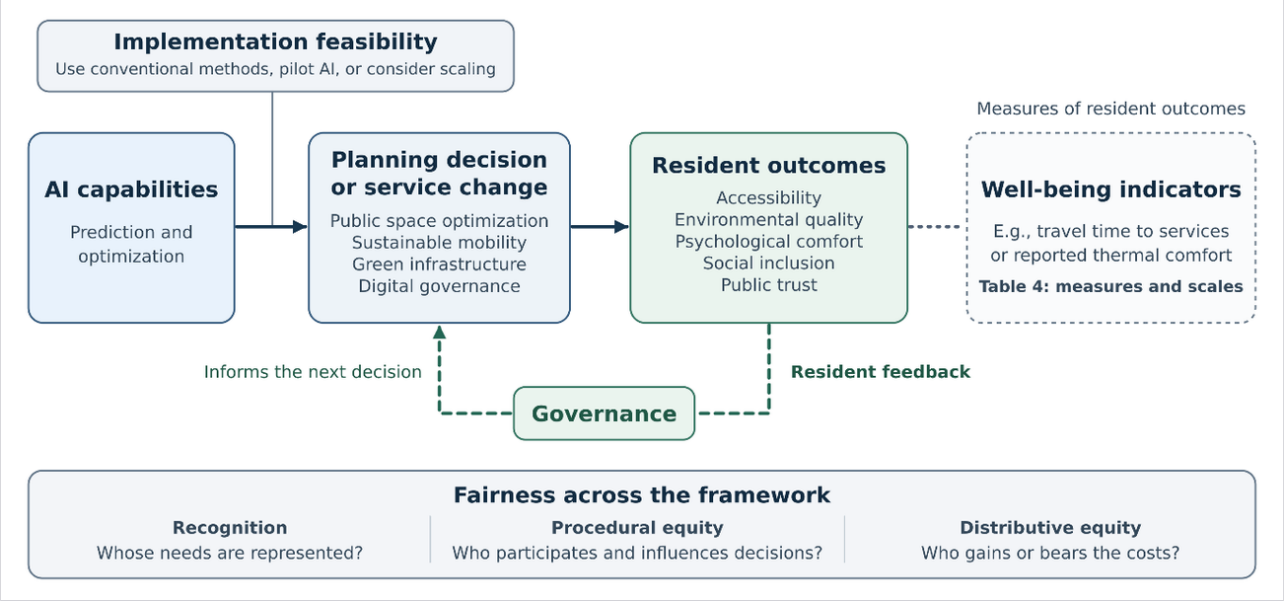


Figure 2. Proposed pathways and resident feedback loops in AI-enabled urban planning.

Note. The solid arrows show the suggested pathway from AI abilities to decision-making or service adjustment to resident outcomes. The dashed arrow shows how resident feedback is used to make future decisions using governance processes, whereas the dotted arrow connects the outcomes with the measures of well-being used to evaluate them. The thin arrow shows the feasibility test that must be done before the AI output can be used to make a decision or to adjust a service. The horizontal line on the bottom shows where recognition, procedural fairness, and distributive fairness cut across the whole process. Together, these arrows indicate proposed relationships that should be empirically tested.

6.1. Illustrative Application: AI-Assisted Bus-Route Redesign

The authors Yoo et al. (2023) use reinforcement learning to model alternative bus routes in Penrith, Australia. The analysis by Yoo et al. (2023) shows that optimizing for overall citywide accessibility does not consider the need for higher transit needs in some neighborhoods; therefore, the transit service need index was included directly in the modeling objective. The walkthrough below uses the modeling study by Yoo et al. (2023) to demonstrate how a transportation authority can operationalize Figure 2. While the modeling route is based on the source study, the local feasibility assessments, evaluation criteria, and governance processes suggested below are additional and have not been tested empirically in this review. Table 5 shows how a transportation authority can implement the framework in the context of this published modeling study.

Table 5. Illustrative application of the framework to an AI-assisted bus-route redesign.

Framework step	Information required	Decision or assessment supported
AI capability and feasibility	Current routes, timetables, walking connections, essential destinations, neighborhood transit needs, and available fleet, staff, and budget.	Compare the route generated by the AI system with both the incumbent network as well as a network proposed by the planner. If there are inadequate data or capacity, then apply traditional planning tools.

