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Systematic Review: Examining the Impacts of Artificial Intelligence on Urban Planning

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ABSTRACT

Since its breakthrough in the mid-20th century, Artificial Intelligence (AI) has held great promise for improving the capacity of urban planning to address complex problems. Despite this, the literature on how AI was specifically utilised and how it impacted urban planning remains limited. This study aimed to examine how AI-driven technology influences the landscape of urban planning. To achieve this, we reviewed 48 articles after conducting a systematic screening of 2,359 journal records in the Scopus database, published since the emergence of AI in urban planning. We found that, based on the recurrence frequency of each technology across the reviewed records, the technologies include ML, Big Data, IoT, DL, Intelligent Transportation, ARIES, Geo AI, and Semantic Web. We found that urban planners have broadly adopted AI to address various complex environmental problems in the making of sustainable and smart cities. The three most common solved problems are sustainability, public transportation, and public participation.

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1. INTRODUCTION

By 2050, urban populations living in global cities are expected to double the current state, which has reached around 4.4 billion inhabitants [1]. The unprecedented population growth can inevitably lead to unexpected outcomes, such as urban crime, poverty, and health issues, [2] with effects that are further compounded by climate change [3]. For urban planners, these problems signal unprecedented challenges in the future and an urgent need for novel methods to address them. Over the past few decades, advancements in digital technology have enabled planners to collect, store, and process large amounts of data at high resolution [4]. This consequently makes urban areas no longer considered a conglomeration of infrastructure but rather a complex ecosystem where data and technology converge to form a sustainable environment [5]. Among these emerging technologies that have evidently increased people's satisfaction with public services and quality of life are Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) [6]. However, the current literature remains limited in informing our understanding of how such technologies, particularly AI, impact urban planning.

AI was designed to imitate human minds and behaviours, encompassing perception, reasoning, learning, planning, and prediction. Its development occurs across three domains: perceptual intelligence, cognitive intelligence, and decision-making intelligence. Perceptual intelligence refers to a machine's capacity to perceive, similar to the senses of humans. Cognitive intelligence refers to a machine’s ability to induce reason, and acquire knowledge. In contrast, decision-making intelligence is the machine’s ability to make optimal decisions, which is achieved only when it possesses both capacities [7]. These capacities enable AI to assist planners in creating schemes, formulating problems, and producing solutions at an early stage [8]. Specifically, AI can enhance the process of creating sustainable and smart cities [9], rapidly analyse real-time data, and generate actionable insights for informed decision-making processes [10]. The history of AI can be traced back to Isaac Asimov (1940s), Alan Turing (1950s), and Marvin Minsky and John McCarthy (1956), who first introduced the terminology in a conference at Dartmouth College [11]. Despite its astonishing progress, the failure of logic-based programs to solve complex problems has led to the suspension of much research funding in those periods. Only after some US universities in the 1980s invented AI systems for solving real-world problems did technology regain its popularity. In 2006, for example, Geoffrey Hinton and colleagues proposed an approach to establishing a deeper neural network through Deep Learning (DL), a subset of Machine Learning (ML) that enables a computer to learn and acquire intelligence without human intervention and even exceed human abilities in handling specific datasets. Since then, AI has grown remarkably in supporting human lives and helping researchers efficiently solve problems by integrating AI algorithms [7].

Research on developing AI systems for urban planning began in the 1960s. However, it was not without challenges: the lack of large-scale datasets and computing capabilities to provide solutions or make predictions contributed to these. During the 1980s, the development of AI-augmented technologies that focused on assisting human work evolved [12]. Many believe in the potential of AI to create a sustainable, resilient, and smart environment. For example, an AI-integrated technology called Google’s Tree Canopy enables planners to mitigate the impacts of extreme heatwaves. It provides aerial imagery of tree canopy coverage in cities and recommendations for the potential locations for planting and maintaining trees [13]. Another advanced AI algorithm, MAIIA, was developed by the National Planning Department of Colombia to identify informal settlements with housing problems and requirements for space improvement in various locations. This software could detect those challenges using algorithmic maps and comprehensive satellite imagery. Other AI-powered tools, such as Virtual Reality and Augmented Reality applications, have also contributed to increasing community participation in planning by allowing them to visualise changes and, thereby, provide feedback to planners [14].

In the daily context, AI has been evident in addressing complex problems. AI can control and predict traffic flows at signalised intersections [15], improve safety via public space monitoring, enhance energy efficiency, advance healthcare by detecting outbreaks, and foster environmental sustainability by managing natural resources or mitigating pollution. Despite these benefits, its adoption can create challenges, mainly concerning ethics and human growth. These include, but are not limited to, potential bias that may lead to unequal outcomes for marginalised communities, transparency issues that can complicate public understanding and trust in planners’ decisions, privacy issues due to its extensive data collection process, potential misuse [16], and counterproductive effects on human creativity, innovation, and diversity of perspectives in decision-making [17].

In this study, we seek answers to these questions: (1) How has the trend of the use of Artificial Intelligence in urban planning changed in the past decades? (2) What are the most common types of AI-driven technology employed in urban planning? (3) How do those types of technology impact urban planning processes? This article aims to provide insights into the current understanding of how technology-driven AI influences the urban planning landscape. Methodologically, we employed systematic review. We identified nine themes that demonstrate the impact of AI on urban planning, including sustainable cities, smart and safe cities, public participation, water management, urban structures and changes, urban ecology, environmental quality, rural-urban living, and public transportation. Regarding the types of AI-driven technology, we found that those commonly utilised in urban planning, from the most to the least, are machine learning, big data, IoT, and deep learning.

2. RESEARCH METHOD

A systematic review is a research method that aims to identify all empirical findings that meet the pre-specified inclusion criteria to answer a research question [18]. Therefore, a clear, specific, and welldefined research question is paramount for conducting a systematic review. In this study, we followed Uman's eight stages of a systematic review, which are: (1) formulate the research question; (2) define inclusion/exclusion criteria; (3) develop a search strategy and locate; (4) select studies; (5) extract data; (6) assess study quality; (7) analyse and interpret results; and (8) disseminate findings [19].

