



Algorithmic urban planning for smart and sustainable development: Systematic review of the literature

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ARTICLE INFO

Keywords:

Artificial intelligence
Big data
Urban planning
Urban development
Sustainable development
Smart cities

ABSTRACT

In recent years, artificial intelligence (AI) has been increasingly put into use to address cities' economic, social, environmental, and governance challenges. Thanks to its advanced capabilities, AI is set to become one of local governments' principal means of achieving smart and sustainable development. AI utilisation for urban planning, nonetheless, is a relatively understudied area of research, particularly in terms of the gap between theory and practice. This study presents a comprehensive review of the areas of urban planning in which AI technologies are contemplated or applied, and it is analysed how AI technologies support or could potentially support smart and sustainable development. Regarding the methodological approach, this is a systematic literature review following the PRISMA protocol. The obtained insights include: (a) Early adopters' real-world AI applications in urban planning are paving the way to wider local government AI adoption; (b) Achieving wider AI adoption for urban planning involves collaboration and partnership between key stakeholders; (c) Big data is an integral element for effective AI utilisation in urban planning, and; (d) Convergence of artificial and human intelligence is crucial to address urbanisation issues adequately and to achieve smart and sustainable development. These insights highlight the importance of making planning smarter through advanced data and analytical methods.

1. Introduction

Since the unprecedented rise of global urbanisation, expected to reach about 70% by 2050, cities are facing growing pressure in relation to economic, social, environmental, and governmental aspects (Perveen et al., 2017). Presently, the pressures of COVID-19, population increase mismanagement, climate change externalities, environmental degradation, housing unaffordability, and insecurities associated with the water-food-energy nexus have been subjects of intense debate amongst scholars, urban planners, and policymakers (Berawi, 2019). In response, the concept of sustainable development has been pushed to the forefront of urban policy debate in the hopes of constructing a desirable urban future (Yigitcanlar & Teriman, 2015). Sustainable development is defined as the balance of sustainable economic growth and ecological regeneration. It is the promise of meeting future urban goals without compromising society's well-being, quality of life, and environment (Berawi, 2019). Accordingly, many cities around the globe have taken

the technocentric approach to the notion of the smart city, utilising advanced technologies in urban planning to achieve smart and sustainable development goals (SDG) (Giuliani et al., 2020; Yigitcanlar et al., 2020a, 2020b). These goals are presented in Fig. 1.

Although using technologies in the management of cities is not an entirely new concept—going back as far as the late 1950s and early 1960s—it is only recently that the potential for these technologies is being widely recognised (Huang, 2021). Particularly in urban planning, meeting SDGs—especially those goals that are more directly linked with urban contexts, i.e., SDG 3,6,7,9,11,15 (Zhou et al., 2022)—more efficiently, is becoming more achievable with the rapid advances in data collection (Sanchez et al., 2022). Currently, the implementation of big data collection sensors that monitor changes in land use, transportation patterns, real-estate investments, and energy use, has accelerated the application of disruptive technologies, both new and mature (Sanchez et al., 2022). These disruptive emerging technologies, including artificial intelligence (AI), internet of things (IoT), machine learning, deep

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Fig. 1. Sustainable development goals (www.un.org/sustainabledevelopment).

learning, artificial neural networks, and 5G/6G, along with big data, have been used to create, expand, and monitor the effectiveness of smart and sustainable development across the globe (Berawi, 2019). As such, AI has been acknowledged as a highly promising technology in smart and sustainable urban development (Sanchez et al., 2022). While most people may encounter the applications of AI every day, such as their social media feeds, emails, and search engines, the

prospects of AI applications in sustainable development and urban planning are as “diverse as land use, zoning and permitting, environmental planning, and transportation” (Sanchez et al., 2022, p.4). More specifically, AI can assist urban planners to provide the best possible and equitable networks for larger traffic management and public transportation. It can help urban designers to respond to and design certain environments, creating more efficient communities. Moreover, AI can

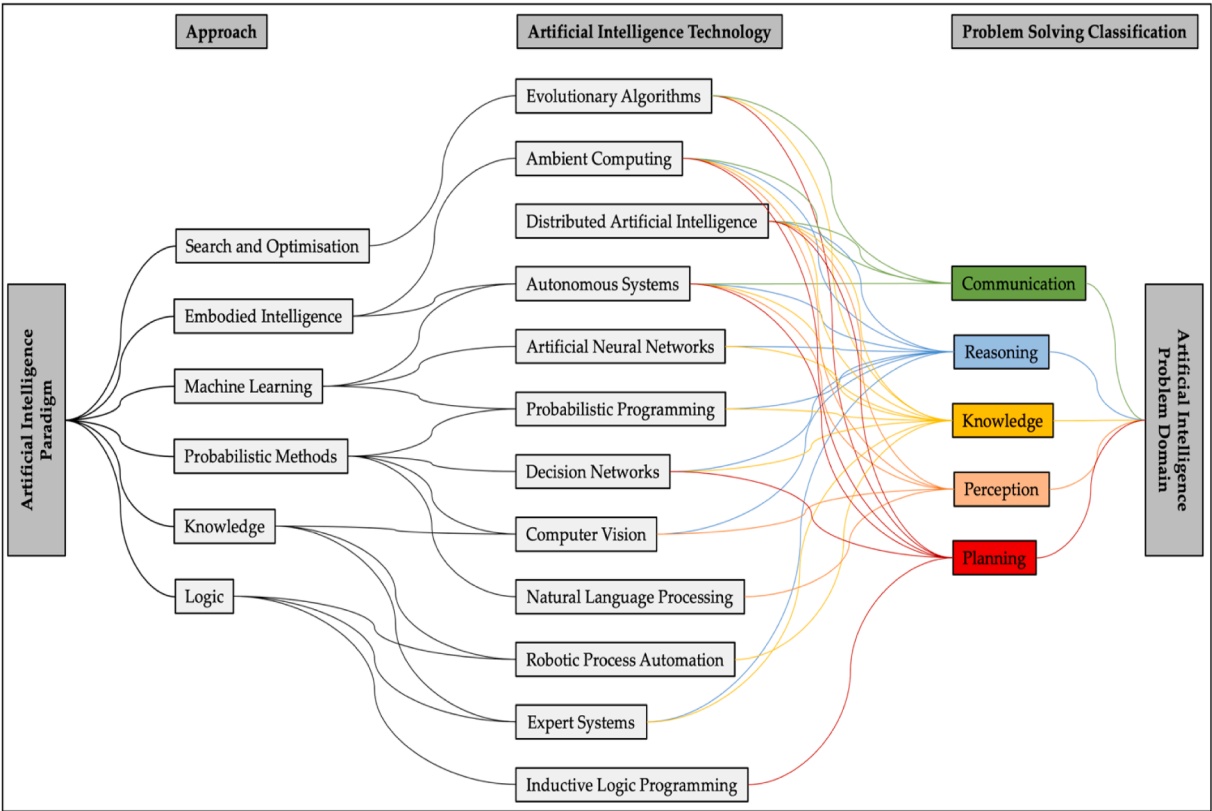


Fig. 2. AI knowledge representation, derived from Corea (2018).

predict and analyse air quality within cities, publishing results for pollution levels, fossil fuel particle density, and future levels, where these provide invaluable input for informing urban administrations and policymakers (Mahendra, 2021).

Today, urban big data analytics and data-driven planning technologies are seen as the foundations of algorithmic urban-planning-based smart and sustainable development (Lazaroiu et al., 2020; Lazaroiu & Harrison, 2021; Nica, 2021). When generating smart and sustainable development through urban planning, a comprehensive and critical understanding of the implemented technologies is paramount. To that end, undertaking a thorough review of the existing knowledge and practice on the topic is essential not only for stocktaking purposes but also as a means of critically examining the risks and limitations, and future opportunities of AI within the urban planning context.

Thus, this paper presents a comprehensive review of the urban planning areas in which AI technologies are contemplated or applied, as well as an analysis of how AI technologies are supporting or could potentially support smart and sustainable development. Regarding the methodological approach, this systematic literature review has followed the Preferred Reporting Items for Systematic Reviews and Meta Analysis (PRISMA) protocol. The PRISMA protocol, hence, is adopted to address the research questions of: (a) In which urban planning areas are AI technologies contemplated or applied? (b) How can AI technologies support smart and sustainable development planning? Here, we note that this systematic literature review primarily covers research activities as opposed to planning practice, as stated by Geertman (2017) there is a large gap between research and implementation in this area.

Following this introduction, the remainder of the article is structured as follows. Section 2 provides a concise literature summary, Section 3 introduces the methodological approach, Section 4 reports the results, followed by a discussion in Section 5 and a conclusion in Section 6.

2. Literature background: artificial intelligence in a nutshell

AI is a widely used term, however, it is not well understood by most people, including urban planners (Sanchez et al., 2022). While the concept of integrating intelligence in machines and systems can be traced back to the 16th century, it was not until 1956 that the term AI was officially coined by computer scientists: John McCarthy, Allen Newell, Cliff Shaw, and Herbert Simon (Press, 2016; Anyoha, 2017; Herath & Mittal, 2022). Back then, AI had yet to be further conceptualised to have a standard definition. Some informal definitions described AI as the capacity to accomplish goals in a variety of uncertain environments within highly adaptive, general-purpose systems through self-directed learning (Legg & Hutter, 2007). A single definition that provides a better, present-day understanding of the AI paradigm describes AI as the machine mimicry of human cognitive traits and actions in learning and problem-solving activities such as communication, reasoning, knowledge, perception, and planning (Corea, 2018; Yigitcanlar et al., 2021; Frankenfield, 2022).

What sets human cognitive abilities apart from AI are the differences in how tasks are performed. While humans automate tasks manually, AI can reliably and efficiently execute high-volume tasks autonomously (Zhang et al., 2022). Furthermore, AI can automate, repeat, learn, discover, and adapt large amounts of data (Testi, 2021). Several limitations were found in existing computer-based approaches to data problem solving (Han & Kim, 1989). Examples such as the ability to comprise great amounts of data, graphs, or figures, or analyse, understand, or establish relationships (Gauglitz, 2019). In response, AI was recommended as the appropriate solution to overcoming problem-solving limitations (Han & Kim, 1989).

As illustrated in Fig. 2, AI-enabled technologies are employed to address specific problem-solving activities. Large collections of data, commonly referred to as big data, are often obtained by means of IoT-enabled infrastructures (Hajjaji et al., 2021). Utilising these data, AI paradigms can be formulated. These paradigms are described as

‘Approaches’ or tools based on: Logic—the knowledge representation and problem-solving; Knowledge—the ontology of notions, information, and rule; ‘Probabilistic’ methods—incomplete information and data; ‘Machine learning’—the ability to learn from historical data; this field also contains its sub-category, namely, ‘Deep learning’; ‘Embodied intelligence’—the ability to affect the physical environment; and ‘Search and optimisation’—the intelligent search and higher outcomes of solutions. It is from these approaches that the different AI-enabled ‘Technology’ is utilised, such as ‘evolutionary algorithms, ambient computing, distributed AI, autonomous systems, artificial neural networks, probabilistic programming, decision networks, computer vision, and natural language processing’ (Corea, 2018).

The variety of AI applications that have evolved in recent years is astounding. These include social sensing (Liu et al., 2015), event detection of road traffic from social media data (Alomari et al., 2021a), AI applications for smart airports and smart districts (Janbi et al., 2020), learning public, industry and research perspectives of transportation and the gaps between them for better planning and policy developments (Ahmad et al., 2022), learning a holistic view of dimensions surrounding families from research and public perspective with the aim to develop broad as well as culture-specific policies and solutions (Alqahtani et al., 2022), co-creating healthcare services from social media (Alahmari et al., 2022), participatory governance of online and in-class education during the COVID-19 pandemic (Alswedani et al., 2022), learning government pandemic measures from social media data (Alomari et al., 2021b), governance of AI in energy systems (Alsaigh et al., 2022), learning age dynamics in labour markets (Alaql et al., 2022), solar energy forecasting and management (Alkhayat et al., 2022), skin disease diagnosis using mobile phones and edge devices (Janbi et al., 2022), DNA forensics (Alotaibi et al., 2022), stock trading (Malibari et al., 2022), and many others.

In recent years, AI also started to be used in local government agencies. The utilisation of AI mainly concerned two distinctive but interconnected areas: (a) Urban service delivery and operations (e.g., traffic control, garbage collection), and; (b) Urban policy, decision-making, and planning tasks (e.g., land use planning, development control) (Allam & Dhunny, 2019; Andrews et al., 2022; Samsurijan et al., 2022). Since AI’s recent emergence and availability in urban applications, smart cities have been utilising the technology to further tackle urban challenges and sustainable development in smarter ways (Kim et al., 2021). Considering the achievement of initiatives, Yigitcanlar et al. (2019a) found that the outcomes of smart city improvements involve productivity and innovation; liveability and well-being; sustainability and accessibility; and governance and planning.

Further, these initiatives can be sectioned under the umbrella terms of economy, society, environment, and governance (Allam & Dhunny, 2019). Accordingly, developing smart cities through urban planning requires learning different dimensions of perspectives, insights, and efficiencies for communities while maintaining attention to the potential bias and negative impacts (Sanchez et al., 2022). As such, urban planning requires strategic direction at all levels. Therefore, in the context of smart cities, urban planning can benefit from the means or incorporation of AI into planning practice for smart and sustainable development, solid economic growth, and improved quality of life of citizens (Nam & Pardo, 2011; Micozzi & Yigitcanlar, 2022).

Today, AI applications can be seen in various parts of the world. Cities in Europe, America, and Asia, particularly in Amsterdam, London, Vienna, Stockholm, Toronto, Singapore, and Hong Kong, have been utilising AI to achieve sustainable outcomes in their smart city transformation objectives (Yigitcanlar et al., 2020c; Tekouabou et al., 2022). For example, enhanced analysis capabilities, planning, awareness, and recovery operations in urban disaster management (Mikulsen & Diduck, 2016). Likewise, urban planning systems have employed, amongst other things, “AI in traffic system management, crime detection, air quality monitoring, efficient energy management, and water leakage detection systems” (Jha et al., 2021, p.938).