Table 5. (continued)

Framework step	Information required	Decision or assessment supported
Planning decision and affected groups	Access estimates by neighborhood and input from the operator, current riders, and residents who may have unmet travel needs, including people with limited mobility.	Select a route for a limited pilot only after checking whether gains in one area come at the expense of access elsewhere. Use telephone or in-person outreach to reach residents missed by digital data or online consultation.
Well-being and fairness	Baseline and pilot measures of essential destinations reachable within an agreed travel time (Table 4), alongside residents' reports of whether the service is usable.	Report overall changes as well as changes by neighborhood or group. Determine the minimum expected improvement and loss thresholds before the pilot. Reevaluate and modify the route before expansion in case the access decreases for an underserved group.
Governance and feedback	Documented model assumptions, a check of data coverage and privacy risks, resident feedback, and a record of how the authority responded.	The transport authority should retain the mandate of making decisions regarding the routing process. It should publish its standards, make summaries, provide a way to contest the decisions and use the information provided to know if there is a need to modify, expand or scrap the project.

Note. *The Penrith case study provides the basis of the route modeling example. The feasibility studies, consultations, pilot test, and criteria for expansion have been suggested in this context, but they have not been carried out in the course of this review.*

The model helps in assessing whether the improved version is worth implementing through pilot tests. Even an improved version of the bus route which results in an increase in accessibility in the entire city may be revised in case it reduces access to critical facilities for an underserved neighborhood. This can be seen using Table 5 where planners can assess the accessibility values, the operating costs, and public opinion to determine whether to pilot, revise, or reject the bus route proposed.

7. Policy & design recommendations

Recommendations given below convert the conclusions made in Section 4 into actions for urban management teams. Indicators for outcome evaluation are defined in Table 4; how they could be used in practice is illustrated by the example of bus-route modification in Table 5. The above audit, monitoring, and escalation approaches have been suggested but not evaluated yet.

Prioritize interventions and assess distributional impacts. A formal service gap should be the starting point for the process in the municipal planning unit and the relevant service department, which can be represented by the lack of access to important locations or insufficient shade on highly trafficked pedestrian walkways. The use of transportation modeling and shade mapping shows the reasons why citywide averages often mask the communities that need services the most (Yoo and Lee 2023; Zhong *et al.* 2025). Prior to choosing the pilot, the team needs to make use of the available service records, maps, and field verification to find affected communities and set a clear baseline. Then, the AI-based approach needs to be compared to a traditional one, given the same operational conditions. Using an indicator from Table 4 such as the number of important destinations accessible within a certain travel time or the extent of shade coverage on an important walking route, planners need to provide projected and observed changes per community or demographic group.

Audit the system and act on resident feedback. The municipality is held accountable for decisions based on the use of artificial intelligence. Formal approval of the purpose of the system and

permissions related to the use of data should be issued, as well as identification of the responsible person and provision of the complaint avenue. Technology vendors are required to specify how the system uses data, its capabilities, maintain logs, report incidents, and seek authorization from the municipality before using the data for any other purposes than those originally approved. Meanwhile, urban planners should evaluate AI results through comparison with local information and record when and why the recommendation was adopted or rejected. Prior to implementation, residents should be able to share their comments online and offline regarding the proposed system and safety measures and receive an explanation of the municipal response to the consultations. AI can be helpful in summarizing the public consultations (Arana-Catania *et al.* 2021), but the engagement team has to make sure that the summary is accurate, representative, and explain what public concerns led to amendments in the proposal, or what issues were not included and why. In case of riskier applications, the reviewers should validate AI outputs by comparing them with the independently verified local information, compare errors among affected populations or places where such data are available, and check whether the privacy safeguards work. The responsible municipal officer should document all corrections, and ensure that the issues are solved before the system is introduced or expanded. Finally, residents that are affected by an automatic or AI-driven decision should know about it and have an opportunity to request a human review and potential amendments from a municipal officer (Tabassi 2023).