To locate the relevant articles, the keywords we used in the Scopus database with a Boolean search query were TITLE-ABS-KEY ("urban planning" AND "artificial intelligence"). The selection criteria we set were that the articles must be sourced from the renowned Scopus database, written in English, categorised as peer-reviewed journal articles, book chapters, or conference proceedings, and published between 2000 and 2023. The year 2000 was determined as the parameter because it was when AI began to be integrated with urban planning. It is worth noting that during that period, the limited power of computers made limited AI to run fundamental data analysis, modelling, and algorithm-based predictions for traffic management and public safety [20].

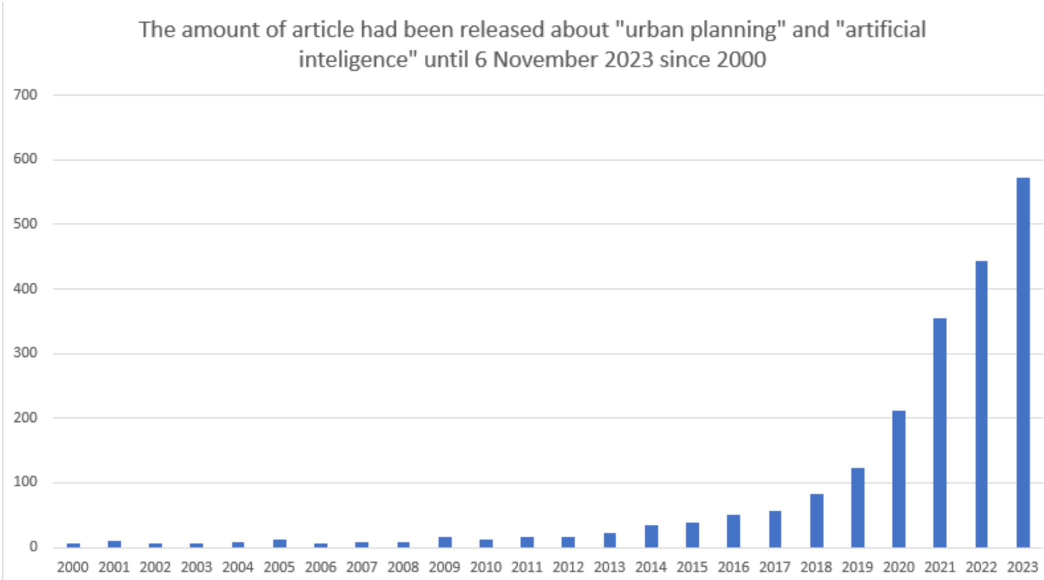
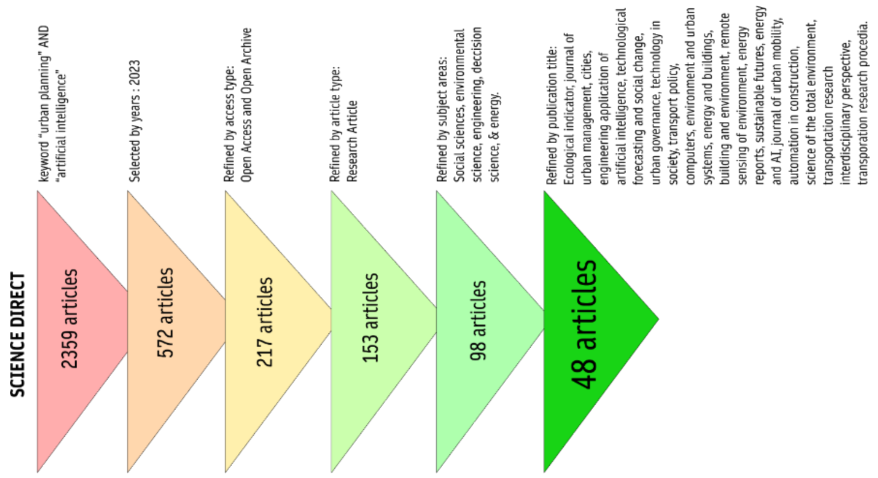


Figure 1. The trend of published articles focusing on AI and Urban Planning from 2000 to 2023

As Figure 1 indicates, publications concerning the impacts of AI on urban planning have increased exponentially from 2000 to 2023. The trend is likely to continue in the future, as scholars' growing interest in using AI in planning and ongoing debates on the subject are expected to drive its expansion. Records in 2023 which reached nearly 600 show a relatively sharp contrast to those in earlier years, leading to our decision to focus on publications in this particular year.

Figure 2 shows the search query we ran in November 2023, which produced 2,359 records. Given the highest number of records in 2023, we limited our selection to published articles in this particular year, resulting in 572 records. Next, to be able to work in a limited resource environment and having readable content, we selected only those with "open access" and "open archive." This phase resulted in the remaining 217 records. Of these, only 153 records were qualified, as we were concerned only with the "research article" type. We then screened the remaining records by specifying the subject areas with the keywords "social sciences, environmental science, engineering, decision science, and energy" to reduce any irrelevant artificial intelligence topics. This resulted in the removal of 105 articles and the inclusion of only 98 records for in-depth analysis (Figure 3). Finally, we further screened the remaining records by selecting only those with titles that used the keyword as defined in Figure 2. The 98 abstract articles were also read to ensure the content. This phase led to only 48 remaining articles to be closely examined. We discussed the themes that emerged from our review by using our research questions as the basis: the "types of AI-driven technology used in urban planning" and the "impacts of the technology on urban planning."



*The systematic filter for research article had been done in 6 November 2023.
The recent added after 6 November 2023 wouldn't be count for research.