Proven to be successful to provide solutions to existing issues and challenges in more efficient means, certain networks, and algorithms, such as random forest, convolutional neural network, and support vector machine algorithms have been efficiently utilised in the classification and pattern analysis of urban data. Other approaches such as cellular automata, spatial logic regression, and agent-based modelling were also identified to be best suited to the study of urban population growth, land use changes, and settlement pattern analysis (Gulshad et al., 2022). A study by Yigitcanlar et al. (2022a, p.1) disclosed the “AI adoption areas, cautionary areas, challenges, effects, impacts, knowledge basis, plans, preparedness, roadblocks, technologies, deployment timeframes, and usefulness” in the context of local governments—where most of the urban planning practice takes place.

It has also been demonstrated that deep learning and computer vision can identify global urban issues that encompass land use, buildings, and the natural environment (Tekouabou et al., 2022), including slums, traffic congestion, and crowd mapping with less effort and data available (Ibrahim et al., 2021). Moreover, the not-so-far-reaching future of AI and its influence on the challenges of urban environments are not only exclusive to the aforementioned areas of smart cities but also cover many multifaceted dimensions (Nikitas et al., 2020). For instance, a decision/planning support system that evaluates the suitability of a building or a space by considering a variety of characteristics such as population distribution and composition, transport accessibility, urban form, and availability of infrastructures, was put to the test in the urban environment of Lyon, France. The system was found to be successful (Sideris et al., 2019). Likewise, a case study in China, which assessed the success of AI, including decision support systems, knowledge-based systems, and artificial neural networks, only called for refinements and improvements (Feng & Xu, 1999).

The effectiveness of AI is even reflected in its ability to understand the emotions and reactions of people at any given time and situation. According to Kaklauskas et al. (2021, p.3), the development of an “affective system for researching emotions in public spaces for urban planning” was based on behavioural economics and “psychology of judgement and decision-making and human emotional affective and physiological states”, which assists urban planners in analysing planning processes more effectively and in reaching a rational decision. In another study, conducted by Zou et al. (2019), the use of AI was improved by 50% in the forecasting of populations and in the spatial modelling of urban environments.

Moreover, the increase in big data availability in recent years led to the emergence of new urban data analytics options for planners, such as GeoAI which offers advanced computing for scalable processing and intelligent analysis of geospatial data (Li, 2020). In sum, assuming urban planners adopt AI broadly, this technology has a significant potential to support decision and policymaking as well as fully automate routine and mental planning tasks—if the shortcomings of AI are considered and addressed in each task (Andrews et al., 2022).

3. Methodology

This study presents a review of AI technologies applied or considered for urban planning, examining their potential in supporting smart and sustainable development. The current body of literature is somewhat fragmented, primarily because it is still relatively new. Nevertheless, it is developing rapidly. The topics are emerging and coalescing, and themes will become more evident as the research matures over time. Performing a systematic literature review on a new body of research with emerging topics and themes serves several purposes. One of the key reasons is to identify the current state of knowledge in the field, which helps researchers understand existing discoveries, innovations, and findings. This provides a foundation for further investigation and exploration. The objective is to also help establish the context and relevance of the emerging topics and themes. By situating these new ideas within the broader context of related research, researchers can gain a better

Table 1
Selection criteria for publication.

Inclusionary criteria	Exclusionary criteria
Urban, City, Town or Regional Planning	AI not in the Urban, City, Town or Regional Planning Field
Artificial Intelligence or AI	Not an AI Technology
Deep Learning	Irrelevant to the Research Aims and Questions
Machine Learning	
Neural Networks	
Sustainable Urban Development	
Smart or Sustainable Cities	
Relevant to the Research Aims and Questions	

understanding of their significance and relevance to the field.

Given the context provided above, two primary research questions have guided the literature review. First, the study focused on identifying: (a) In which urban planning areas are AI technologies contemplated or applied? Secondly, it concentrated on answering: (b) How can AI technologies support smart and sustainable development planning? In this systematic review, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol has been employed (see Regona et al., 2022). The PRISMA protocol is a widely accepted and recognised framework designed to enhance the transparency, consistency, and comprehensiveness of systematic reviews.

The protocol encompasses several stages, including defining eligibility criteria for study selection, developing a thorough literature search strategy, selecting relevant studies, extracting data, assessing the risk of bias, and synthesising and analysing the data. Each stage is performed by at least two independent reviewers’ involvement—i.e., the first two authors of this paper—to minimise biases and ensure accuracy. In cases of disagreement, a third reviewer—i.e., the third author of this paper—was consulted. By adhering to the PRISMA protocol, our systematic review has maintained a high level of methodological rigour, which enhances the reliability and validity of the findings. Furthermore, this approach facilitates the identification of emerging patterns, trends, and gaps in the existing body of literature, ultimately contributing to a more comprehensive understanding of the research topic. A search for relevant publications from Scopus and Web of Science (WoS) databases was performed, as they are the two leading bibliographic databases for scholarly work that contain the body of literature we are focusing on.

To ensure the diversity and relevance of the documents collected from the databases, various search keywords were combined to reference existing and emerging AI technologies. In September 2022, a Boolean search query was completed that included the following keywords: (TITLE-ABS-KEY("urban planning") OR TITLE-ABS-KEY("city planning") OR TITLE-ABS-KEY("town planning") OR TITLE-ABS-KEY("regional planning")) AND (TITLE-ABS-KEY("artificial intelligence") OR TITLE-ABS-KEY("AI") OR TITLE-ABS-KEY("machine learning") OR TITLE-ABS-KEY("deep learning") OR TITLE-ABS-KEY("neural networks")). The publication date range was set to no limit on the start date and August 2022 as the end date. The search disclosed the date of the earliest relevant publication was 1986. The search criteria were also limited the records written in English; categorised as either a journal article, book chapter or conference paper; and the full text had to be available online.

The search query produced 5537 records in total from both databases (Scopus = 3430 and WoS =2107). The records were checked for duplication, where 4343 records were removed; and then their titles and keywords were checked to see if they were fit. This process has led to the further removal of 627 records. The remaining list of records ($n = 567$) was then screened against the inclusion and exclusion criteria by focusing individually on the records’ abstracts (Table 1). This has resulted in removal of 399 records—leaving 168 records for full-text screening. The remaining 168 full-text records were read and their compliance with the inclusion and exclusion criteria was checked. This

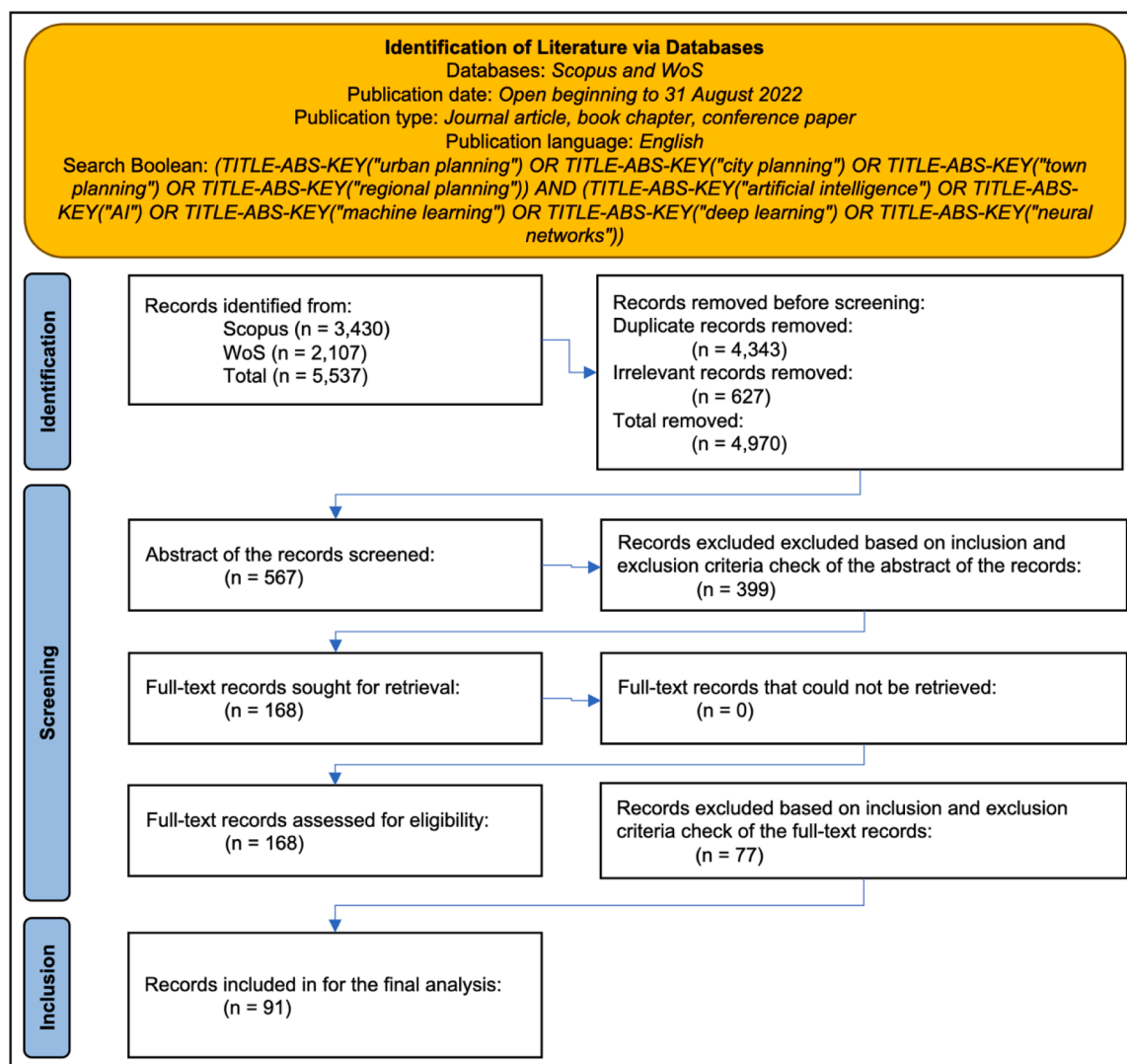


Fig. 3. Literature selection process.

exercise has removed a further 77 records. This screening reduced the final selection of publication numbers to 91. Fig. 3 details the literature review selection process.

The final selection of 91 publications was analysed and clustered into four categories, based on the following urban planning areas in which AI technologies are contemplated or applied: (a) Urban data analytics and planning decision support; (b) Urban and infrastructure management; (c) Urban monitoring and development control; and (d) Urban environmental and disaster management. The list of reviewed publications and summary of the findings of the review for each paper, is presented in Appendix Table A1. Additionally, the PRISMA 2000 checklist is included in Appendix Table B1.

4. Results

4.1. General observations

From the total of 91 selected publications, little over 78% were journal articles ($n = 71$) and almost 22% were book chapters and conference papers ($n = 20$). These publications were clustered into four categories through a full-text analysis of each publication, followed by an assignment of the best fitting category. The categorisation has shown heavy dominance of AI applications in planning concerning the areas of 'urban data analytics and planning decision support' and 'urban

monitoring and development control'.

'Urban data analytics and planning decision support' was a relevant category to 49.5% of the reviewed publications ($n = 45$). It was followed by 'urban and infrastructure management' with 20.9% ($n = 19$), 'urban environmental and disaster management' with 15.4% ($n = 14$), and 'urban monitoring and development control' with 14.2% ($n = 13$).

The most common application type of AI was found in machine learning ($n = 76$), which accounted for 84% of publications. This was followed by deep learning ($n = 46$) with about 51%, and neural networks ($n = 31$) with 34%—as the reviewed publications reference multiple AI applications, numbers and percentages do not add up to 100%.

The top-3 commonly published journal outlets were Environment and Planning B ($n = 4$), Sustainability ($n = 4$), and Remote Sensing ($n = 4$). In terms of conference proceedings, IEEE conference series on various technology foci were the most popular ones ($n = 5$), followed by the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences ($n = 2$) and International Conference on Computer-Aided Architectural Design Research in Asia ($n = 2$). Fig. 4 indicates the number of publications per year. In total, approximately 77% of the identified publications were published within the past four-year period (2019–2022)—indicating the recent emergence of the importance of AI for urban planning. The analysis revealed a strong relevance of AI in urban planning with the smart city notion (about 78%

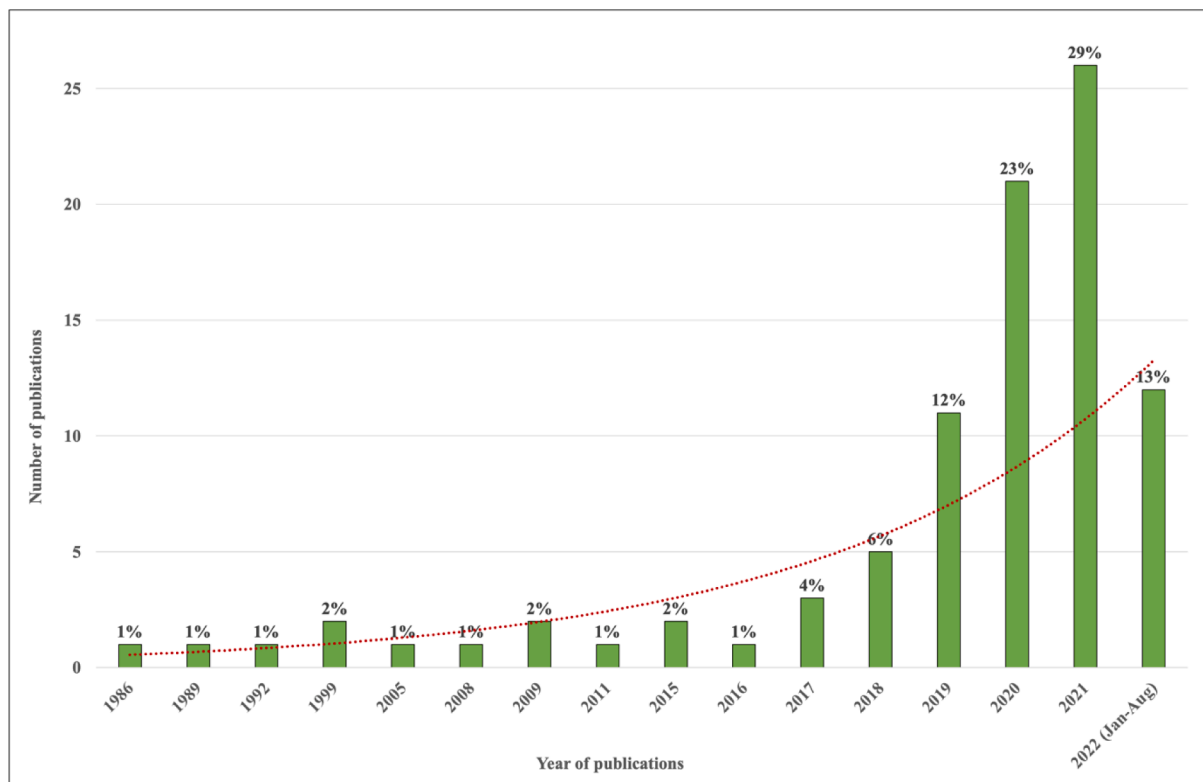


Fig. 4. Publications by year.

of reviewed papers concerned the smart city context) in the context of advanced technology utilisation to achieve improvements in the performance of cities.