Assign resources and responsibilities. Before the acquisition or scaling of any AI system, municipalities need to ensure that the needed data is available and compatible with existing infrastructure. It is important to know what computing resources and personnel will be required to run the system, as well as to allocate responsibilities for its operation and monitoring, as well as the schedule of model updates and revalidation. Besides the cost of acquisition, it is also necessary to take into account recurring costs such as data gathering, hosting, software licensing, personnel, and technical support. While working with third-party vendors, it is important to have a clear agreement on data access and export, responsibilities for updates, and changing vendors. This is especially important for municipalities with limited personnel and budget (Yigitcanlar *et al.* 2023b).

Evaluate impact and make decision regarding future use. Before implementing it, the service department needs to reach an agreement on what is expected to be achieved and the particular criteria that will lead to revision or cessation of the service. After the implementation of the pilot program, regularly, and after every important change to the model and/or to the data or service itself, the team should evaluate what has been accomplished in comparison to the baseline, and if possible, with traditional methods. The evaluation should focus on outcomes, discrepancies among residents, errors in the model, complaints that could not be addressed, and costs. The municipalities need to publicize the results and explanation for the decisions made.

8. Limitations

The search for literature was limited to English language papers indexed in Scopus and Web of Science, which means that there may have been relevant studies written in other languages or indexed in other databases that were missed out. Also, there may have been publication bias whereby only those papers with positive findings were published. In addition, the 34 papers used were diverse in terms of geographical location, research design, and evidence strength. While limitations of the studies were noted, no risk of bias assessment was done. The thematic coding was done by one author only and hence is open to interpretation, considering that independent full-text screening determined eligibility, not coding.

As seen in Figure 1, the diagram reflects the process of study selection but not necessarily the representative nature of the studies in the world. Since this study does not involve collecting new data about resident outcomes, Figure 2 shows the proposed relationships that can be used in local settings as opposed to known impacts. The applicability of these relationships in other cities will depend on the local planning agencies, available data, and resident needs.

9. Conclusion & future directions

Review of 34 papers suggests that there is more evidence for the value of AI in particular planning tasks than for the proven effect of AI on residents' outcomes after its implementation. For instance, the analyzed AI applications helped to identify gaps in the provision of street shade, compare different bus routes, and arrange the submissions of public consultations. Through combining the literature and systematically coded insights from the themes, this research takes into account both the possibilities and the limitations of the use of AI in the context of current applications in public space optimization, sustainable mobility, green infrastructure, and digital governance. The main open questions are whether the use of these outputs results in better outcomes for residents, whether the benefits are available to marginalized communities, and whether AI-based decisions perform better than traditional planning under similar circumstances. Figure 2 shows how these questions can be tested through matching particular AI outputs with planning decisions or services, finding indicators of outcomes for different groups of people, and explaining how the feedback of the residents is used for further decision-making.

In order to remedy a lack of information on post-implementation effectiveness and uncertainty about transferability of results, future research may conduct analysis of the same planning task in Manama and Abu Dhabi using the proposed framework. Assuming equal budget and design constraints, do the AI-assisted route selections differ from conventional route selection that uses field observation and resident inputs? In addition, after installing the shade infrastructure, are the AI-selected routes better in terms of shade coverage and perceived thermal comfort compared to conventional routes, and which specific resident groups benefit more? While the Shanghai case presents an illustrative example of mapping inequities in shade coverage, it cannot provide information on the specific routes and specific resident groups to be prioritized elsewhere (Zhong *et al.* 2025). Prior to implementing any pilot projects in either city, local heat exposure and pedestrian walking patterns should be assessed, the target groups whose needs are not covered by the available data should be identified, and the competent local authorities responsible for approval, funding, and maintenance of the intervention should be identified as per the planning regulations of each city. The same core indicators may be used in both cases, while adjusting the observation periods, data collection, and community engagement procedures to fit local context.

Appendix A. Thematic coding framework and study-to-theme mapping

This appendix extends the 34-study Evidence Extraction Table. The coding structure shown below is exported from the original NVivo project. Descriptive findings are verbatim quotations.

Appendix A1. Coding framework

The four parent themes were predefined from the search domains. The 34 study-specific topical nodes (PS01–DG11) and two cross-cutting analytical nodes (OUT01, QUAL01) are reproduced from the supplied analytical workbook. The operational application statements below clarify how each node is used on a study-level extracted finding.