Figure 2. Systematic review phases

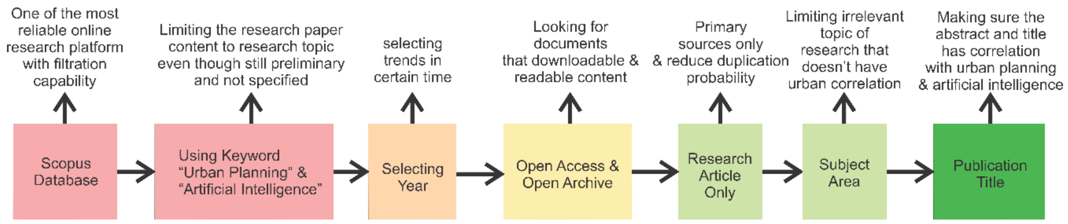


Figure 3. Reasoning flowchart for reliability

3. RESULTS AND DISCUSSION

3.1 Impact of Different AI Technology on Urban Planning

To visualise the correlation between these categories, we developed a visual Sankey chart (Figure 4). In percentage, the top three AI-driven technologies that impacted urban planning in 2023 are Big Data (25%), IoT (21.3%), and Machine Learning (19.7%). This chart also illustrates how these and other technologies significantly influenced urban planning, with the concepts of “sustainable city” (20%), “public transportation” (15.3%), and “public participation” (12.9%) being the most prominent themes that emerged during our review. Smart city (red colour) is more likely to be addressed through various AI technologies, and Big Data has the highest correlation with smart city. Machine learning is more likely to contribute to sustainable city problem-solving. Based on the diverse applications of all AI technologies, it appears that there is no AI-specific technology to address a specific theme problem. A single AI technology can solve many themes. However, from a versatility perspective, Machine Learning, Big Data, IoT, and Intelligent Transportation Systems stand out (solve all or almost all the themes). Rural living is the theme that needs more specific AI technology. Although it contributes 10.5% of the total theme, only Machine Learning, Big Data, and IoT can solve the problem.

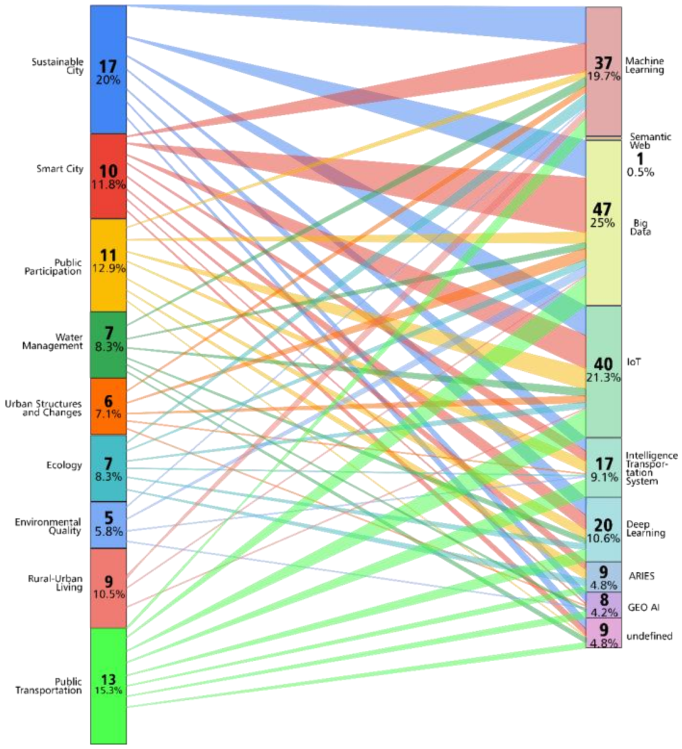


Figure 4. The impacts of different AI-driven technologies on various themes in urban planning in percentage

3.2 Types of artificial intelligence-driven technology in urban planning

Of the 48 records we reviewed, eight types of AI-driven technology were widely adopted in urban planning. These refer to Machine Learning, Big Data, Internet of Things, Deep Learning, Intelligent Transportation Systems, ARIES, Geo AI, and Semantic Web (Figure 4). In this section, we will outline the characteristics of each and explain how they impact urban planning. Two main areas of research in AI are machine learning and Big Data.

The total sum of the graph below is above 48 because there might be more than one AI in a research paper. If there is more than one AI used in a research, all of the AI would be counted in Figure 5. The number of AI in this graph also differs in the Sankey chart (Figure 4) because the Sankey chart's numbers for every type of AI might be duplicated if the AI has more than one impact. For example, machine learning has an impact on sustainable and smart cities, therefore, it will be counted as two in Figure 4, but only one in Figure 5 because Figure 5 only counts the AI, not the sum of impacts caused by AI. Figure 4 did not contradict Figure 5; it simply presented data differently and expressed correlation differently.

In this graph (Figure 5) below, and by correlating with Figure 4 above, it can be clearly stated that although machine learning and big data have the same research frequency (19), the versatility impact of big data (47) is higher than that of machine learning (37). The most versatile impact of AI is the Intelligent Transportation System (17), even though it has been researched only six times. That is more than triple the impact of diversity, ITS surpassed big data in terms of impact on diversity. AI can have more than one impact; it can, on average, have two thematic impacts. However, the semantic web and undefined AI are more likely to have a more specific effect. Machine learning also tends to have a more particular impact than multiple impacts. The sub-chapter below explains the definition and gives examples of how the AI has been used in previous research.

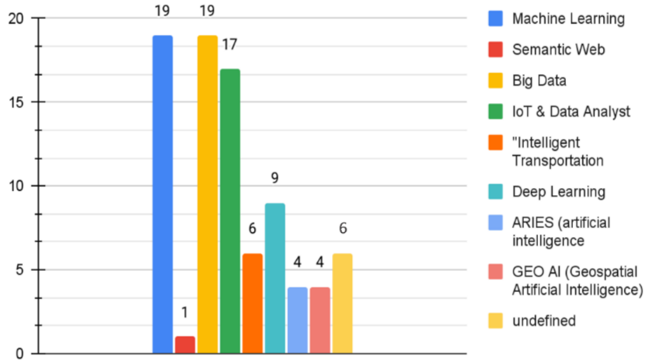


Figure 5. Types of AI found to play in city development towards urban planning

Further subsections will explain the definition of artificial intelligence while also giving some examples of its implementation. Not every case will be explained; the chosen sample case is the most likely to be discussed. It is not possible to summarise all cases because it will overwhelm the number of pages and words.