The association of each article with the relevant SDG has shown common alignment with goals 3, 6, 7, 9, 11, 15 and 17. Unsurprisingly, the most common goal was aligned *Goal 11 – Sustainable Cities and Communities* ($n = 70$). The topics associated to this goal are *disaster risk reduction; sustainable transport; and, sustainable cities and human settlements*. Most of the articles were aligned to the *sustainable cities and human settlements* topic due to the nature of the research question. The second most common goal was aligned to *Goal 17 – Partnerships for the Goals*, specifically the *Technology* topic ($n = 52$). This SDG is not commonly associated with urban planning, however, in the context of the use of developed and deployed AI across urban planning, technology will be critical in addressing the challenges that growing urbanisation poses to building sustainable cities.

An analysis of co-occurrence and frequencies for SDGs and AI technologies, in the context of the papers reviewed in this study, is shown in Fig. 5. The node size is the degree (frequency) and the edge shows frequency of appearing together. As its evident in Fig. 5, SDGs 3 and 11 are the most frequent (Good Health and Well-being, Sustainable Cities and Communities), followed by SDGs 1, 6, and 15 (No Poverty, Clean Water and Sanitation, Life on Land). On the contrary, SDGs 8 and 10 appear the least often (Decent Work and Economic Growth, Reduced Inequality), where SDGs 11 and 17 appear together most often (Sustainable Cities and Communities, Partnerships to Achieve the Goal). Information on the relevance of each reviewed paper and the SDGs is available in Appendix Table A1.

4.2. AI for urban data analytics and planning decision support

Smart city planning, in theory, is focussed predominately on utilising AI technology to improve efficiency, effectiveness, innovation and build a more sustainable and resilient city. Nevertheless, in practice, there

exists a limited, but growing number of examples of the utilisation of AI technologies in urban service delivery and operations, and urban policy, decision-making, and planning tasks (Cugurullo, 2020). The expectation is that the overall economic productivity of a city will be influenced by AI through contributing to improvement in many areas across the city, including health, traffic, planning, air quality, and the like (Jha et al., 2021). These overarching uses of AI could support planning decisions. The most common areas where AI is used or considered for analytics and decision support includes air quality, urban/public health, planning tasks, traffic management, urban policy, and urban service delivery and operations.

The results show that many instances of AI have been applied to address urban planning practices in smart cities (Jain, 2011; Cugurullo, 2020) and the risks and opportunities related thereto (Gray & Kovacova, 2021). Innovative solutions that improve the use and analysis of big data in cities could lead urban planners to having a greater understanding of the range of factors involved, that were not perceivable without the use of AI. The desirable engagement or stakeholder activities, associated with the planning decision process, are often not possible to achieve due to time, efficiency and budget limitations. Thus, AI can support some of the planning processes to support the planning decision. AI enabled deep learning, can assess citizens' urban perception of streets (Yao et al., 2019) or address the environmental concerns of pollution in cities (Ameer & Shah, 2018).

This would normally require extensive amounts of resources and time. Traffic management in smart cities is a complex problem with a vast array of research and AI applications that are attempting to improve traffic efficiency, congestion, and management. AI has been used to analyse big data and understand the current transportation use and traffic forecasting of complex transportation networks (Jha et al., 2021). A framework has been developed to measure the social impact of a development during its design process (Ferreira et al., 2015). Another alternative model can provide sustainable planning strategies that respond to social issues in cities (Koehler et al., 2009). Additionally,

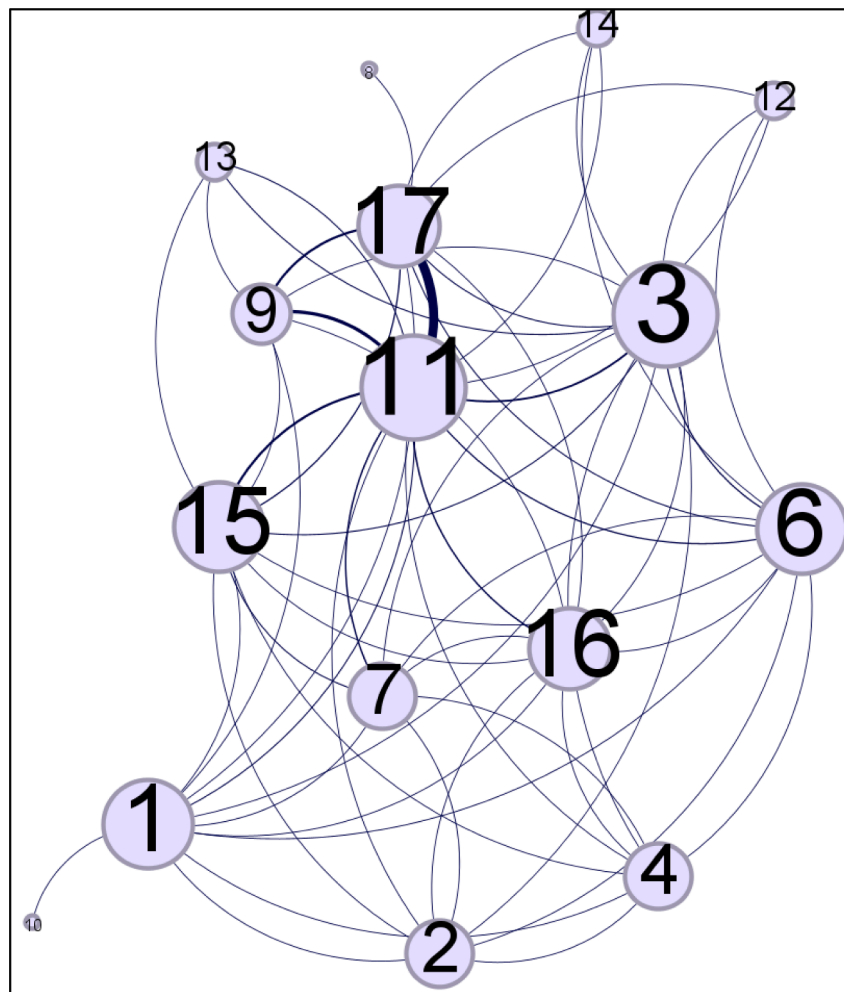


Fig. 5. Co-occurrence and frequencies for SDGs and AI technologies.

deep learning technologies have assisted in the spatial distribution patterns of jobs and housing (Yao et al., 2020). All these processes require extensive data to be collected, analysed, and processed; with the support of AI the efficiency is far greater.

Other more traditional planning decisions can be supported by AI. The literature highlights that AI, generally expert systems, were used for master planning, including the creation of drawings and renderings (Ye et al., 2022) and the assessment of the feasibility of the master plan (Polydorides & Petropoulos, 1989). There is great potential in streamlining some planning decisions with the support of AI. For example, land use mapping continues to be a human decision-making involvement as part of land use planning (Balling et al., 1999). However, numerous examples identify how AI can support land use planning (Chaturvedi & de Vries, 2021; Meeran & Conrad Joyce, 2020; Yuan et al., 2022). Traffic also affects the adjoining land uses as part of the greater smart city transport network (Meeran & Conrad Joyce, 2020). The reliability and performance of land use planning has a significant impact on the productivity and efficiency of a city.

The results in this domain show that there are AI systems that are used to assist and inform human decision-making (Tanic, 1986). More recent examples include the Smart Design Framework where AI is used to support and inform the design process as part of an overall integrated workflow (Quan et al., 2019). Furthermore, urban planners could direct and influence how AI is integrated in urban planning processes (Karvonen et al., 2020) and allow for risk mitigation and ethical considerations to be at the forefront of urban planning. While many difficult urban issues and challenges can be solved with the support of AI, there

was a common concern that denoted that these AI-supported applications may have unethical effects on daily life and urban planning (Engin et al., 2020). Even though the results demonstrate the integration of AI systems can provide better solutions (Chaturvedi & de Vries, 2021), it is suggested that greater collaboration between interdisciplinary teams in sharing data to improve outcomes is needed (Bazan-Krzywoszańska et al., 2020).

Appendix Table A1 presents a summary—including the aim, relevance, technologies, and findings—of the 45 papers concentrating on AI for urban data analytics and planning decision support.

4.3. AI for urban and infrastructure management

This domain is concerned with the development, governance, and management of cities, particularly, with the management of the urban environment and infrastructure for more resilient and sustainable smart city developments. The literature indicates that as cities continue to grow, it is expected that the urban environment and infrastructure within a city will become ever more challenging to plan, design, and comprehend (Fang et al., 2022). Alongside this foreseeable challenge, the results largely indicate that the incorporation and implementation of AI-enabled technologies in urban planning practices can assist in the future management of smart and sustainable urban environments and infrastructures (Javed et al., 2022). Achieving not only a smart but also a sustainable city requires the collaboration of multiple stakeholders; the implementation of AI will assist in the implementation of smart city initiatives that respond to urban and infrastructure challenges (Anthony

Jnr, 2021).

As more complex urban issues arise each day, urban planners are required to respond to them appropriately and efficiently; however, many of them are impenetrable and thus, it is not always feasible for an urban planner and/or decision-maker to undertake the problem solving themselves. Thereby, the results indicate that this is a key factor associated with the interest in implementing AI to assist urban planners, particularly in resolving complex problems in (smart) cities. More specifically, AI has been demonstrated to support the problem-solving associated with urban design and modelling of city infrastructures. amongst these AI technologies are machine learning, deep learning, and conventional neural networks, as well as ad hoc managerial and design processes, including the automatic and interactive detection, generation, prediction, measurement, information, mapping, and categorisation of street networks (Boulange et al., 2018; Law et al., 2020; Ibrahim et al., 2021; Fang et al., 2022; Yerram et al., 2022). Notably, Lee et al. (2022) have demonstrated an implementation of AI which assessed pedestrian satisfaction with the physical and visual characteristics of the street infrastructure. These results illustrate how AI is used to support smart city urban planning procedures, particularly for urban and infrastructure management processes.

Another highly elaborate problem cities face is the management of land use and transportation. As the urban environment of cities changes, it impacts the management, organisation, and planning for new development and related transportation infrastructure (Azad & Wang, 2021). In sum, the results show that AI can effectively learn, predict, estimate, store, manage, and analyse data related to traffic and housing developments (Ito et al., 2020; Azad & Wang, 2021). These approaches to utilising AI lead to improved and more efficient means of enhancing land use planning, transportation planning, development, and management (Kröl, 2016; Kouziokas, 2017; Anastasiou et al., 2019; Aqib et al., 2019). Moreover, these results unveiled the benefits of AI for public safety. For example, the use of AI in improving transportation management policies such as crime risk prevention strategies in transportation networks (Kouziokas, 2017; Nikitas et al., 2020).

Ultimately, the results pointed to a common theme, namely, that the utilisation of AI in urban and infrastructure management can empower previous and traditional methods, specifically problem-solving-related activities. In turn, smart and sustainable development in the planning of cities, especially within the domain of urban and infrastructure management, establishes a new change in its fundamental processes (Nikitas et al., 2020). It should be noted that while the results suggest positive AI utilisation in urban design and land use/transportation management, it is not at all exclusive to it; Utilisation of AI within the urban and infrastructure management domain shows potential in the planning and management of healthcare, education, telecommunication, waste management, food supply, water, industrial and energy-related infrastructures (Nikitas et al., 2020; Anthony Jnr, 2021). Thus, the results highlight AI's role as an instrument and tool for successful and efficient smart and sustainable city development.

Appendix Table A1 presents a summary—including the aim, relevance, technologies, and findings—of the 19 papers concentrating on AI for urban and infrastructure management.

4.4. AI for urban environmental and disaster management

The urban environmental and disaster management domain examines the implications of various environmental hazards and emergencies within cities, including weather events, effects of urban development, and the impact of a city's energy use on the natural and physical environment. These issues must be addressed in urban planning for a smart city to maintain sustainable development and environmental quality. According to the findings, AI has already been used to address many of the usual environmental concerns for management. Tree management (Timilsina et al., 2019), noise pollution (Mrówczyńska et al., 2019), population growth (Mulligan, 2021), and air pollution (Demmler et al.,

2021) are principal examples of the problems to which AI has provided solutions. Urban disaster management (Abid et al., 2021), flood resistance (Ye et al., 2021), and flood risk assessment (Pham et al., 2021) for urban areas are amongst the other AI-supported applications.

Each paper highlights the extent to which AI influences and supports the applications used to plan the natural and physical environment in the creation of smart cities. For instance, it may be inferred that the purpose of any AI approach is to enhance the physical and natural environment for inhabitants to be more comfortable and have increased accessibility to urban spaces (Bienvenido-Huertas et al., 2020). The results of the review also show that these urban issues can have significant impacts on a sizable population, highlighting the value of using AI-supported technologies, such as machine learning, for urban managerial processes. The studies in this domain disclose that AI can offer historical and current analyses during crucial times when it comes to environmental concerns (Demmler et al., 2021).