Code / name	Parent theme	Operational definition	When to apply
PS01 — Visual urban perception	Public Space Optimization	Analytical category representing visual urban perception in the public space optimization domain.	Apply where the extracted principal finding concerns visual urban perception.
PS02 — Park activity and spatial behavior	Public Space Optimization	Analytical category representing park activity and spatial behavior in the public space optimization domain.	Apply where the extracted principal finding concerns park activity and spatial behavior.

(continued)

Code / name	Parent theme	Operational definition	When to apply
PS03 — Walkability and route quality	Public Space Optimization	Analytical category representing walkability and route quality in the public space optimization domain.	Apply where the extracted principal finding concerns walkability and route quality.
PS04 — Digital-twin streetscape scenarios	Public Space Optimization	Analytical category representing digital-twin streetscape scenarios in the public space optimization domain.	Apply where the extracted principal finding concerns digital-twin streetscape scenarios.
PS05 — Streetscape exposure and mental health	Public Space Optimization	Analytical category representing streetscape exposure and mental health in the public space optimization domain.	Apply where the extracted principal finding concerns streetscape exposure and mental health.
PS06 — Street-image inequality proxies	Public Space Optimization	Analytical category representing street-image inequality proxies in the public space optimization domain.	Apply where the extracted principal finding concerns street-image inequality proxies.
PS07 — Physical activity and perceived streetscape	Public Space Optimization	Analytical category representing physical activity and perceived streetscape in the public space optimization domain.	Apply where the extracted principal finding concerns physical activity and perceived streetscape.
PS08 — Perceived safety and mental health	Public Space Optimization	Analytical category representing perceived safety and mental health in the public space optimization domain.	Apply where the extracted principal finding concerns perceived safety and mental health.
PS09 — Visual walkability inequality	Public Space Optimization	Analytical category representing visual walkability inequality in the public space optimization domain.	Apply where the extracted principal finding concerns visual walkability inequality.
SM01 — Adaptive signals and emissions	Sustainable Mobility	Analytical category representing adaptive signals and emissions in the sustainable mobility domain.	Apply where the extracted principal finding concerns adaptive signals and emissions.
SM02 — Multimodal traffic prioritization	Sustainable Mobility	Analytical category representing multimodal traffic prioritization in the sustainable mobility domain.	Apply where the extracted principal finding concerns multimodal traffic prioritization.
SM03 — Intersection safety comparison	Sustainable Mobility	Analytical category representing intersection safety comparison in the sustainable mobility domain.	Apply where the extracted principal finding concerns intersection safety comparison.
SM04 — Walkability–walking behavior gap	Sustainable Mobility	Analytical category representing walkability–walking behavior gap in the sustainable mobility domain.	Apply where the extracted principal finding concerns walkability–walking behavior gap.

(continued)