3.2.1 Machine Learning (ML), Total Theme Impact Contribution: 19.7%, Research Freq.: 19

Machine Learning (ML) is widely regarded as the heart of intelligence and data science [21]. It trains algorithms—a sequence of instructions that transforms input to output [22]— to understand data patterns and predict outcomes based on statistical analysis [23]. ML is also known for its capacity to learn to adapt to a changing environment, making it considered a part of Artificial Intelligence [22]. ML enables planners not only to predict phenomena but also to stimulate urban development and develop tools to monitor air pollution in real time by incorporating IoT and AI [21].

Its applications can also be found in the context of natural disasters. For example, Wang, M. et al. (2023) integrated ML with the XGBoost algorithm to establish a model to investigate the relationships between inundation depth in urban flooding scenarios and an assortment of risk-reducing factors in Shaanxi City, China. The technologies helped them develop models that can be trained to conform to the urban sub-catchment environment. These models are predictive in nature and can assist planners in making the right decision [24].

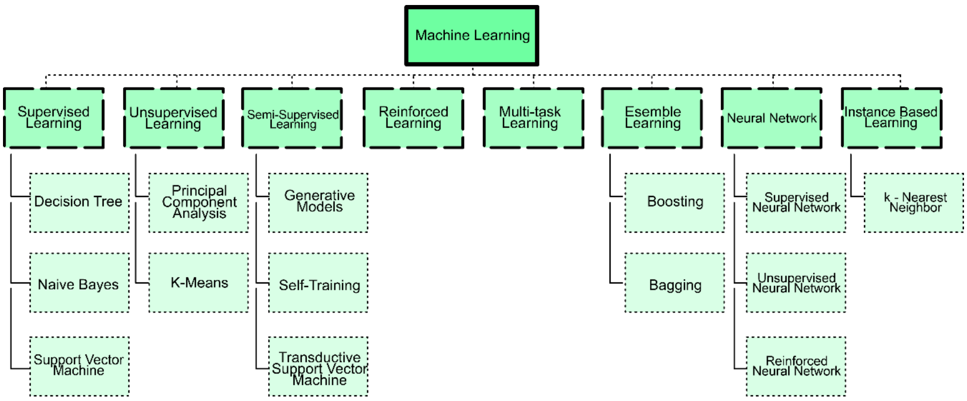


Figure 6. The classification of Machine Learning. Adapted from [25]

3.2.2 Big data, Total Theme Impact Contribution: 25%, Research Frequency: 19

Big data is originally defined as any data with an unprecedented volume, as it is collected from almost all human activities [26]. Recently, its definition has expanded to also include variety and velocity [27]. Variety refers to the structural heterogeneity in a dataset. Velocity refers to the rate at which data are generated and the speed at which they should be analysed and acted upon, for example, there is an unprecedented rate of data produced by smartphones. As a process, big data is categorised into two groups: management and analytics (Figure 6). Data management entails processes and supporting technologies to acquire, record, extract, clean, annotate, integrate, aggregate, and represent data. Data analytics refers to techniques used to analyse intelligence from big data through modelling and interpretation [28].

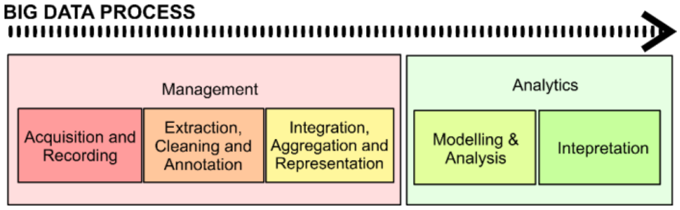


Figure 7. The general processes of Big Data. Adapted from [29]

Big data has been used widely in urban planning. For example, Liu and Miller (2021) show how routinely collected real-time data can be used to develop measures for evaluating the risks of missing bus transfers and consequent delays in Columbus [30]. Another example is the capacity of researchers to collect around 1 billion records of travelers who tapped in and tapped out of the public transport systems with smart 'Oyster' cards in London for over six months [26].

3.2.3 Internet of Things (IoT), Total Theme Impact Contribution: 21.3%, Research Frequency: 9

The Internet of Things (IoT) encompasses a network of interconnected smart devices, which are embedded with sensors, software, and connectivity capabilities [31]. These devices are considered "smart" as they can sense, communicate, store, and visualise data without human intervention (Figure 7). The internet facilitates connections and integration among different devices, enabling them to be able to exchange data and control various processes and systems [31]. To enhance users' experiences and evaluate the device's performance, IoT usually requires integrating "big data" with "machine learning" [32]. However, given the nature of big data, IoT often faces issues with memory and computational power.

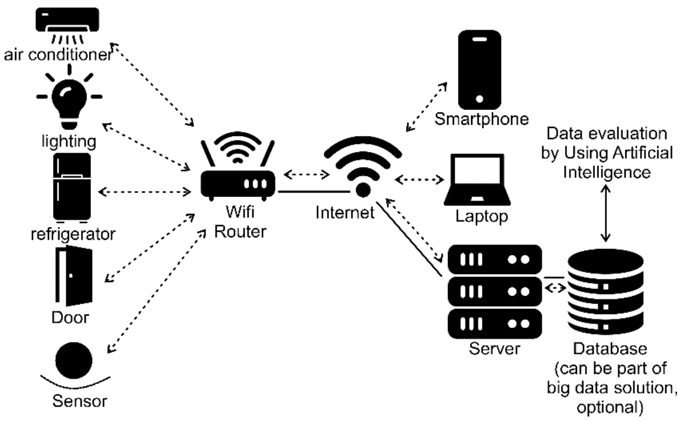


Figure 8. The general block diagram of IoT. Adapted from [32]

The applications of IoT in urban planning can be found in many cases, such as vehicular traffic, surveillance, and smart parking. In a day-to-day context, IoT enables citizens to determine how long the travel to a destination will be. In this case, IoT uses recent information on traffic intensity and the average speed of vehicles to produce the information. The government can also benefit from IoT by using the information on road blockage to manage traffic. Another example is the capacity of researchers to predict future demand for electricity by analysing its consumption from previous years [33].