AI outcomes have been shown to be long-lasting, sustainable, and positive for the environment, which has a favourable knock-on effect on urban residents' standard of living. For example, the reviewed papers indicated that the utilisation of AI can encompass more than responding to environmental disasters and the effects of climate change (Abid et al., 2021; Milojevic-Dupont & Creutzig, 2021). More specifically, AI-supported applications have been introduced to improve strategies that detect, measure, and manage waste volumes in cities, which in turn can provide better outcomes at a much lower cost (Conley et al., 2022; Gupta et al., 2022). Again, these results translate into improvements in the quality of the natural and physical environment, demonstrating the application potential of AI. Because of urban planning processes that ensure the management and long-term sustainable development of smart cities, the quality of life of the citizens is improved. Along with these studies, AI has also been used in urban studies and planning research to measure the urban heat island effects—e.g., Yu et al. (2020), Guan et al. (2022).

Appendix Table A1 presents a summary—including the aim, relevance, technologies, and findings—of the 14 papers concentrating on AI for urban environmental and disaster management.

4.5. AI for urban monitoring and development control

As smart cities continue to increase in both population and land size, the scope and scale of monitoring and the subsequent control of urban development will become more demanding. AI technologies have been used to address urban monitoring as a tool to support development control. At a neighbourhood scale, AI has been used to monitor and predict crime hotspots in cities (He & Zheng, 2021), allowing for policies and measures to be installed to help foster greater safety in areas of concern. Whereas a more common use of AI is to assist in the monitoring and analysis of land use and urban sprawl (Lan et al., 2021). Also, AI has been used to monitor and identify where road improvements are needed by means of remote sensing (Exner et al., 2020).

Productive land use throughout cities can support population increase and drive economic development and infrastructure projects. Land use planning and management is a fundamental aspect of urban planning and is time-consuming and heavily reliant on data processing and manual expert knowledge. The use of AI in land use planning not only supports efficiencies in urban planning practice but more importantly helps improve the city. There have been various supervised and unsupervised AI learning tools that can provide varying classifications and analyse land use and some deep learning techniques (Lv et al., 2015) and other multimodal techniques (Srivastava et al., 2019) can automate the entire process. The analysis of the urban footprint can be difficult and time-consuming, nevertheless, AI can analyse local urban features in the planning and design, including building configurations (Shen et al., 2009; Ding et al., 2020). This form of AI provides another layer of analysis and information that can be used to understand the efficiency of urban areas.

As cities continue to grow, horizontally and/or vertically, so does the land area that needs to be managed for optimum performance. Innovative solutions help achieve faster and better land use analyses in cities, providing urban planners with a greater understanding of the range of factors involved in establishing development controls for urban growth that were not perceivable without the use of AI. The reviewed papers in this domain revealed that controlling urban sprawl and speculating about the effects can be difficult to predict, nonetheless, AI has been used to simulate urban growth through the analysis of land use patterns and street networks (Shen et al., 2020) and comparative analysis of similar urban environments (Gharaibeh et al., 2020) could be used to simulate similar planning policies in other comparative urban contexts.

These AI technologies could be used to support development controls; there have been examples of AI use to measure the changes in urban density (Ding et al., 2020) and the impact of urban infrastructure on the surrounding urban areas (Feng et al., 2018) and compliance of urban development with local planning codes (Heikkilä & Blewett, 1992). The integration of the efficiency of AI with the expertise of humans can lead to great possibilities and innovations in how urban planners tackle complex urban problems. The ease of forecasting and modelling urban solutions by AI, as demonstrated in the literature, can result in positive solutions assuming that planners will implement these tools judiciously. The effective monitoring and control of urban areas can lead to sustainable city development using AI technologies (Koumetio Tekouabou et al., 2021). The effective and productive use of land in cities relies on connections between urban monitoring and effective development controls to ensure sustainable growth in cities. Along with these studies, Long et al. (2015), Liang et al. (2018), and Kaviari et al. (2019) also provided insights into spatial optimisation, agent-based models, and urban growth boundaries that are amongst the key methods for AI-based urban development control.

Appendix Table A1 presents a summary—including the aim, relevance, technologies, and findings—of the 13 papers concentrating on AI for urban monitoring and development control.

5. Findings and discussion

5.1. Urban planning areas in which AI technologies are contemplated or applied

With the ever-increasing amount of big data available in cities, there is a range of urban planning areas in which AI can be applied. Land use planning and the subsequent urban developments are the two predominant planning areas that could provide the greatest scope to support urban planners as part of their practice. Arguably, the task of classifying land use and zoning, and the analysis of proposed developments, is the most significant and time-consuming task that urban planners undertake. The findings of this review suggest that big data and AI intervention could improve efficiency in these tasks (Khediri et al., 2021). The application of big data could have a broad reaching, positive impact on health, traffic, air quality, and the physical environment, creating a more sustainable smart city.

Planning interventions can directly produce urban data that creates continued monitoring and control by urban planners. When AI becomes more commonly used in planning practices, it is expected that these interventions will create even greater amounts of big data that will require monitoring as part of the urban planning process. Therefore, any area that adopts AI technologies will have a need for a holistic integration of AI as part of the wider urban planning practice, addressing the complexities associated with urban environments (Jha et al., 2021).

The review results indicate that AI technologies will offer promising applications in the future, to deal with the urban environmental and disaster management of cities. The range of urban environmental and disaster matters that AI technologies can be applied to include both the natural and physical environment, supporting urban planning processes, public policy creation, and emergency responses. Integrating planning

processes with AI technologies, not only helps in monitoring, analysing, and evaluating the urban environment but also improves the quality of life for citizens and ensures the long-term sustainability of smart cities. One of the main challenges that urban planners face, is monitoring and quantifying large data sets to assess specific environmental issues, such as the management of negative externalities, natural disasters, and improvements to infrastructure (Abid et al., 2021).

The results strongly point to the existence of a consensus on the importance of urban planners and policymakers capitalising on the opportunities of emerging AI technologies to enhance the sustainable development of cities. The review results reflected literature on the critical and real-time analyses of machine learning techniques. Although urban environmental issues remain complex, the labour and resources can be effectively minimised with these AI technologies. Integrating AI technology is linked to reducing the error rate and improving the overall efficiency of existing systems (Shin et al., 2017). Coinciding with the research literature, these benefits ultimately lead to improving urban policy and planning tools in the smart and sustainable development of the city environment, improving the quality of life for citizens.

On an interesting note, while the results demonstrate positive sustainable impacts on citizens and the physical environment, further research on the development of AI models and algorithms is recommended, as well as the scope of planning applications. Even though the results have demonstrated that public bodies and institutions can develop adequate and sustainable urban environmental policies using AI, the analysis of the different factors relative to the urban environmental issue is required. This ensures that the results are at their upmost accuracy (Bienvenido-Huertas et al., 2020). Once this is achieved, the application of AI technology to environmental policy solutions will have scalable potential, with the possibility of efficiently reaching urban environments at the local, state, and national levels (Milojevic-Dupont et al., 2021).

Opportunities in the use of AI to support the development, governance, and management of cities are evident from the results of the review. As the results suggest, AI can assist in tackling future problem-solving-related urban environment and infrastructure managerial processes. Thus, collaboration of relevant stakeholders can be advocated as a means of pushing the implementation of AI (Nikitas et al., 2020). The results not only illustrate that numerous applications of AI can be implemented in complex urban problems such as urban design and modelling of infrastructure, but with further improvements to the technology, a more sustainable smart city can be achieved (Yerram et al., 2022). Conversely, as the technology is still regarded as relatively new, additional research can be beneficial for its accessibility and increase the likelihood of it being implemented at the different scales of urban and infrastructure management processes. In other words, a healthy level of caution is needed before embarking on large-scale AI adoption and testing the possible externalities and capacity of the organisation and planners.

Additionally, the application of AI to support urban and infrastructure management processes is gaining application ground to improve the management, organisation, and planning of land use and transportation (Ito et al., 2020; Azad & Wang, 2021). More specifically, it can be observed that by implementing AI as a support tool to the above-mentioned managerial activities, complex problems that concern many stakeholders can be addressed more efficiently, reaching solutions and decisions sooner. This suggests that AI has the capabilities to generate and adapt to different agents and more importantly, agents involving the sustainable development of smart cities. Of course, this leads to the ethical issues of AI, which have already been raised by the existing literature—How we mitigate the ethical concerns of AI, especially as urban planning activities involve human-centred approaches (Ljubenkov, 2020). Since the technology would presumably be implemented through the volition of urban planners, the cognitive bias would need to be acknowledged and presented. Perhaps, by taking a holistic approach, an agreed set of guidelines could be presented amongst the relevant

stakeholders during urban planning practices and developments. This would ensure that the processes remain transparent, legal, fair, and safe (Ljubenkova, 2020).

As AI brings forth a new direction for urban planners and decision-makers to improve the processes for the development of a more sustainable and smarter city, an integrated, collaborative, and holistic approach is needed. Agents of different disciplines, both public and private, would have to exhibit equal opportunity in fully understanding and utilising the technology. Even then, as there are different scales of governance and private companies, a major barrier would be that there may be no real capability to implement innovation in existing processes (Nili et al., 2022). Nevertheless, the technology exists, and future works need to shift AI research and development to implementation in real-world urban and infrastructure practices. Not only does this present the opportunity of shaping a more sustainable smart city, but also confronts the associated risks of AI head on, minimising them in the future.

5.2. How AI technologies are supporting or could support smart and sustainable development

A range of AI technologies currently supports smart and sustainable development, including traffic system management, crime detection, air pollution, energy management and water leakage detection as part of smart city planning and management (Milton & Roumpani, 2019). The energy sector uses AI within smart cities most commonly (Nosratabadi et al., 2020) and various technologies support the monitoring, analysis, and application of planning processes to mitigate the effects of pollution in urban environments (Mrówczyńska et al., 2019). Efficient public transport networks can be optimised with deep learning applications (Aqib et al., 2019) helping to promote sustainable transport options in smart cities.

Big data is often used to promote a range of spatial and land use modelling to support the preservation of natural environments (Zou et al., 2021). AI can support a range of urban planning practices, helping promote the integration of sustainable urban technologies, such as the use of IoT, (Gray et al., 2021) to achieve further efficiencies and support sustainable city governance and/or management (Lan et al., 2021). Due to the scale of IoT data, AI can not only support city development but also regional development while considering the impact of environmental and sociocultural sustainability issues (Bienvenido-Huertas et al., 2020). Regional planning can be supported by machine learning to predict future regional growth and development (Mulligan, 2021). Especially the emerging applications integrating AI with IoT infrastructure, in other words artificial intelligence of things (AIoT) (Zhang & Tao, 2020), offer invaluable data-driven knowledge for planning both at urban and regional scales (Kuguoglu et al., 2021; Yang et al., 2021).

Smart cities pose a range of complex problems for urban planners; AI technologies have demonstrated their potential to promote sustainable resolutions (Jha et al., 2021). In the future, there will be further opportunities for more advanced AI technologies to analyse big data and assist in solving these complex problems (Ullah et al., 2020) through better urban design solutions (Quan et al., 2019). This will require greater collaboration with all urban planning disciplines (Ye et al., 2022) and greater community-led collaboration and engagement (Calixto et al., 2021).

The impact of autonomous cities has resulted in smart cities being shaped by AI technologies (Cugurullo, 2020) due to the ever-increasing use and application of big data in urban planning processes (Jiang, 2020). Nevertheless, urban planners can continue to do more with AI technologies to better support urban planning practices and the issues affecting cities now and into the future (Karvonen et al., 2020). There will be many challenges on the way, however, the advancements in AI technologies will allow for a revolution in the urban environment and planning practices (Javed et al., 2022).

Having said that, the current gap between AI capabilities and their planning applications to support smart and sustainable development is

also driven from the complexity of sustainable development (Redclift, 2005; Klopp & Petretta, 2017; Fu et al., 2019) and urban reality (e.g., urban shrinkage/rapid growth, and citizen/stakeholder behaviours, along with socioeconomic, political and governance challenges) and the difficulty of exploring human-environment interactions (Kashef et al., 2021). The potential of AI in supporting the mechanism of sustainable urban change and human-urban interactions for future sustainable urban planning is of great importance, and hence should be a future development trend in urban AI.

5.3. Insights, study limitations, and research directions

This review revealed a series of important insights for urban planning scholars, decision-makers, and practitioners. The first one is that early adopters' real-world AI applications in urban planning are paving the way to wider local government AI adoption (Nili et al., 2022). This is to say, in the infancy of AI in urban planning, learning from success and failure examples is a treasured opportunity for local government planning departments as it would lead to improving the prospects and limiting the constraints of the AI technology and its integration in the urban policymaking and planning mechanisms (Wu & Silva, 2010; Wang et al., 2022).

The second key insight is that a major contributor to achieving wider AI adoption for urban planning is to promote collaboration and partnership between key stakeholders. Wider engagement of stakeholders—for example, ranging from local government chief technology officers, policymakers, and planners to development companies, service providers, community organisations, and end-users—will help in not only effective and efficient but also a responsible use of AI in planning (Urban et al., 2021; Deshpande & Sharp, 2022).

The next insight relates to problems associated with data. AI is a data hungry system, and the recent popularisation and availability of big data is an integral element for effective AI utilisation in urban planning. Many local governments are aware of the necessity of big data for more accurate urban analytics and there are attempts to obtain such data from both in-house and outsourced channels (Pencheva et al., 2020; Watson & Ryan, 2020).

The fourth insight is that in such a complex system as that of our cities, tackling complicated planning decisions cannot be done without the aid of advanced technology such as AI. The mistake, however, would be seeing these intelligent technologies as systems that could run with little human supervision or oversight. The misuse of AI across the globe has demonstrated that the convergence of artificial and human intelligence is crucial to address urbanisation issues adequately and to achieving smart and sustainable development (Gauglitz, 2019; Araujo et al., 2020; Yigitcanlar et al., 2022b).