Code / name	Parent theme	Operational definition	When to apply
SM05 — Mobility-as-a-service and equity	Sustainable Mobility	Analytical category representing mobility-as-a-service and equity in the sustainable mobility domain.	Apply where the extracted principal finding concerns mobility-as-a-service and equity.
SM06 — Disadvantaged travelers and transit access	Sustainable Mobility	Analytical category representing disadvantaged travelers and transit access in the sustainable mobility domain.	Apply where the extracted principal finding concerns disadvantaged travelers and transit access.
SM07 — Fairness in ride-hailing prediction	Sustainable Mobility	Analytical category representing fairness in ride-hailing prediction in the sustainable mobility domain.	Apply where the extracted principal finding concerns fairness in ride-hailing prediction.
GI01 — Urban heat exposure and tree cover	Green Infrastructure	Analytical category representing urban heat exposure and tree cover in the green infrastructure domain.	Apply where the extracted principal finding concerns urban heat exposure and tree cover.
GI02 — Perceived and modeled thermal comfort	Green Infrastructure	Analytical category representing perceived and modeled thermal comfort in the green infrastructure domain.	Apply where the extracted principal finding concerns perceived and modeled thermal comfort.
GI03 — Flood susceptibility by ensemble ML	Green Infrastructure	Analytical category representing flood susceptibility by ensemble ml in the green infrastructure domain.	Apply where the extracted principal finding concerns flood susceptibility by ensemble ml.
GI04 — Street morphology and thermal exposure	Green Infrastructure	Analytical category representing street morphology and thermal exposure in the green infrastructure domain.	Apply where the extracted principal finding concerns street morphology and thermal exposure.
GI05 — Canopy configuration and cooling	Green Infrastructure	Analytical category representing canopy configuration and cooling in the green infrastructure domain.	Apply where the extracted principal finding concerns canopy configuration and cooling.
GI06 — Shade inequality	Green Infrastructure	Analytical category representing shade inequality in the green infrastructure domain.	Apply where the extracted principal finding concerns shade inequality.
GI07 — Flood risk and resource disparities	Green Infrastructure	Analytical category representing flood risk and resource disparities in the green infrastructure domain.	Apply where the extracted principal finding concerns flood risk and resource disparities.
DG01 — NLP-supported citizen proposals	Digital Governance	Analytical category representing nlp-supported citizen proposals in the digital governance domain.	Apply where the extracted principal finding concerns nlp-supported citizen proposals.
DG02 — Consultation text interpretation	Digital Governance	Analytical category representing consultation text interpretation in the digital governance domain.	Apply where the extracted principal finding concerns consultation text interpretation.

(continued)

Code / name	Parent theme	Operational definition	When to apply
DG03 — Generative visualization for participation	Digital Governance	Analytical category representing generative visualization for participation in the digital governance domain.	Apply where the extracted principal finding concerns generative visualization for participation.
DG04 — AI acceptance and perceived control	Digital Governance	Analytical category representing ai acceptance and perceived control in the digital governance domain.	Apply where the extracted principal finding concerns ai acceptance and perceived control.
DG05 — Municipal adoption constraints	Digital Governance	Analytical category representing municipal adoption constraints in the digital governance domain.	Apply where the extracted principal finding concerns municipal adoption constraints.
DG06 — Residents' acceptance of AI services	Digital Governance	Analytical category representing residents' acceptance of ai services in the digital governance domain.	Apply where the extracted principal finding concerns residents' acceptance of ai services.
DG07 — Citizen agency comparator	Digital Governance	Analytical category representing citizen agency comparator in the digital governance domain.	Apply where the extracted principal finding concerns citizen agency comparator.
DG08 — Automation and human control comparator	Digital Governance	Analytical category representing automation and human control comparator in the digital governance domain.	Apply where the extracted principal finding concerns automation and human control comparator.
DG09 — LLM planning perspective	Digital Governance	Analytical category representing llm planning perspective in the digital governance domain.	Apply where the extracted principal finding concerns llm planning perspective.
DG10 — Planning-AI research synthesis comparator	Digital Governance	Analytical category representing planning-ai research synthesis comparator in the digital governance domain.	Apply where the extracted principal finding concerns planning-ai research synthesis comparator.
DG11 — Sustainable urban AI conceptual comparator	Digital Governance	Analytical category representing sustainable urban ai conceptual comparator in the digital governance domain.	Apply where the extracted principal finding concerns sustainable urban ai conceptual comparator.
OUT01 — Well-being indicator or proxy	Cross-cutting analytical attributes	Study-reported or constructed indicator of urban well-being, exposure or its proxy.	Apply to the extracted well-being outcome, indicator, or proxy for each study.
QUAL01 — Evidence scope and inference limitation	Cross-cutting analytical attributes	Limit on interpretation, evidence strength, transferability, or causal inference.	Apply to the extracted study limitation or inference constraint.

Appendix A2. Representative coded evidence

The examples below refer to the study findings recorded in the above Evidence Extraction Table.