3.2.4 Deep Learning (DL), Total Theme Impact Contribution: 10.6%, Research Frequency: 17

As Figure 8 shows, Deep Learning (DL) is a part of ML and AI, whose algorithm relies on past data [34], [35]. DL is generated from conventional neural networks but performs considerably better than its predecessors. Its development was indeed inspired by the information-processing patterns in the human brain. Despite this, its operations do not require any human-created instructions. Instead, they rely on vast data to map the given input to some specific labels [35]. DL is, therefore, marked by its ability to extract complex patterns from vast urban datasets, allowing decision-makers to yield unprecedented insights into urban dynamics, transportation networks, and environmental sustainability [5]. With this capacity, it is not surprising that DL can outperform human capacities on many tasks [36].

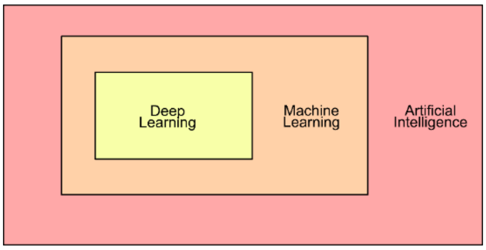


Figure 9. Correlation of AI, ML, and DL. Adapted from [36]

DL is effective for "determining the initial urban configuration and for proposing schemes to change the configuration based on data analysis" [34]. When integrated with AI, DL can provide a more precise estimation related to natural disasters [5], [35] and information about the functioning aspects of smart cities, such as logistics [34]. Among various DL-based techniques, the recurrent neural network (RNN) is considered very influential in urban planning. For example, an RNN can help planners address short-term traffic flow predictions based on traffic patterns over brief time intervals. Considering spatial and temporal correlations in its data analysis, RNN can also produce complex traffic patterns and variations that are important for improving traffic management [37].

3.2.5 Intelligent Transportation System, Total Theme Impact Contribution: 9.1%, Research Frequency: 6

An Intelligent Transportation System is a technology that specifically provides images to address road safety concerns, enhance traffic management, and improve drivers' comfort. ITS communications rely on vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), each of which enables vehicle users to enhance safety and vision through wireless data exchange (Figure 9). In its operation, the data is collected from infrastructure roadside units (RSUs) and other sensors installed on roads, buildings, or human bodies. The data is then disseminated to the vehicle cloud to inform the vehicle's wireless transceiver, enabling users to control traffic congestion [38].

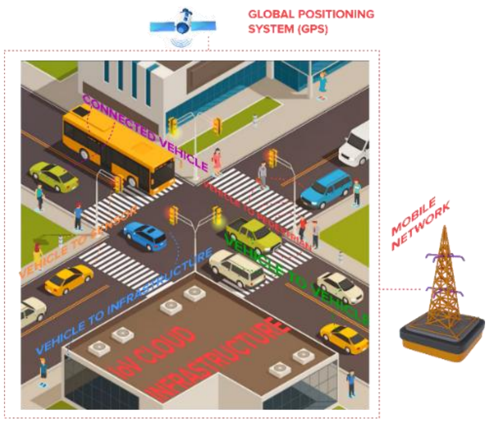


Figure 10. The framework of Intelligent Transportation System. Adapted from [38]

Tools typically involved in ITS are smart cards, mobile phones, GPS, and sensor-based devices, while methods analysing the data retrieved are data clustering, pattern mining, location-oriented queries, and trajectory-oriented queries. When integrated with Big Data, ITS can detect and predict polluted areas in real time [28]. In Nanjing, for example, the ITS and traffic data are used to monitor vehicular emissions based on traffic dynamics 24 hours a day. The emission patterns resulting from this will serve to examine traffic restriction solutions under various traffic scenarios [39]. When combined with Big Data, ITS can alleviate transportation and environmental problems. However, there are still concerns arising around Big Data, such as data inaccuracy/incompleteness, privacy, volume, and processing timelines [28].

3.2.6 Artificial Intelligence for Ecosystem Services (ARIES), Total Theme Impact Contribution: 4.8%, Research Frequency: 4

Artificial Intelligence for Ecosystem Services Model (ARIES) is a web-accessible and web-based application of advanced ecoinformatics that facilitates accurate and science-based ecosystem services analysis while reducing the analysis's complexity and cost. The application builds and runs ad-hoc models of ecosystem services provision, use, and spatial flow in each area based on users' set of goals [40]. With the presence of global data and models and the availability of hosted networked geo-services, users can now run the ARIES models anywhere. These models are accessible via an open-source software package, known as the Knowledge Laboratory (k.LAB) Integrated Development Environment.

ARIES can be run by selecting a spatiotemporal context, model resolution, optional scenario conditions, and the underlying ecosystem service to be observed (Figure 10). The software also offers tools to write new models or modify the existing ones [41]. In its operations, ARIES employs spatial Bayesian networks to create probabilistic models for all assessments and combines models of provision, use, and absorption of each benefit into a dynamic flow analysis [40].

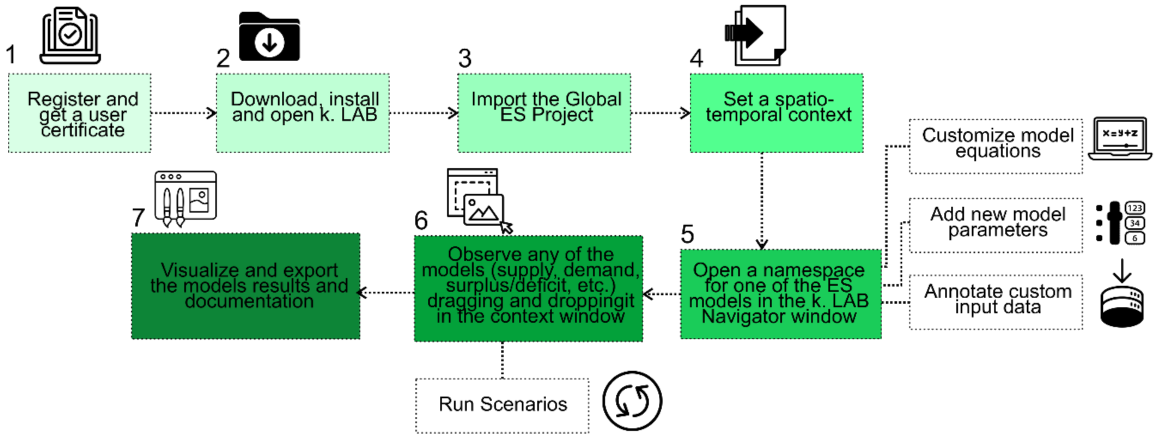


Figure 11. The workflow framework of ARIES. Adapted from [41]

Its application in urban planning can be found in the case used by Tang et al. (2023). Respectively, ARIES provided ecological assessment models for running a quantitative analysis of the impacts of urban expansion on habitat quality in the Yellow River Basin, China, and predicting the impacts through different scenarios [42].