Moreover, while AI has significant potential in urban planning practice, gaps and limitations remain within the research. There also remains a significant gap between research and practice. The literature provides a range of frameworks, theories, and applications, however, there is limited evidence of wider implementation of AI across the sector. Understandably, the fear of AI amongst the public and of its potential impact on the profession of urban planners and their role, is a significant factor in the reduced uptake of AI technology (Yigitcanlar et al., 2022c). However, as big data increases and complex urban issues continue to increase, it should be imperative that AI technologies be adopted sooner than later to ensure successful and productive implementation. On the other hand, AI utilisation without considering its risks, such as cybersecurity, privacy, bias, etc., and without skilling up urban planners to understand those risks pose a serious threat. There is, hence, an urgent need for developing innovation adoption processes, upskilling planners, and educating planners to become AI literate via formal university education and/or professional development training.

Unsurprisingly, the literature suggests that to achieve the sustainable development of the urban environment, the knowledge gap between AI and its applications needs to be addressed and reduced. An increase in

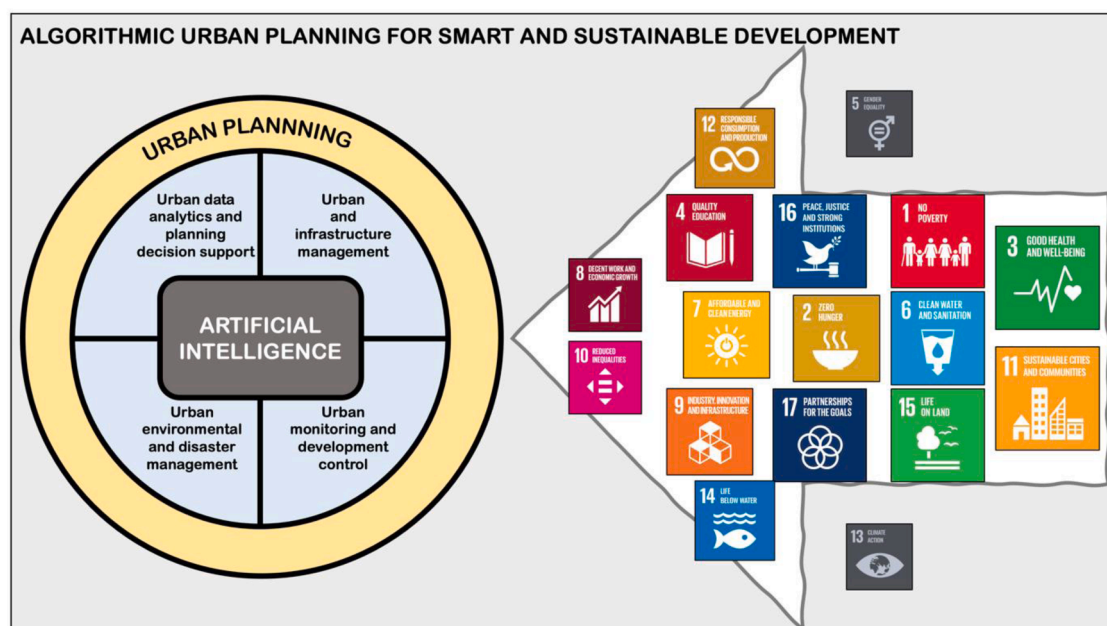


Fig. 6. Current landscape of algorithmic urban planning to achieve smart and sustainable development.

public awareness could support the best urban planning outcomes. Nevertheless, the emergence of AI technology in planning practices can seem too novel for many planning departments and practitioners. Further practical explanations of AI are needed so that urban planners and policymakers can efficiently utilise the technology (Ye et al., 2021a). Moreover, one major detected limitation was that AI technologies require the possession of high-quality data and training (Srivastava et al., 2019; Exner et al., 2020). Therefore, it can be suggested that to surpass this limitation, the procurement of data relative to the urban issue need to be either institutionalised or accessible. Consequently, this leads to legal implications associated with data protection and big data management. The public also has concerns regarding the data being collected and the methods used for collection.

Likewise, unbiased big data and adequate training with the correct criteria and rules/principles will help decrease the bias and increase the efficiency of AI operations. Besides, as cities become more data-rich, better laws and regulations need to be implemented to ensure citizens are protected from any privacy breaches. In turn, citizens are incentivised in participating and providing relevant data for the development of urban solutions (Exner et al., 2020). This would lead to the betterment of sustainable urban planning and AI practice.

Besides, AI theory and practice in the context of cities at large, and particularly in urban planning, is still in its infancy, despite the increasing number of successful and in many cases not-so-successful examples. The reasons for this include the recent emergence of responsible application perspectives for AI technologies and limited application opportunities due to a lack of funds or local technical knowledge or regulations (Yigitcanlar et al., 2022a). There is, however, a growing interest in urban policy and practice circles toward AI adoption in urban planning and the development of smart and sustainable cities. Nevertheless, the current knowledge on how to adopt AI in urban planning mechanisms is opaque. As also stated by Sanchez (2023), much of the current planning-related discussion about AI is related to smart city technologies used to capture and analyse data for optimization processes, such as traffic management and energy production; currently much less attention is being paid to the use of AI in urban planning and associated decision-making activities, including scenario planning and generative designs.

Next, AI is expected to play an important role in future development activities as well as in the planning and management of cities for

sustainability, resilience, and equity in both the short and long terms. Planners must be prepared for the changes this will bring to how the cities of the future are planned, designed, and managed (Sanchez, 2023). Nonetheless, for planners to be ready for the AI revolution, the following challenges should be overcome: (a) Fear and uncertainty; (b) The need for new skills; (c) Changing data needs and considerations; (d) Unclear goals; (e) Incorporating transparency and explainability; (f) Encountering bias; (g) Addressing ethical issues that may arise with new methods and data (Sanchez, 2023).

In that perspective, mapping out the current understanding and practice in algorithmic urban planning to achieve smart and sustainable development is critical. This paper attempts to bridge this gap. Below, Fig. 6 illustrates the existing knowledge and practice landscape of algorithmic urban planning to achieve smart and sustainable development. The sizes of the SDG boxes represent the popularity and coverage they have achieved in our literature analysis, as shown in Fig. 5. Two SDGs (SDG5: Gender Equality and SDG 13: Climate Action) unfortunately were not covered in the reviewed 91 articles, which should not be taken as an indication of unimportance. Instead, these two SDGs are of utmost importance in achieving the smart and sustainable development of cities, given that they represent the inclusion and grassroots and government action—that are the core foundations of change for good (Yigitcanlar et al., 2019b).

While considering these insights, the following study limitations should be noted: (a) The selection of the search keywords may have led to the omission of some of the literature—possibly due to concentration on Scopus and WoS databases and unconscious selection bias; (b) The review has not included grey literature, where the most recent technology developments and industry practices are reported; (c) Urban planning is a vast domain, hence, the study might have not been able to cover all AI utilisation or adoption areas in the field; (d) Unintentional bias in analysing the literature and interpreting the study results may have led to the omission of the impact of the reported findings; (e) The review has been undertaken manually—as opposed to using dedicated scientometric or bibliometric software or data visualisation software—which might result in some human error; (f) The study has not focused on generating an understanding of the research ecosystem—e.g., most active regions, institutions, and researchers/authors in the field, and citation, co-authorship and collaboration trends, and so on; (g) Insights offered in this paper are driven or generalised from the reviewed

Table A1

List of reviewed publications and review summaries.

Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Jiang et al. (2022)	2022	A survey on deep learning-based change detection from high-resolution remote sensing images	Remote Sensing	To provide a review of deep-learning change detection algorithms using HR remote sensing images in the detection of more delicate changes.	Discusses the various deep learning structures and the challenges in change detection.	Machine Learning, Deep Learning, Neural Networks	Contribute to the research and applicability of deep learning in remote sensing technology.	Urban data analytics and planning decision support	n/a
Lei et al. (2022)	2022	SNLRUX++ for building extraction from high-resolution remote sensing images	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	To develop a new deep learning network for building extraction.	Explores urban planners' use of building extraction to analysis of demographic and urban characteristics.	Machine Learning, Deep Learning	Improves the prediction performance of high-resolution and high-semantic feature maps with more stable and accelerated network convergences.	Urban data analytics and planning decision support	17
Li et al. (2022)	2022	POI detection of high-rise buildings using remote sensing images: a semantic segmentation method based on multitasking attention Res-U-Net	IEEE Transactions on Geoscience and Remote Sensing	To propose a new semantic segmentation model using deep learning for building extraction, focusing on improving the extraction of the boundaries of building roofs and building shapes.	Contributes to the development of deep learning utilisation for urban and regional planning processes.	Machine Learning, Deep Learning	Found that the proposed model demonstrated promising results however requires a large quantity of manually labelled data and further research is needed.	Urban data analytics and planning decision support	9, 11, 17
Lyu et al. (2023)	2022	IF-City: intelligible fair city planning to measure, explain and mitigate inequality	IEEE Transactions on Visualization and Computer Graphics	To propose an AI-enabled interactive visual tool to assist urban planners in achieving equal access to amenities that can benefit different types of groups.	Examines the opportunities of utilising AI for assessing fairness in the urban environment.	Machine Learning	Demonstrated and evaluated the usage and capabilities of the proposed method for collaborative fair urban design involving AI and human planning.	Urban data analytics and planning decision support	1, 10
Wang and Biljecki (2022)	2022	Unsupervised machine learning in urban studies: a systematic review of applications	Cities	To review the applications of unsupervised machine learning in urban studies.	Describes how unsupervised learning such as deep learning is applied and researched in urbanisation and regional studies, built environment, urban sustainability, and urban dynamics.	Machine Learning, Deep Learning	Uncovered potential research opportunities in unsupervised machine learning within urban studies.	Urban data analytics and planning decision support	n/a
Ye et al. (2022)	2022	MasterplanGAN: facilitating the smart rendering of urban master plans via generative adversarial networks	Environment and Planning B:	To reduce the time to complete master planning drawings and renderings.	Identifies an AI system that produces master plan renderings automatically.	Machine Learning, Generative adversarial networks, neural networks	Found the system could be useful across number of design and planning disciplines with further development.	Urban data analytics and planning decision support	17
Yu et al. (2022)	2022	A combined convolutional neural network for urban land-use classification with GIS data	Remote Sensing	To propose a deep learning model for complex and diverse urban land-use classification.	Investigates how AI can improve urban land use classification.	Machine Learning, Deep Learning	Found the proposed model outperformed other models, illustrating its effectiveness and feasibility in land-use classification.	Urban data analytics and planning decision support	11, 17
Yuan et al. (2022)	2022	Fine-grained classification of urban functional zones and landscape pattern analysis using	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	To propose a deep learning-based approach for fine-grained urban functional zones	Describes deep learning approaches capability in classifying multispectral and hyperspectral data.	Machine Learning, Deep Learning	Found that the deep learning-based classification algorithm performs better than traditional supervised	Urban data analytics and planning decision support	11, 17

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Table A1 (continued)

Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Calixto et al. (2021)	2021	hyperspectral satellite imagery: a case study of Wuhan A layered approach for the data-driven design of smart cities	Association for Computer-Aided Architectural Design Research in Asia	mapping, enabling better landscape pattern analysis. To evaluate how the design of AI can be improved to assist in planning smart cities from the bottom-up.	Examines how AI can be a tool to support in the design and planning of a smart city.	Machine Learning	methods, as well as retain as much information as possible. Found that AI needs to improve their comprehensiveness to allow for wider implementation across disciplines.	Urban data analytics and planning decision support	11, 17
Chaturvedi and de Vries (2021)	2021	Machine learning algorithms for urban land use planning: a review	Urban Science	To review which AI techniques are suitable for land use and spatial analyse.	Identifies planning problems, datasets, and suitable AI techniques.	Machine Learning	Noted various AI applications and the potential for integrating systems together to improve outcomes.	Urban data analytics and planning decision support	11
Khediri et al. (2021)	2021	improving intelligent decision making in urban planning: using machine learning algorithms	land	to assess the opportunities of ai to use big data to design and plan cities.	identifies a range of ai-based tools that support planning processes to address urban problems.	multiple ai	provide a broad overview of how big data is being utilised as a part of urban planning practices.	urban data analytics and planning decision support	11, 17
Gray and Kovacova (2021)	2021	Internet of things sensors and digital urban governance in data-driven smart sustainable cities	geopolitics, history, and international relations	to identify the opportunities, risks, and priorities of urban technologies, including machine learning-based analytics and smart software systems, in smart cities.	explores the opportunities of smart cities integrating sustainable urban technologies.	machine learning	noted the integration of sustainable urban technologies, particularly iot, is beneficial to the sustainable urban governance networks.	urban data analytics and planning decision support	9,11, 17
Jha et al. (2021)	2021	A review of AI for urban planning: towards building sustainable smart cities	International Journal of Business Analytics	To develop AI that can assist in resolving challenging urban problems.	Reviews where AI is lacking and proposes a set of AI that can support, decision making that is informed by the physical and social aspects of the city.	Machine Learning, Naïve Bayes Classifier	Found that a range of technologies provided suitable outcomes, however, greater integration between the systems is needed to improve efficiency.	Urban data analytics and planning decision support	17
Kamrowska-Zaluska (2021)	2021	Impact of AI-based tools and urban big data analytics on the design and planning of cities	Information	To develop a land-cover semantic segmentation model using a hybrid of deep learning techniques.	Proposes a hybrid network, utilising two deep learning models, for land cover semantic segmentation using high-spatial resolution satellite images.	Machine Learning, Deep Learning, Convolutional Neural Networks	Provides further understanding of efficient utilisation of deep learning techniques to provide accurate segmentation maps compared to other methods.	Urban data analytics and planning decision support	9, 11, 17
Podrasa et al. (2021)	2021	Machine learning for land use scenarios and urban design	ISPRS International Journal of Geo-information	To propose a city-scale approach to façade colour measurement using AI methods.	Provides insight to the opportunities of AI for urban colour identification and urban renewal information.	Machine Learning, Deep Learning	Found that the approach has satisfied accuracy for building façade segmentation, colour deviation and overall accuracy for building functional classification compared to other methods.	Urban data analytics and planning decision support	n/a
Wan and Shi (2021)	2021	Research on urban renewal public space design based on convolutional neural network model	Security and Communication Networks	Explores the feasibility in machine learning, deep learning, and other AI-enabled image processing for urban design.	Describes the use of AI in urban design.	Machine Learning, Deep Learning	Found than the AI-enabled methods are not accurate enough due to limited computer hardware and algorithm.	Urban data analytics and planning decision support	11, 17
Wang and Lee (2021)	2021	Regional population forecast and analysis based on machine learning strategy	Remote Sensing	To assess AI capabilities in semantic segmentation of light detection and ranging point clouds.	Provides insight on deep learning approaches for segmentation tasks.	Machine Learning, Deep Learning	Explored the potential of deep learning-based approaches on point clouds for urban scenarios, demonstrating the promising future of AI in	Urban data analytics and planning decision support	9, 11, 17