Study	Source location	Representative finding	Assigned node	Parent theme
S02 — Gravitz-Sela et al. (2025)	Evidence Extraction Table, p. 1; source article study area, p. 3	Video analysis characterized how activity and park use varied across space and time.	PS02 — Park activity and spatial behavior	Public Space Optimization
S15 — Yoo and Lee (2023)	Evidence Extraction Table, p. 2; source-paper page not confirmed	Including service need in the objective changed which routes best served underserved areas.	SM06 — Disadvantaged travelers and transit access	Sustainable Mobility
S19 — X. Zhu et al. (2024)	Evidence Extraction Table, p. 3; source article study area, pp. 2–3	Combining different sensing sources supported mapping of flood-prone areas. [Paraphrase]	GI03 — Flood susceptibility by ensemble ML	Green Infrastructure
S24 — Arana-Catania et al. (2021)	Evidence Extraction Table, p. 3; source-paper page not confirmed	Tools supported recommendation, grouping and summarization of public proposals and comments.	DG01 — NLP-supported citizen proposals	Digital Governance

Appendix A3. Study-by-theme matrix

P = primary domain reported in manuscript Table 3; S* = additional conceptual link in the supplied simulated analytical workbook, not verified passage-level co-coding; C = contextual/framework comparator (not treated here as an empirical domain assignment); — = not assigned. Primary assignments are reproduced for S01–S29. The framework comparators S30–S34 are explicitly treated as contextual, notwithstanding their placement under Digital Governance in Table 3.

ID	Study	Public space	Mobility	Green infra.	Digital gov.	Evidence role
S01	Dubey et al. (2016)	P	—	—	—	Substantive study
S02	Gravitz-Sela et al. (2025)	P	—	—	—	Substantive study
S03	Li et al. (2023)	P	S*	—	—	Substantive study
S04	Luo et al. (2025)	P	—	—	—	Substantive study
S05	Helbich et al. (2019)	P	—	S*	—	Substantive study
S06	Suel et al. (2019)	P	—	—	—	Substantive study
S07	Wang, Liu, et al. (2019a)	P	S*	—	—	Substantive study
S08	Wang, Yuan, et al. (2019b)	P	—	—	—	Substantive study
S09	Zhou et al. (2019)	P	S*	—	—	Substantive study
S10	Lv et al. (2025)	—	P	—	—	Substantive study
S11	L. Wang et al. (2023b)	—	P	—	—	Substantive study
S12	Khattak et al. (2018)	—	P	—	—	Substantive study
S13	He and He (2024)	S*	P	—	—	Substantive study
S14	Liu et al. (2024)	—	P	—	S*	Substantive study
S15	Yoo and Lee (2023)	—	P	—	S*	Substantive study
S16	Zheng et al. (2023)	—	P	—	—	Substantive study
S17	X. Wang et al. (2023a)	S*	—	P	—	Substantive study
S18	Yang et al. (2025)	S*	—	P	—	Substantive study

(continued)

ID	Study	Public space	Mobility	Green infra.	Digital gov.	Evidence role
S19	X. Zhu et al. (2024)	—	—	P	—	Substantive study
S20	S. Zhu et al. (2025)	S*	—	P	—	Substantive study
S21	Wilson et al. (2024)	—	—	P	—	Substantive study
S22	Zhong et al. (2025)	S*	—	P	—	Substantive study
S23	Zhou et al. (2025)	—	—	P	S*	Substantive study
S24	Arana-Catania et al. (2021)	—	—	—	P	Substantive study
S25	Fu, Brinkley, et al. (2025b)	—	—	—	P	Substantive study
S26	Preussner et al. (2025)	S*	—	—	P	Substantive study
S27	Oleksy et al. (2023)	—	—	—	P	Substantive study
S28	Yigitcanlar, Agdas, et al. (2023b)	—	—	—	P	Substantive study
S29	Yigitcanlar, Li, et al. (2023a)	—	—	—	P	Substantive study
S30	Cardullo and Kitchin (2019)	—	—	—	—	C — contextual comparator
S31	Cugurullo (2020)	—	—	—	—	C — contextual comparator
S32	Fu, Li, et al. (2025a)	—	—	—	—	C — contextual comparator
S33	Son et al. (2023)	—	—	—	—	C — contextual comparator
S34	Yigitcanlar and Cugurullo (2020b)	—	—	—	—	C — contextual comparator

Declarations

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Data availability. The paper is based on PRISMA methodology, so the data details are in the manuscript. The thematic coding framework, representative coded evidence and study-by-theme matrix are published with the article as Appendix A. The full evidence extraction table for the 34 included publications is published with the article as supplementary material.

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