3.2.7 Geospatial Artificial Intelligence (GeoAI), Total Theme Impact Contribution: 4.2%, Research Frequency: 4

Geospatial Artificial Intelligence (GeoAI) is a technology solution to data and computing-intensive geospatial problems and leads to a new phase of data-intensive exploration that combines empirical, theoretical, and computational paradigms. GeoAI integrates a knowledge-driven approach with a data-driven approach. The former uses deductive reasoning and relies on prior knowledge, domain knowledge, pre-existing logical rules, and constraints to stimulate real-world entities and draw conclusions. The latter uses inductive reasoning and relies heavily on ML, which allows GeoAI to uncover hidden patterns within big data and to make predictions [43]. GeoAI combines the strengths of GIScience and AI, leading to the improved ability of dynamic perception, intelligent reasoning, and knowledge discovery of geographical phenomena and the accompanying processes [44]. It combines powerful learning algorithms (e.g., ML, DL) to develop innovative solutions for geospatial purposes. Currently, GeoAI continues offering new integrations with other technologies, such as Big Data (Figure 11).

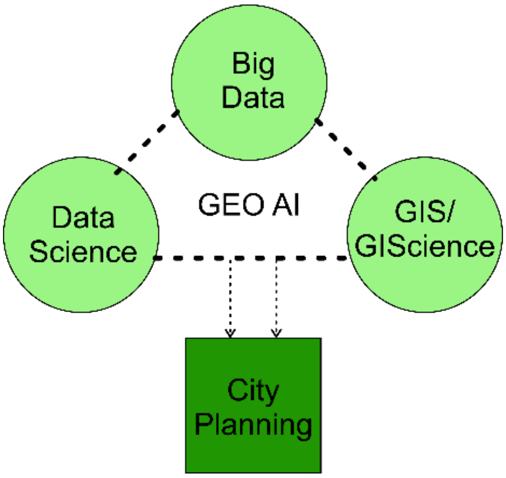


Figure 12. The GeoAI framework combines data science, GIS, and big data for city planning. The authors simplified the framework of [43]

In urban planning, GeoAI has been evident in addressing complex problems, which relate to land use analysis, natural hazards, and social issues. For instance, GeoAI allowed de Carvalho et al. (2022) to identify objects in beach settings by using multispectral panoptic segmentation with WorldView-3 images. It allowed them to retrieve a detailed mapping and count tourist infrastructure and features of beach areas [45]. The other instance is the work of Zhang et al. (2022), which employed machine learning algorithms to explore flash flood factors, identify clustered homogeneous regions, and generate a flash flood regionalisation of Jiangxi [46].

3.2.8 Semantic Web, Total Theme Impact Contribution: 0.5%, Research Frequency: 1

The Semantic Web is built to link individual pieces of data and facts in a machine-readable way [47]. This technology is considered effective in solving data fragmentation problems and supporting the utilisation of big data in urban planning [48]. The architecture of the Semantic Web (Figure 12), comprises six features: (1) URI, aimed at identifying and locating resources on the Web and Unicode, which is the standard for computer character representation; (2) Extensible Markup Language (XML), a markup language that enables the machine to read and have a format; (3) Resource Description Framework (RDF), the framework for representing metadata and describing the semantics of information on the Web in a machine-accessible way; (4) Ontology vocabulary, a common vocabulary and grammar to keep data readable and understandable by different entities; (5) Logic and Proof, used to evaluate and resolve consistency problems and redundancy of the translation, and (6) Trust, which concerns the trustworthiness and the quality assurance of the information on the Web [49]. Scholars in Singapore, for instance, utilised the Semantic Web to improve urban regulatory data access, integration, and usability by linking the ontology to geospatial data stored in a knowledge graph. This technology, known as OntoZoning, allows planners to perform site selections and site explorations [47].

3.3 The Impacts of artificial intelligence-driven technology on urban planning

Our review found eleven themes in the field that are impacted by AI (Figure 13), among which are sustainable cities and public participation. In Figure 14 below, the total sum number is above 48 because it might be possible that more than one theme is discussed in the paper. Figure 14 data numbers must be the same as Figure 4 (left side), because both figures have the same expression, which is an impact theme that researchers would like to solve by using AI. Researchers are more likely to discuss sustainable cities than public transportation and least discuss environmental quality. In contrast, the Figure 15 number is different from the Figure 14 number because the counting method is different. One AI might have more than one impact, and one research paper might use more than one AI. So, Figure 15 is more suitable to present the correlation between AI usage implementation and the theme that they solved. While Figure 14 is more suitable for presenting the theme that trends are to be discussed lately.

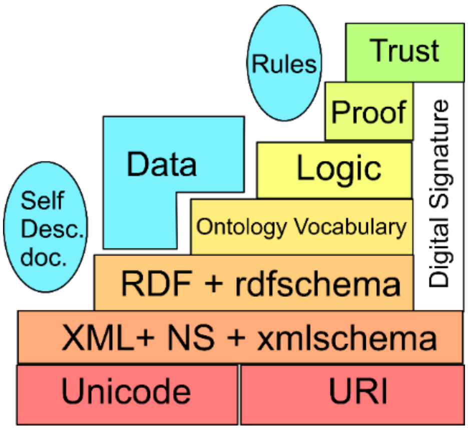


Figure 13. The architecture of the Semantic Web. Adapted from [49]