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Table A1 (continued)

Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Zhang et al. (2021)	2021	Development of a city-scale approach for façade colour measurement with building functional classification using deep learning and street view images	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	To propose AI-enabled models in capturing and aggregating urban multi-scale contextual information on urban building.	Describes a new type of convolutional neural networks model that can produce high-precision building segmentation from high resolution sensing images and preserve detailed spatial information of small and complex building images.	Machine Learning, Convolutional Neural Networks, Deep Learning	providing more accurate and efficient results. Addressed the challenging task of providing automatic building extraction from high-resolution remote sensing imagery with the use of a new convolutional neural network segmentation model, which can greatly benefit urban planning, navigation, and disaster management.	Urban data analytics and planning decision support	11, 17
Zou et al. (2021)	2021	Towards urban scene semantic segmentation with deep learning from lidar point clouds: a case study in Baden-Württemberg, Germany	Heliyon	To enhance the temporal and spatial modelling by training AI-enabled models in predicting land-use changes.	Integrates the use of artificial neural network into cellular automata Markov chain to ensure higher accurate estimates of land-use changes.	Machine Learning, Artificial Neural Network	Contributed to the improvement in AI-enabled model predictions, assisting in the preservation of ecosystems and sustainable development of urban areas.	Urban data analytics and planning decision support	11, 15, 17
Bazan-Krzywoszariska et al. (2020)	2020	City as a system supported by artificial intelligence	Urban and Regional Planning	To utilise AI to assist in effective urban management.	Demonstrates how AI and data can be used in planning decision-making.	Deep Learning	Found that increased Interdisciplinary collaboration and sharing of data can assist in urban planning practice.	Urban data analytics and planning decision support	11, 16
Cugurullo (2020)	2020	Urban artificial intelligence: from automation to autonomy in the smart city	Frontiers in Sustainable Cities	To investigate how AI is shaping autonomous cities.	Identifies a range of AI practices used in urban planning in smart cities.	Multiple AI	Defined autonomous cities and the evolution AI will have in these developing cities.	Urban data analytics and planning decision support	7, 11
Engin et al. (2020)	2020	Data-driven urban management: mapping the landscape	Journal of Urban Management	To review how AI is being utilised in urban management and planning practices.	Reviews real-time and evidence-based analyse to complex urban problems.	Machine Learning	Noted that further investigation is needed to consider the challenges and ethical implications of AI based urban management.	Urban data analytics and planning decision support	n/a
Jiang (2020)	2020	Urban planning reform trend based on artificial intelligence	Journal of Physics	To review how AI is supporting urban planning reform in China.	Examines a range of technologies that will support urban planning practices into the future.	Multiple AI	Noted that AI will continue to impact urban planning as more big data is accessed and utilised in practice.	Urban data analytics and planning decision support	11
Karvonen et al. (2020)	2020	Urban planning and the smart city: projects, practices, and politics	Urban Planning	To review how urban planners are planning smart cities.	Identifies smart urbanisation practices in smart cities.	Machine Learning	Found that urban planners have an opportunity to direct technological innovation in relation to urban governance of smart cities.	Urban data analytics and planning decision support	9, 11, 16
Meeran and Conrad Joyce (2020)	2020	Machine learning for comparative urban planning at scale: an aviation case study	Remote Sensing of Environment	To propose an AI-enabled model in automated land use mapping prediction.	Proposes a deep learning-based approach to automate land use mapping to minimise time and labour.	Machine Learning, Deep Learning, Convolutional Neural Networks	Proposed multimodal model performed more accurately than other models by a large margin, demonstrating AI's capabilities and opportunities in urban planning.	Urban data analytics and planning decision support	17
Schmidt and Kada (2020)	2020	Object detection of aerial image using masque-region convolutional neural network (masque R-CNN)	IEEE Access	To propose a deep learning method to assess the quality of data in OpenStreetMap.	Describes the assessment capabilities of OpenStreetMap through AI-enabled methods.	Machine Learning, Deep Learning	Found that the deep learning method assesses OpenStreetMap accurately and effectively and provides insight for urban planning opportunities where it lacks the data.	Urban data analytics and planning decision support	17

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Table A1 (continued)

Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Nice et al. (2020)	2020	The “Paris-end” of town? Deriving urban typologies using three imagery types	Urban Science	To propose a deep learning neural network method to bridge the gap of efficiently rationalising the different level features in building extraction.	Improves current deep learning methods in building extraction with a proposed deep learning method.	Machine Learning, Deep Learning	Found that the proposed deep learning method performed better in terms of training and response time and quality value compared to other deep learning methods.	Urban data analytics and planning decision support	17
Qian et al. (2020)	2020	Coupling cellular automata with area partitioning and spatiotemporal convolution for dynamic land use change simulation	Environment and Planning B	To demonstrate how AI can be used to predict building configurations.	Identifies how AI can support early stages of design with potential solutions.	Machine Learning, Generative Adversarial Network	Found the accuracy of generative adversarial network will further support urban planning solutions.	Urban data analytics and planning decision support	11
Ullah et al. (2020)	2020	Applications of artificial intelligence and machine learning in smart cities	Computer Communications	To review how AI has been used in smart cities over time.	Identifies how types of AI have addressed many urban planning problems.	Machine Learning & Deep Reinforcement Learning	Found that with further technological advancements the use of big data will have greater applications to support smart cities.	Urban data analytics and planning decision support	7, 11, 15
Yao et al. (2020)	2020	Delineating mixed urban “jobs-housing” patterns at a fine scale by using high spatial resolution remote-sensing imagery	Complexity	To propose a deep learning model to determine the spatial distribution pattern of jobs and housing.	Provides insights into the use of AI in spatial analysis.	Machine & Deep Learning,	Found that the method was able to understand complex urban and spatial structures.	Urban data analytics and planning decision support	8, 17
Milton and Roumpani (2019)	2019	Accelerating urban modelling algorithms with artificial intelligence	International Conference on Inventive Computation Technologies	To review which AI is being used in developing smart cities.	Identifies the use of AI to support traffic system management, crime detection, air pollution, energy management and water leakage detection as part of smart city planning and management.	Multiple AI	Noted a range of AI that have been used across smart cities domains.	Urban data analytics and planning decision support	11
Quan et al. (2019)	2019	Artificial intelligence-aided design: smart design for sustainable city development	Environment and Planning B	To demonstrate how smart design framework can be used to design sustainable urban development.	Demonstrates how the integration of AI can assist in human decision making that is not possible with knowledge-based AI.	Machine Learning, Genetic Algorithm	Noted better urban design solutions by using AI as a supporting aid to the design process.	Urban data analytics and planning decision support	17
Yao et al. (2019)	2019	A human-machine adversarial scoring framework for urban perception assessment using street-view images	International Journal of Geographical Information Science	To propose an AI-enabled urban perception assessment model.	Develops a deep learning, street view imagery and iterative feedback framework that efficiently and cost-effectively assess urban perceptions.	Machine Learning, Deep Learning	Explored the potential of AI, and although the proposed method is found to be feasible, efficient, and highly accurate, many limitations found need to be further researched to ensure reliability and accuracy.	Urban data analytics and planning decision support	11, 17
Ameer and Shah (2018)	2018	Exploiting big data analytics for smart urban planning	IEEE Conference on Vehicular Technology	To manage and analyse pollution in smart cities using IoT sensors data.	Identifies the potential for AI to produce real-time processing with reduced errors.	IoT, Machine Learning, Neural Network	Found that machine learning can assign the relevant air quality index classification by unsupervised learning.	Urban data analytics and planning decision support	13
Yang et al. (2018)	2018	Building extraction in very high-resolution imagery by dense-attention networks	Remote Sensing	To develop an object detection method of aerial image by using region convolutional neural network.	Explores machine learning-based artificial neural networks for machine object detection.	Machine Learning, Deep Learning, Neural Network	Found that the proposed method provides significant accuracy. This was benefitted by the increased image training and epoch time.	Urban data analytics and planning decision support	17

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Table A1 (continued)

Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Zhang et al. (2018)	2018	Measuring human perceptions of a large-scale urban region using machine learning	Landscape and Urban Planning	To propose a deep learning-based approach in predicting human perception of street view images.	Describes how deep learning approaches can measure perceptions of a place in large urban scales.	Machine Learning, Deep Learning	Found that the proposed model can assist in predicting, analysing, and determining perceptions of places.	Urban data analytics and planning decision support	11, 17
Ferreira et al. (2015)	2015	Urbane: a 3D framework to support data driven decision making in urban development	IEEE Conference on Visual Analytics Science and Technology	To propose a framework that analyses the social impact of a development during the design and decision-making process.	Identifies the social impacts development will have on urban areas.	Machine Learning	Revealed that the framework could be applied to other cities with the assistance of readily available big data.	Urban data analytics and planning decision support	16
Jain (2011)	2011	A review study on urban planning & artificial intelligence	International Journal of Soft Computing and Engineering	To review how AI has been used in urban land dynamics.	Identifies how AI is being used in urban planning practices in smart cities.	Machine Learning, Expert systems, decision support systems & integrated systems	Noted that the different AI techniques had varying results and efficiencies.	Urban data analytics and planning decision support	11
Koehler et al. (2009)	2009	Computer-based methods for a socially sustainable urban and regional planning	International Conference on Computational Science and Its Applications	To develop a model that provides sustainable planning strategies that respond to social issues within cities.	Examines AI to analyse spatial structures, residential segregation and interactions between the built environment and socio-spatial stakeholders.	Embodied, Agent based modelling	Found that a range of AI applications can provide insight into the social sustainability of a city.	Urban data analytics and planning decision support	11
Turkienicz et al. (2008)	2008	Turkienicz, B., Gonçalves, B. B., & Grazziotin, P. (2008). CityZoom: a visualization tool for the assessment of planning regulations. International Journal of Architectural Computing, 6(1), 79-95.	International Conference on Asian Language Processing	To develop an AI-enabled query engine to facilitate urban planning process.	Demonstrates the architecture, construction, and opportunities of an AI-enabled query engine, opening future promises to which planners can capitalise the technology.	Machine Learning, Deep Learning, Convolutional Neural Networks	Explored the capabilities of AI in assisting urban planning processes to sustainable growth, such as informed decisions from large quantities of data.	Urban data analytics and planning decision support	11, 17
Witlox (2005)	2005	Expert systems in land-use planning: an overview	Expert Systems with Applications	To review expert systems in urban planning practices.	Identifies which types of AI have been used in urban planning practices.	Knowledge Base, Expert systems, decision support systems & integrated systems	Noted improvements to the identified AI, however, since publication large number of these limitations have been addressed by advancements in technology.	Urban data analytics and planning decision support	11
Balling et al. (1999)	1999	Multiobjective urban planning using genetic algorithm	Transportation Research Procedia	To use AI to understand current transportation trends and improve the network	Explores different AI applications efficiency in analysing complex transportation networks.	Machine Learning, Genetic Algorithm & Artificial Immune System	Found that both systems provided good outcomes, however, a combined system would allow for both systems' benefits to be recognised.	Urban data analytics and planning decision support	9, 11, 17
Feng and Xu (1999)	1999	Hybrid artificial intelligence approach to urban planning	Expert Systems with Applications	For AI to suggest alternative developments based on real time data.	Identifies how AI can be used when trying to solve complex urban planning problems of smart cities.	Knowledge Base, Fuzzy Logic & Neural Networks	Noted that integrating the three technologies resulted in solving complex problems.	Urban data analytics and planning decision support	11, 17
Polydorides and Petropoulos (1989)	1989	An expert system for the evaluation of urban plans	Ekistics	To demonstrate how AI can evaluate a master plan based on consistency, efficiency, and feasibility of the plan.	Identifies the practicability of a master plan before it is implemented to support sustainable development.	Knowledge Base, Expert System	Noted that the AI is being more broadly tested in a current context and further evidence will be forthcoming.	Urban data analytics and planning decision support	11, 17
Tanic (1986)	1986	Urban planning and artificial intelligence: the URBYS system	Computers, Environment and Urban Systems	To propose an AI system that will support urban planning knowledge-	Explores how AI can be used in planning practice.	Knowledge Base, Expert System	Presented an early form of knowledge-based AI.	Urban data analytics and planning decision support	11, 17