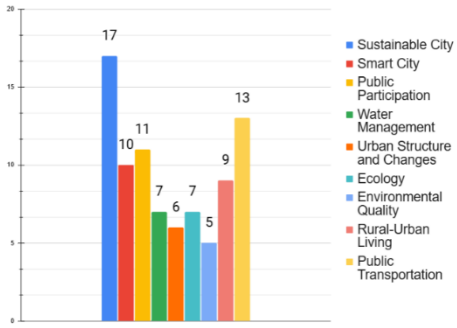


Figure 14. The identified themes in urban planning based on a systematic review

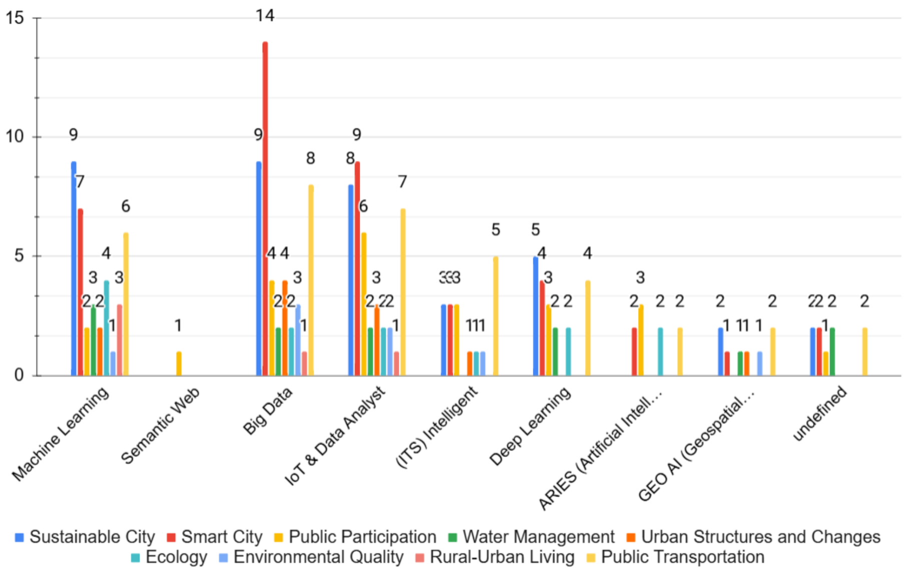


Figure 15. The correlation of AI implementation and various themes in urban planning problems

Of the 48 articles we reviewed, Big Data is the type of AI-driven technology mostly adopted in urban planning in efforts to attain certain goals, such as creating a smart and safe city (14) (Figure 15). Besides Big Data, other technologies that are worth mentioning here are IoT, ML, and DL. Semantic Web was indicated as the least adopted type in urban planning, where public participation is the only theme that we found in our examination. What is also profound is IoT (7), Big Data (8), and ITS (5) are more likely to solve public transportation problems in the future. Their contribution to public transportation is quite outstanding. At the same time, machine learning (9) and deep learning (5) are also quite outstanding for sustainability problems. Even though Big Data and IoT also contribute to sustainability, they do not contribute as much to smart city. A certain type of artificial intelligence is more likely to solve certain problems, and it's shown in Figure 15.

This section will explain nine themes that emerged during our systematic review. These themes were captured based on their recurring patterns across the reviewed records in relation to the goals of urban planning when adopting AI-driven technologies. We discussed and ordered each theme based on its frequency (i.e., the total number of recurrence/emergence), which, from the highest to the lowest, are (1) sustainable city, (2) public transportation, (3) public participation, (4) smart city, (5) urban ecology, (6) water management, (7) rural and urban living, (8) urban structures and changes, and (9) environmental quality.

3.3.1 Sustainable city (20%)

Of the 48 articles we reviewed, 17 discussed how AI is utilised in urban planning to create a 'sustainable city'. This subject seems to have been of interest to urban planners in the past decade, particularly in the face of unprecedented population growth and the intensifying effects of climate change. Moreover, the United Nations has emphasised an urgent need for decision-makers and planners to act and collaborate to address those challenges by emphasising the eleventh goal of sustainable development (SDGs), which is to "make cities inclusive, safe, resilient, and sustainable" [50].

Those articles demonstrate how AI-driven technologies are favoured because they can assist planners in solving urban problems, such as optimising solar photovoltaic energy and promoting green infrastructure. In terms of technologies, the topologies, from most to least important in efforts to create a sustainable city, are ML and DL. The former is generally integrated with some methods like Artificial Neural Networks, Long Short-Term Memory [51], Gated Recurrent Unit [52], Recurrent Neural Networks [34], Adaptive Neuro-Fuzzy Inference Systems, and Extreme Gradient Boosting (XGBoost) [24], [53]. The latter is widely integrated with other methods, such as Gated Recurrent Units, Spatial Decision Support Systems (SDSS) Tools [54], [55], Agent-Based Models (ABM) [56], Cellular Automata (CA) [57], GIS-based Spatial Multicriteria Decision Analysis (GIS-MCDA) [58], and digital twin to facilitate model simulations of physical features [59].

3.3.2 Public transportation (15.3%)

Based on our review, we indicate 13 records in 2023 that discussed the adoption of AI-driven technologies in transportation planning. These technologies are Big Data, which is integrated with Intelligent Transportation Systems (ITS) to ameliorate the efficiency of the transportation system; GIS and GPS, which are combined with 'cloud computing' and 'clustering techniques' to solve traffic congestion problems [28]; GPS and DBSCAN, a density-based algorithm, which are aimed to assess the congestion along the day and for different days of the week [60], and other technologies (e.g., AI, IoTs) which are used to manage traffic problems [61], and GeoAI, which is used to understand urban morphology and dynamics related to transportation network [43]

3.3.3 Public participation (12.9%)

One of the benefits of the emerging AI-driven technologies in urban planning is to speed up producing urban models by automating the design process with a great amount of data and testing numerous options that consider multiple criteria, including human-related factors (e.g., perceptions) in the process. Of 48 records, there were 11 which shared this theme. The technologies involved in this are: (1) Semantic Web, which is integrated with AI to semantically link a wide range of planning-related data and thus, increase the efficiency of accessing the data, evaluating options, automating tasks, and developing models of land uses [47]; (2) Software Intelligent Agent (SA) that uses AI in participatory heritage planning by eliciting and modelling actors' preferences, such as land-use preferences and revealing their values for empowering people and developing awareness [62]; (3) Convolutional Neural Networks (CNNs) and Vision transformers (ViTs), two types of DL algorithms that can be used to estimate land price by considering streetscape and human subjective perceptions [63], and (4) the Convolutional Neural Network and Visual Geometry Group Network (VGGNet) structure that can be used to extract image features and measure urban perceptions of street view images [64].