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Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Fang et al. (2022)	2022	Incorporating planning intelligence into deep learning: a planning support tool for street network design	Journal of Urban Technology	based decision-making processes. To propose the use of deep neural networks and planning guidance to automate a context-aware, learning-based, and user-guided street-network generator.	Develops an AI-enabled tool that provides more realistic predictions of street configurations.	Machine Learning, Conventional Neural Network, Deep Learning	Discussed the opportunities in the systematic and intuitive integration of combining deep learning algorithms and subjective planning knowledge.	Urban and infrastructure management	11, 17
Javed et al. (2022)	2022	Future smart cities: requirements, emerging technologies, applications, challenges, and future aspects	Cities	To identify the latest technological advancements of AI for future smart city application frameworks.	Discusses how the future technologies for smart cities are going to revolutionise the urban environment, and the requirements needed in the application and implementation of strategies.	Machine Learning, Deep Learning, Neural Networks	Described the requirements, strategies, and challenges for the implementation in future smart city technologies.	Urban and infrastructure management	17
Lee et al. (2022)	2022	A machine learning and computer vision study of the environmental characteristics of streetscapes that affect pedestrian satisfaction	Sustainability	To understand the urban design of pedestrian-friendly cities with the AI analyses of the visual streetscape and inclusion of urban theory.	Identified pedestrian satisfaction with machine learning techniques, particularly the physical and visual characteristics of the urban street landscapes.	Machine Learning, Deep Learning, SHAP	Suggested a methodology using computer vision techniques, such as machine learning, to identify pedestrian satisfaction and what the urban planning of streets should consider.	Urban and infrastructure management	11
Yerram et al. (2022)	2022	Extraction and calculation of roadway area from satellite images using improved deep learning model and post-processing	Journal of Imaging	To propose a method deep learning method to calculate the area of roads covered in satellite images.	Gives insight into the efficiency of AI-enabled models compared to traditional methods.	Machine Learning, Deep Learning	Found that the model improves existing models in extracting and calculating roadway areas from satellite images.	Urban and infrastructure management	9, 11, 17
Anthony Jnr (2021)	2021	A case-based reasoning recommender system for sustainable smart city development	AI & Society	To achieve a sustainable society with stakeholders strategically deciding smart city initiatives with the support of a recommender system that promotes smart city planning.	Identifies the potential for urban planners/decision-makers of the adoption in supported AI-integrated best practice recommendation and retention of smart city initiatives. Providing insight on alternative strategies to future urban issues and better understanding the dimensions of a smart city.	Knowledge-Based, Case-Based Reasoning	Advocated that in mitigating present challenges of urbanisation and improving smart city's healthcare, transportation, education, energy sectors, AI-supported systems are applicable and should be adopted.	Urban and infrastructure management	1, 2, 3, 4, 6, 7, 11, 15, 16
Azad and Wang (2021)	2021	Land use change ontology and traffic prediction through recurrent neural networks: a case study in Calgary, Canada	ISPRS International Journal of Geo-information	To use distinct expressions of how land use changes relate to the integration of temporal land use information, utilising deep neural network to predict traffic.	Utilises deep learning methods and effective data mining computing to predict traffic flow and land use change impacts.	Machine Learning, Deep Learning	Contributed to AI's potential in urban planning, specifically land use transportation planning, by demonstrating that the deep learning approach predicts more accurately and better than other existing models.	Urban and infrastructure management	11, 17
Ibrahim et al. (2021)	2021	URBAN-i: from urban scenes to mapping slums, transport modes, and	Environment and Planning B	To introduce AI-enabled frameworks in	Develops a framework that utilises a convolutional neural network, resulting in	Machine Learning, Deep Learning,	Provide urban planners a better understanding of urban structures including the	Urban and infrastructure management	1, 9, 11, 17

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Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
		pedestrians in cities using deep learning and computer vision		advancing urban modelling.	a reliable a reliable framework.	Convolutional Neural Networks	pedestrian, transport modes, and settlement conditions, categorising them as either planned or unplanned settlements.		
Ito et al. (2020)	2020	A method for estimating the number of households in a region from the number of buildings estimated by deep learning with the adjustment of its number using ancillary datasets: case study in Djakarta	The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	To investigate transport, AI and the smart city and their effect on urban areas.	Identifies smart vehicles and the interaction with AI, IoT and Industry 4.0 as part of a smart city.	Machine Learning, Deep Learning	Found AI has a transformative ability but needs to operate within a responsible, user-centred, and sustainable framework.	Urban and infrastructure management	9, 11
Law et al. (2020)	2020	Street-frontage-net: urban image classification using deep convolutional neural networks	International Journal of Geographical Information Science	Develop further past experiments of a convolutional neural network that evaluates street frontage quality.	Proposes a new and improved convolutional neural network model in successfully evaluating street frontage as either being active or blank.	Machine Learning, Deep Learning, Convolutional Neural Networks	Contributes to more efficient and alternative methods using deep learning methods in geographic information and urban design.	Urban and infrastructure management	11, 17
Ljubenkov et al. (2020)	2020	Optimizing bike sharing system flows using graph mining, convolutional and recurrent neural networks	Science of the Total Environment	To propose an AI-enabled land use change model for decision support and urban planning.	Compares and tests the proposed method traditional methods and demonstrates the improved approach.	Machine Learning, Deep Learning, Convolutional Neural Networks	Found that the model achieved good performance however due to identified limitations, the proposed model is not recommended for the projection of longer periods of time.	Urban and infrastructure management	17
Nikitas et al. (2020)	2020	Artificial intelligence, transport, and the smart city: definitions and dimensions of a new mobility era	Journal of Sensors	To propose a classification approach to an existing deep learning model for detailed urban mapping.	Demonstrates the improved deep learning classification approach to other AI-enabled models, such as SVM and conventional neural networks, by producing unvaried mapping results and preservation of details.	Machine Learning, Deep Learning	Demonstrates the increasing opportunities of AI by demonstrating a new classification model against old AI-enabled models.	Urban and infrastructure management	n/a
Anastasiou et al. (2019)	2019	ADMSv2: a modern architecture for transportation data management and analysis	International Journal of Architectural Computing	To develop software that combines multiple software applications and further integration to use AI to extend functionality.	Explores how CityZoom effectively visualises urban areas as part of the planning process.	Probabilistic Methods, Decision support system	Noted that further development could include greater AI functionality to become an autonomous system.	Urban and infrastructure management	11
Aqib et al. (2019)	2019	Rapid transit systems: smarter urban planning using big data, in-memory computing, deep learning, and GPUs	Sustainability	To optimise the spatiotemporal planning of urban transportation networks, specifically, train-based rapid transit systems.	Identifies the challenges of holistically analysing and predicting urban metro systems with a computing platform.	Machine Learning, Deep Learning, GIS, Remote sensing, Big Data, Neural Networks	Contributed to the novel deep learning models, algorithms, application, analysis methods, and software tools in the analysis of metro systems.	Urban and infrastructure management	9, 11
Gora (2019)	2019	Designing urban areas using traffic simulations, artificial intelligence and acquiring feedback from stakeholders	Journal of Urban Planning and Development	Use of algorithms to map and assess land use plans.	Examines how land use maps can be assessed against a range of objectives to assist planners in decision-making.	Machine Learning, Genetic Algorithm	Noted the plans still require decision theory when choosing a plan.	Urban and infrastructure management	11, 17

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Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Xie et al. (2019)	2019	OpenStreetMap data quality assessment via deep learning and remote sensing imagery	IEEE European Technology and Engineering Management Summit	To identify and predict dynamic patterns of bikes using neural networks.	Utilises both convolutional and artificial recurrent neural network to find and predict bike flows.	Machine Learning, Deep Learning, Convolutional and Artificial Recurrent Neural Network	Findings benefit urban planners and bike-sharing companies by optimising the manual transportation of bikes by saving time and cost with AI-enabled analysing systems.	Urban and infrastructure management	3
Boulange et al. (2018)	2018	Improving planning analysis and decision making: the development and application of a walkability planning support system	Journal of Transport Geography	To develop, apply, and trial a functional and practical walkability planning support system with local spatial planners.	Examines how AI can be used to support the planning process.	Machine Learning, Walkability PSS	Indicated that the AI could be extended to health and environmental issues to support real time decision making.	Urban and infrastructure management	3, 11
Kouziokas (2017)	2017	The application of artificial intelligence in public administration for forecasting high crime risk transportation areas in urban environment	Conference on Sustainable Urban Mobility	To use AI to identify crime risks in the transportation network.	Identifies potential crime risks allowing for greater transportation management policies to be introduced and build safe communities.	Machine Learning, Neural Networks	Indicated the model provided high prediction accuracy that could be used to develop a safe transportation network.	Urban and infrastructure management	11
Shin et al. (2017)	2017	Towards a deep learning powered query engine for urban planning	Transportation Research Procedia	To propose AI that will support traffic management and associated land use implications.	Investigates a Traffic Simulation Framework to support traffic management and its impact on the associated land use.	Machine Learning, Neural Networks	Noted that further testing is required but has potential for greater efficiency for planners.	Urban and infrastructure management	9, 11
Kröl (2016)	2016	The application of the artificial intelligence methods for planning of the development of the transportation network	International Conference on Geographical Information Systems Theory, Applications and Management	To develop an urban modelling and visualisation tool to reflect real time planning interventions.	Identifies AI modelling that can provide planners different scenarios when developing new city interventions.	Machine Learning, Deep Learning	Found the AI could be applicable to other planning practices including zoning and trip calculations.	Urban and infrastructure management	11, 17
Conley et al. (2022)	2022	Using a deep learning model to quantify trash accumulation for cleaner urban stormwater	Computers, Environment and Urban Systems	To use vehicle mounted cameras and deep convolutional neural networks to monitor, prioritise, and measure trash inputs to local waterways and the ocean, in the effectiveness of its reduction.	Generates insight on the opportunities of deep learning trash detection models to efficiently monitor trash that goes in waterways and the ocean.	Machine Learning, Deep Learning, Convolutional Neural Networks	Improves the narrative in deep learning-based monitoring approaches by revealing that the approach provides greater data collection, understanding of urban trash sources, and stormwater regulatory requirements compared to visual assessments.	Urban environmental and disaster management	3, 6, 11, 14, 17
Gupta et al. (2022)	2022	A deep learning approach based hardware solution to categorise garbage in environment	Complex & Intelligent Systems	To propose a deep learning-based hardware solution for quicker and efficient garbage classification.	Utilises image classification through different convolutional neural network systems in segregating garbage between biodegradable and non-biodegradable objects at a base level.	Machine Learning, Convoluting Neural Networks	Contributed to the problem solving in urban issues, such as garbage detection in unhealthy environments.	Urban environmental and disaster management	3, 6, 11, 12, 17
Abid et al. (2021)	2021	Toward an integrated disaster management approach: how artificial intelligence can boost disaster management	Sustainability	To understand how AI is used as part of the disaster management process of mitigation, preparedness, response, and recovery.	Explores how AI is used to manage and respond to disasters that affect urban areas.	Machine Learning, Deep Learning, GIS, Remote sensing	Found that AI has great potential to respond to disasters, however, effectiveness is based on data management and team success.	Urban environmental and disaster management	11

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Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Demmler et al. (2021)	2021	A novel approach of creating sustainable urban planning solutions that optimise the local air quality and environmental equity in Helsinki, Finland: the CouSCOUS study protocol	PLOS One	To utilise AI to provide urban planning solutions that addresses urban air pollution issues.	Discusses the use of AI for air pollution optimisation.	Machine Learning, Deep Learning, Neural Networks	Provided an insight for policy makers and developers in opportunities of effectively analysing the dynamics of population characteristics and urban disparities to minimise air pollutants, accessibility, transportation, and environmental impacts, resulting into better city planning models.	Urban environmental and disaster management	3, 11, 13, 15
Khan et al. (2021)	2021	Deep hybrid network for land cover semantic segmentation in high-spatial resolution satellite images	Journal of King Saud University Computer and Information Sciences	To explore the application of machine learning in mitigating challenges of modern urban planning.	Identifies the challenges, opportunities, and future research directions of machine learning methods for intelligence urban planning applications.	Machine Learning, Deep Learning, Neural Networks	Found several areas in machine learning models can be applied in urban planning, including but not limited to, the prediction of urban sustainability issues, the smart, digital and connect creation of cities, the development of sustainable urban forms, and the use of urban space.	Urban environmental and disaster management	11, 17
Milojevic-Dupont and Creutzig (2021)	2021	Machine learning for geographically differentiated climate change mitigation in urban areas	Sustainable Cities and Society	To use an AI framework that provides policy solutions to urban areas, streets, buildings, and household contexts.	Identifies AI that can inform the improvement of urban infrastructure.	Machine Learning, Remote Sensing	Low-carbon urban infrastructure would greatly benefit cities; however, the use of AI and well-designed policy is needed to resolve this issue.	Urban environmental and disaster management	9, 11, 15
Mulligan (2021)	2021	Computationally networked urbanism and advanced sustainability analytics in internet of things-enabled smart city governance	Entropy	To propose a machine learning based method to analyse and forecast population growth.	Describes the use of machine learning to close any gaps including bias.	Machine Learning, Deep Learning	Found that the approach objectively observes features of importance in present and future regional growth and provides an objective reference for urban and regional planning.	Urban environmental and disaster management	11, 17
Pham et al. (2021)	2021	Flood risk assessment using hybrid artificial intelligence models integrated with multi-criteria decision analysis in Quang Nam Province, Vietnam	Journal of Hydrology	To develop a flood risk assessment map using Multi Criteria Decision Analysis method, with integration of AI-enabled models.	Explores the AI or Machine Learning method integration with MCDA to minimise human bias, estimating the relevant criteria in the decision-making processes for flood risk assessment and frameworks.	Machine Learning, Deep Learning, Neural Network	Found that the approach is suitable and reliable in flood risk mapping as it reduces time series meteorological, and streamflow data. However, this approach cannot analyse frequencies of flooding in the mapping and was only tested in one location.	Urban environmental and disaster management	11, 15, 17
Ye et al. (2021)	2021	Towards an AI-driven framework for multi-scale urban flood resilience planning and design	Computational Urban Science	To demonstrate how AI can facilitate flood resistance when planning and designing in coastal areas.	Identifies a framework that bridges the gap between the planning and design disciplines when developing new coastal urban areas.	Machine Learning, Convolutional Neural Networks	Created a query tool that could be useful for multiple disciplines in the creation of resilient cities.	Urban environmental and disaster management	11, 15, 17
Bienvenido-Huertas et al. (2020)	2020	Comparison of artificial intelligence algorithms to estimate sustainability indicators	Sustainable Cities and Society	To monitor sustainability indicators of a region so that policies can be	Explores how public bodies can manage environmental and sociocultural issues	Machine Learning, Regression algorithms, multiple linear regressions,	Suggested a methodology using MSP and multilayer perceptions provided the best indication of sustainability.	Urban environmental and disaster management	11, 16, 17

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Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Nosratabadi et al. (2020)	2020	State of the art survey of deep learning and machine learning models for smart cities and urban sustainability	International Conference on Global Research and Education	established to advance sustainable development. To investigate the different types of machine and deep learning used in current urban planning practices in smart cities.	pertaining to sustainability through the assistance of AI. Identifies the most used AI applications in smart cities.	multilayer perceptron Machine & Deep Learning, Artificial neural networks, support vector machines, Ensembles, Bayesians, hybrids, and neuro-fuzzy, deep learning	Noted that the energy sector used AI the most often and AI of varying applications have been used across a range of domains of a smart city.	Urban environmental and disaster management	7, 11
Mrówczyńska et al. (2019)	2019	The use of artificial intelligence as a tool supporting sustainable development local policy	Sustainability	To use AI to track noise pollution and apply it to local planning policies	Identifies noise pollution by using AI to plan for a sustainable urban city	Machine Learning, Support Vector Machines	Found numerous planning conventions that could be implemented in cities to reduce noise pollution by using AI	Urban environmental and disaster management	11
Timilsina et al. (2019)	2019	Mapping urban trees within cadastral parcels using an object-based convolutional neural network	ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences	To review remote sensing AI's effectiveness of urban tree management.	Identifies how AI technology can be used to assist in urban management to support sustainability of cities.	Machine Learning, Convolutional Neural Networks	Found that a combination of CNN and OBIA methods provided more accurate outcomes.	Urban environmental and disaster management	11
Miao et al. (2017)	2017	City afforestation: abstracting the urban geometries into tree structures for urban fabric optimization	SIGSPATIAL International Conference on Advances in Geographic Information Systems	To evaluate the effectiveness of an AI based transportation management system.	Identifies how AI can help improve traffic forecasting and bus arrival time estimation through real-time and historical data.	Machine Learning, Deep Learning	Found that this AI could be transferrable to the management of air quality and weather.	Urban environmental and disaster management	3, 9, 11, 13
He and Zheng (2021)	2021	Prediction of crime rate in urban neighborhoods based on machine learning	Engineering Applications of Artificial Intelligence	To use AI to identified crime hotspots in cities.	Identifies areas of concern and introduces measure for the prevention of crime in urban areas.	Machine Learning, Generative Adversarial Network	Noted that the information identified could be used in developing strategies to support master planning interventions.	Urban monitoring and development control	11
Koumetio Tekouabou et al. (2021)	2021	Reviewing the application of machine learning methods to model urban form indicators in planning decision support systems: potential, issues and challenges	Technology Forecasting and Social Change	To build a healthy and effective regional economy with green, healthy, and sustainable urban development.	Proposes a deep learning and neural network algorithm to analyse urban sprawl levels.	Machine Learning, Deep Learning, Neural Networks	Proposed model efficiently analyses the urban sprawl environment, contributing significant value to urban and regional value, specifically, in urban sprawl analysis systems.	Urban monitoring and development control	11, 15
Lan et al. (2021)	2021	Constructing urban sprawl measurement system of the Yangtze River economic belt zone for healthier lives and social changes in sustainable cities	Geopolitics, History, and International Relations	To provide an understanding of how smart sustainable city governance and management optimise IoT with AI technologies.	Identifies the benefits of deep learning techniques in smart city paradigms.	Machine Learning, Deep Learning	Provide insight in the smart sustainable city governance and management of the development in AI-enabled technologies.	Urban monitoring and development control	11, 17
Luca et al. (2021)	2021	A survey on deep learning for human mobility	ACM Computing Surveys	To explore the predictive and generative tasks of human mobility and the significance of deep learning model approaches.	Examines perspectives on deep learning approaches to human mobility.	Machine Learning, Deep Learning	Found that net-location and crowd flow predictions, and trajectory and flow generation can be improved with deep learning approaches compared with traditional models.	Urban Monitoring and Development Control	9, 17

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Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
Ding et al. (2020)	2020	P-linknet: linknet with spatial pyramid pooling for high-resolution satellite imagery	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences	To test the effectiveness of deep learning using satellite/aerial images in spatial analysis.	Proposes a new method for estimating the density within a 100-metre grid cell radius using deep learning and adjustments from statistical data.	Machine Learning, Deep Learning	Demonstrated the practicing use potential in spatial analysis. Although the paper suggests that the deep learning within this model needs to be improved.	Urban monitoring and development control	11, 17
Gharaibeh et al. (2020)	2020	Improving land-use change modelling by integrating ANN with cellular automata-Markov chain model	Urban Science	To demonstrate how AI can compare urban typologies of different cities.	Explores how AI can be used as part of planning practice to inform processes.	Machine Learning, Neural networks	Found that the AI successfully compares cities and can provide context to a local area by referencing similar planning policy in similar contexts when planning urban areas.	Urban monitoring and development control	11
Shen et al. (2020)	2020	Machine learning assisted urban filling	International Conference on Computer-Aided Architectural Design Research in Asia	To use AI to simulate urban growth.	Investigates how AI can support urban growth planning by considering land use patterns and street networks.	Machine Learning, Cellular automata	Found the AI simulation was comparable to real urban spaces and has the potential to assist in future urban growth planning.	Urban monitoring and development control	11
Srivastava et al. (2019)	2019	Understanding urban land use from the above and ground perspectives: a deep learning, multimodal solution	International Conference on Urban Development, Regional Planning and Information Society	To demonstrate how supervised and unsupervised learning can complete land-use scenarios.	Identifies how AI can be part of the planning process and not just analysis of the design phase of urban development.	Machine Learning, Neural Networks	Found that supervised learning while time consuming provides design solutions, whereas unsupervised learning provided analysis of land use.	Urban monitoring and development control	11, 17
Feng et al. (2018)	2018	Urban zoning using higher-order Markov random fields on multi-view imagery data	Association for Computer Aided Design in Architecture Conference	To understand the impact of airports on the surrounding urban context.	Identifies and categorises airports based on satellite imagery to understand the impact to local urban areas and informs planners of the required actions needed to resolve issues.	Machine Learning, Neural Networks	Found that using AI across a continent provided greater information that what would have been possible at a human scale.	Urban monitoring and development control	11, 17
Lv et al. (2015)	2015	Urban land use and land cover classification using remotely sensed SAR data through deep belief networks	European Conference on Computer Vision	To develop AI model for urban zoning based on multiple imagery datasets.	Explores multiple imagery datasets that support land use zoning practices.	Machine Learning, Markov Random Fields	Noted the framework completed land use zoning practices automatically and reduces the time needed for urban planners to undertake the process.	Urban monitoring and development control	11, 17
Shen et al. (2009)	2009	Geosimulation model using geographic automata for simulating land-use patterns in urban partitions	International Conference on Computers in Urban Planning and Urban Management	To develop a prototype AI that can synthesise urban features.	Identifies how AI can analyse street networks and land use to inform planning practices.	Machine Learning, Cognitive Design Computing	Found the prototype to be useful but there is a large amount of work required to optimise the application.	Urban monitoring and development control	11, 17
Heikkila and Blewett (1992)	1992	Using expert systems to check compliance with municipal building codes	Journal of the American Planning Association	To assess how expert systems can be used in local governments to assess developments adherence to building codes.	Examines how AI can be effectively used in statutory planning to support enforcement of planning policies.	Logic & Knowledge Based, Expert System	Noted that the system could be modified to meet each local government's preferred decision-making guidelines and staff implications.	Urban monitoring and development control	11, 17
Exner et al. (2020)	2020	Monitoring street infrastructures with artificial intelligence	Real Corp 2020: Shaping Urban Change Livable City Regions for the 21st Century	To use AI to monitor road infrastructure.	Identifies road improvements without the need for physical inspection using AI.	Machine Learning, IoT & Remote Sensing	Noted the aspirational goals of the framework are reliant on community participation which at the time of publication might not be possible. However, there is opportunity for	Urban monitoring and development control	11, 17

(continued on next page)

Table A1 (continued)

Author	Year	Title	Outlet	Aim	Relevance	Technology	Finding	Category	SDG
							implementation of the framework in stages to be achievable in the long term.		

literature along with supplementary literature cited/quoted; but the authors extensive experience in fields related to this study might have resulted in sharing some biased views.

Lastly, further research is needed to understand how AI is being used in current planning practices and the opportunity for broader dissemination of information across the profession. Hence, it will be possible to configure the most suitable and responsible ways for its adoption in planning. Current research is focused primarily on frameworks and theories that have only been trialled in limited or defined urban contexts. Real-world applications are needed to support the introduction of AI properly to the urban planning practice (Kirwan & Zhiyong, 2020; As & Basu, 2022; Matsuo & Iwamitsu, 2022).

6. Conclusion

As cities become more digitally transformed and continue to face massive economic, social, environmental, and governance complexities, there is a need for AI to support urban planning practices. Likewise, as stated by Popelka et al. (2023, p.13), “the real impact of AI in cities is not on the technology but on its implementation in urban planning and design. It is in the plan-making process of cities that AI, e.g., in the form of machine learning, has its major impact”. The study reported in this paper suggests a range of current and emerging technologies that could be utilised to meet these challenges, and advocates that responsible algorithmic urban planning could support smart and sustainable development. Nonetheless, interaction and collaboration between researchers, planners, organisation, and communities—the key urban decision stakeholders—are needed for a broader and more holistic adoption of AI in our cities. Privacy, biases, and inequality continue to be complex issues that need thoughtful consideration in the best way to minimise these risks when implementing AI technologies for urban planning.

Moreover, the perceptions of both planners and the community will have a significant role in how these challenges can be overcome, and how adequate and responsible AI technology solutions could be adopted. As the literature suggests, AI has been and can be used in a range of urban planning tasks to address complex urban development challenges and meet the needs and priorities of local communities. There is great potential for AI to assist in improving the overall safety experience, liveability, and sustainability of cities and their inhabitants in smarter ways. Nevertheless, we also need to be aware of the shortcomings of AI and find ways to tackle them. Finally, urban planners must understand the benefits of AI methods that they will be using and effectively communicate this to apprehensive stakeholders.

Furthermore, existing and emerging applications of AI in urban planning could be useful to potentially pave the way to wider AI adoption. This is particularly likely in the case that present and future capabilities and capacities of AI cater for urban planners’ needs. This paper is an attempt to contribute to this issue. Likewise, we not only believe in coupling different AI algorithms/applications—such as AI and IoT—, but also in coupling human and artificial intelligences which have the potential to help solve our complex urban planning problems.

Moreover, it is critical to start developing and actioning strategies for responsible AI adoption in planning. In this perspective, as Sanchez (2023) puts forward, a useful way to think about where and how AI might fit into everyday sustainable planning practice is to consider strategic points of intervention that represent the work that planners do: (a) Community visioning; (b) Plan making; (c) Standards, policies, and incentives; (d) Development work, and; (e) Public investments. Planners can think about what tasks comprise the work of each of these points and from there explore how they might be able to use AI to automate any of those tasks. At the same time, planners can consider how data that is generated through their planning work can be optimally collected and configured to power AI analyses for better data-driven and evidence-based decision making for achieving sustainable outcomes.

We conclude the article with a quote from Professor Regina Barzilay

Table B1

PRISMA 2000 checklist (http://prisma-statement.org/documents/PRISMA_2020_checklist.pdf).

Section and Topic	Item #	Checklist item	Location where item is reported
Title			
Title	1	Identify the report as a systematic review.	Title
Abstract			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Abstract
Introduction			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Introduction
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Introduction
Methods			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Methodology
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Methodology
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Methodology
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Methodology
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Methodology
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g., for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Methodology

Table B1 (continued)

Section and Topic	Item #	Checklist item	Location where item is reported
	10b	List and define all other variables for which data were sought (e.g., participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	n/a
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Methodology, and Findings and Discussion
Effect measures	12	Specify for each outcome the effect measure(s) (e.g., risk ratio, mean difference) used in the synthesis or presentation of results.	n/a
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g., tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Methodology
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	n/a
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Results
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	n/a
	13e	Describe any methods used to explore possible causes of heterogeneity amongst study results (e.g. subgroup analysis, meta-regression).	n/a
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	n/a
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	n/a

(continued on next page)

Table B1 (continued)

Section and Topic	Item #	Checklist item	Location where item is reported
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	n/a
Results			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Methodology
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	n/a
Study characteristics	17	Cite each included study and present its characteristics.	Appendix Table A1
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	n/a
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Results
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias amongst contributing studies.	Results
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g., confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Results
	20c	Present results of all investigations of possible causes of heterogeneity amongst study results.	Results
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	n/a
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	n/a
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	n/a
Discussion			

Table B1 (continued)

Section and Topic	Item #	Checklist item	Location where item is reported
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Findings and Discussion
	23b	Discuss any limitations of the evidence included in the review.	Findings and Discussion
	23c	Discuss any limitations of the review processes used.	Findings and Discussion
	23d	Discuss implications of the results for practice, policy, and future research.	Findings and Discussion, and Conclusion
Other information			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	n/a
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	n/a
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	n/a
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	Acknowledgements
Competing interests	26	Declare any competing interests of review authors.	Acknowledgements
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Acknowledgements

of MIT's Computer Science and Artificial Intelligence Laboratory ([Sacan, 2022](#), p.16): "When the technology shifted from steam power to electricity, the first attempts to bring electricity to industry were not very successful because people were just trying to copy steam machines. I think something similar is now going on with AI. We need to figure out how to integrate it into many different areas: not only in healthcare, but also in education, in the design of materials, in urban planning, and so on. Of course, there is more to be done on the technological side, including making better algorithms, but we are bringing this technology into highly regulated environments, and we have not really looked at how to do that yet".

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This research was funded by the Australian Research Council Discovery Grant Scheme, grant number DP220101255. The authors thank the editor and anonymous referees for their constructive comments. The authors declare no conflict of interest. The sources of the data used in this paper are listed in Appendix Table A1 and available upon request.

Appendix A.

Table A1

Appendix B.

Table B1

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