3.3.4 Smart city (8.3%)

Smart city is the other theme that we identified from our review of ten records. A smart city can be defined as a concept that is not only focused on the implementation of Information and Communication Technologies (ICTs) but also on how the implementation is immersed to efficiently integrate the different urban dimensions and achieve technological affordance for building creative and inclusive urban spaces [65]. It is developed as a response to problems, such as waste management, mobility, and energy supply, resulting from fast-growing urbanisation [66]. The advancing technologies mentioned in those records include (1) the integration of AI and ICT to forecast weather and release early warning messages in an automatic way [67]; (2) Big Data, GeoAI, and Data Science to enhance the efficiency of urban services and functions, improve quality of life, address the societal, ecological, and economic changes, and contribute to the production of spatial data, information and knowledge on human-urban dynamics [43]; (3) IoT which is used to monitor the turbine for reliable communication between the turbine and control centre and provide a garbage notification system; and (4) the integration of AI with ML, which is potential to optimize energy use based on vast amounts of data and provide insights into energy consumption patterns [66].

3.3.5 Urban ecology (8.3%)

Of the 48 reviewed records, seven are identified as those that discussed how AI contributed to ecological improvement. The technologies include AI and the long short-term memory recurrent network (LSTM-RNN), which is a model based on DL and aimed at exploring and forecasting urban-rural vegetation disparities. Such technology has also been used to study mangroves, urban forests, smart farming, and wetland ecological security patterns [51]. It is worth mentioning that the applications of some emerging technologies, such as AI, ML, IoT, and Digital Twins, have not been substantially discussed in studies of ecology except those of urban resilience, smart cities, and transportation.

3.3.6 Water management (8.3%)

This theme was developed based on our review, which led to the identification of 7 records published in 2023. Water systems have recently become one of the global concerns, resulting from the acceleration of urbanisation and the compounding effects of climate change (e.g., urban floods) and water management issues [75]. The AI-driven technologies applied to this concern are XG Boosts, Shapely Additive exPlanations, and Partial Dependency Plots, which are commonly used to assess how urban morphology influences urban flooding and recommend adaptations to storms at the city scale [24] and AI-integrated methods, which are used to collect data for ecosystem services [75].

3.3.7 Rural and urban living, (7.1%)

There are nine records published in Scopus-indexed journals that discussed how the advancing technologies could assist planners in improving urban and rural living in different domains, from healthcare to energy use. Among the technologies mentioned in those records are (1) AI and ML which often use sensing technology, big data, robotics, drones, and autonomous vehicles to support business sectors, monitor the environment, and supervise infrastructural management [68]; (2) big data and chatbot, which are used to inform citizens and expedite their access to public services, suggest policies, and improve the performance of governance [69]; and (3) AI, blockchain, ML, big data analytics, and Virtual and Augmented Reality (VAR) to automate property buying, management, and planning [70].

3.3.8 Urban structures and changes (7.1%)

Urbanisation has created vast challenges, such as excessive human consumption, urban waste discharge, urban heat island, and land use change, which dramatically decrease the environmental quality of urban areas. With the emergence of technologies, planners could enhance their contributions in addressing such problems. We found six records in 2023 that discussed this planners-technology relationship and developed this theme respectively. Among AI-driven technologies that help analyse urban structures and their changes are the Geodetector and the Machine Learning of Random Forest, which ease the analysis of the interrelationships between multifactor and dynamics of urban areas from year to year [71] and Metronamica, a type of Cellular Automata modelling that can stimulate spatial and temporal land use changes [57].

3.3.9 Environmental quality (5.8%)

Of 48 reviewed records, we identified five that discussed the integration of AI into planning with concerns about environmental quality. The specific technologies mentioned include the AI-based multi-objective evolutionary algorithms (MOEAs), which supports planning for elderly's accessibility and path conditions [72], the Shapley Additive exPlanations (SHAP), which overcomes the limitations of the Extreme Gradient Boosting (XGBoost) by extracting explanations for individual predictions in greater detail thus increasing the reliability of the results in relation to energy use predictions [53], and other technologies, which can create flexible, market-responsive, cleaner, quieter, and lighter manufacturing products [73], generate the dataset from big data and multi-source satellite data for analysing air pollutant the urban area [74].

4. CONCLUSION

In this article, we have demonstrated the implications of AI-driven technologies in urban planning by addressing our research questions. We found that the use of AI in urban planning increased from 2000 to 2023. Articles based on empirical research and literature reviews published in Scopus-indexed journals from 2018 to 2023 show an unparalleled increase, evidencing the emerging use of AI in the field. In addition, we listed eight types of AI-driven technologies that planners commonly adopt. These, based on the recurrence frequency of each technology across the reviewed records, are ML, Big Data, IoT, DL, Intelligent Transportation, ARIES, Geo AI, and Semantic Web. These technologies are often deployed to attain planning goals (based on frequency sequence) concerning sustainable cities, public transportation, public participation, smart cities, rural and urban living, urban ecology, urban structures and changes, environmental quality, and water management.

Among the eight AI-driven technologies we identified, the first three types (ML, Big Data, and IoT) are predominantly adopted in urban planning. ML assists planners in understanding patterns, predicting outcomes, and optimising a performance criterion. Big Data, with its benefits in terms of volume, variety, and velocity (3V), allows planners to stimulate the transformations of multiple and diverse techniques for data mining and resource shift. IoT enables planners to connect and integrate data from various devices and sources, collect and exchange data autonomously, and provide real-time information or predictions.

Despite the significance of these findings in filling the gap in the current body of planning literature, the article has limitations. First, we recognised that limiting our review to records published in 2023 and the Scopus database may risk the reliability of our findings. However, we argued that the published articles in that year are representative enough, given that the indicated technologies are the latest in impacting urban planning. Second, during our review, we found more than five published records that did not specify the type of AI-driven technologies used. This inevitably hinders our capacity to explain the research findings in greater detail.

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