land

Review

Impact of AI-Based Tools and Urban Big Data Analytics on the Design and Planning of Cities

Dorota Kamrowska-Załuska

Faculty of Architecture, Gdansk University of Technology, 80-233 Gdańsk, Poland; dzaluska@pg.edu.pl

Abstract: Wide access to large volumes of urban big data and artificial intelligence (AI)-based tools allow performing new analyses that were previously impossible due to the lack of data or their high aggregation. This paper aims to assess the possibilities of the use of urban big data analytics based on AI-related tools to support the design and planning of cities. To this end, the author introduces a conceptual framework to assess the influence of the emergence of these tools on the design and planning of the cities in the context of urban change. In this paper, the implications of the application of artificial-intelligence-based tools and geo-localised big data, both in solving specific research problems in the field of urban planning and design as well as on planning practice, are discussed. The paper is concluded with both cognitive conclusions and recommendations for planning practice. It is directed towards urban planners interested in the emerging urban big data analytics based on AI-related tools and towards urban theorists working on new methods of describing urban change.

Keywords: artificial intelligence; big data; urban design and planning; urban change

Citation: Kamrowska-Załuska, D. Impact of AI-Based Tools and Urban Big Data Analytics on the Design and Planning of Cities. *Land* **2021**, *10*, 1209. https://doi.org/10.3390/land10111209

Academic Editor: Simon Elias Bibri

Received: 13 October 2021
Accepted: 3 November 2021
Published: 8 November 2021

1. Introduction

Large volumes, velocities, varieties, and veracities of geo-referenced data, actively and passively produced by users, bring more comprehensive insights into depicting socio-economic environments [1]. With the widening access to big data and their increasing reliability for studying current urban processes, new possibilities for analysing and shaping contemporary urban environments have appeared [2]. Emerging AI-based tools allow designing spatial policies enabling agile adaptation to urban change [3]. This paper aims to investigate the possibilities provided by AI-based tools and urban big data to support the design and planning of the cities, by seeking answers to the following questions:

- What is the potential of using urban big data analytics based on AI-related tools in the planning and design of cities?
- How can AI-based tools help in shaping policies to support urban change?

Existing studies show various applications of AI-based tools in different sectors of planning. Wu and Silva [4] review its role in predicting land-use dynamics; Abduljabbar et al. [5] focus on transport studies, while Yigitcanlar et al. [6] analyse applications of those tools in the context of sustainability. Other reviews focus on specific areas; for example, Raimbault [7] focuses on artificial life, while Kandt and Batty [8] focus on big data. Allam and Dhunny [9] identify the strengths and limitations of AI in the urban context but focus mainly on its role in building smart cities. Thus, there rarely exist studies that focus on both urban big data analytics and AI-based tools in an urban context, which asks for a comprehensive framework to assess, based on existing studies, the impact of the use of urban big data analytics using AI-related tools to support the design and planning of cities. In order to bridge this gap, a conceptual framework to assess the influence of the emergence of AI-based tools and urban big data on the design and planning of cities in the context of urban change was made. The result of this framework is a typology of the use of AI and big data to support urban change. The paper determines the implications of the application of AI-based tools and geo-localised big data on both solving specific research problems in the field of city design and planning, as well as on planning practice.

The paper is divided into six main sections. The introduction, presenting research questions, is followed by the description of previous works enabling definition of the gap in the existing literature, which this paper addresses. The background section presents a literature review with strong focuses on big data analytics and AI-based tools. The third section includes the methodology applied in this paper. It is followed by analyses of data sources and types of AI-based tools used in urban analytics. In the same section, various fields of use of AI-based tools and urban big data are discussed and assessed in terms of the impact of AI and urban big data analyses on the design and planning of the cities. In the Results Section, the main findings are discussed through the lens of the research questions and the state-of-the-art presented at the beginning of this study. It allows for the identification of six major fields where these tools can support the planning process. Finally, cognitive conclusions, recommendations for planning practice, and future application trends defining the main points for big data and AI-based analysis to better reach policymakers and urban stakeholders are formulated and followed by directions for further research.

2. Background: Urban Change and the Opportunity to Use Big Data Analytics and AI-Based Tools

The availability of urban big data offers new opportunities for the development of many aspects of urban living. This availability of data showcases that it can be useful in making informed decisions for the optimal usage of resources [9], while new technologies such as the Internet of Things, artificial intelligence, and machine learning can greatly contribute to this process, allowing researchers and planners to conduct more in-depth and accurate urban analyses [10].

After the industrial revolution, humankind entered the Anthropocene [11], as human activities are having increasing impacts on the environment on all scales. At the same time, human settlements and cities are becoming more complex than ever before. This complexity escaped the attention of researchers until the 1960s, when the science of cities started to flourish [12]. Further, the 1990s brought numerous applications of complexity theories to urban planning [13–15]. In a city, human behaviour is impacted by different factors, such as the urban microclimate, morphology, connectivity, and accessibility of public and commercial facilities. To model this complexity, current cities require the introduction of new forms of planning [16,17] based on profoundly critical engagement with cities, analysis of the interrelationships between human activity and urban space, as well as intellectual and ethical guideposts for transformative actions [18]. As urban space is a dynamic system, composed of human and commercial activity, flows of energy and matter, and their interactions [19], we can no longer analyse the urban environment as a static space built of structures and roads. At the same time, in recent years, one can observe an increasing amount of big data mining applications in urban studies and planning practices [20–22]. Urban big data mining—i.e., extrapolating patterns and obtaining new knowledge from existing data sources—allows new types of data to be used to improve system performance and to take full advantage of its real-time nature [23]. At the same time, these new insights can also be an advantage for urban planning analyses. In this paper, the author argues that big data and AI-based tools applied in the planning of cities can describe this complexity and help successfully manage urban change. This can be achieved by providing methods to model (including using big data analytics based on AI-related tools) and conditions to manage urban processes which are influenced by urban dynamics and the heterogeneity of the urban space. Due to its specificity, big data analyses can better support the preparation of urban strategies and plans that answer the abovementioned challenges, which often need to be studied in between the formal statutory scales of government [24].

Additionally, data-driven city planning based on urban big data analysis, planned and managed in real time can support those changes. Urban big data [25], also called geo-big data [26], allows for new types of more detailed analyses, which can influence the design of cities and support the creation of data-based policies, plans, and projects. Real-time data mining and pattern detection using high-frequency data can now be carried out on a large scale [8]. Development of and access to **AI-based tools** allow for fuller use of the potential of big data from different sources by both conducting analyses that were previously impossible, such as object detection and categorisations in data-scarce environments (e.g., in the study of urban informalities [27] or mapping cultural heritage [28]) but also advancing existing type of analyses (e.g., simulations of urban growth, which allow the study of the complexity of those processes [29,30]). Allam and Dhunny [9] argue that the processing of big data through AI can increase the liveability of urban space and help to plan more connected, efficient, and economically viable cities, which is why it is relevant to study the role of both big data analytics and AI-based tools together.

Various urban research scholars argue that big data analytics supported by AI-based tools promise benefits in terms of real-time prediction, adaptation, higher energy efficiency, higher quality of life, and accessibility [8,31–33]. Data-driven technologies, such as artificial intelligence, suggest ways to establish a new generation of GIS systems, as they enable the building of frameworks connecting multiple data sources [2]. AI-based tools are applied in the studies which require accurate predictions with a high spatiotemporal resolution, such as urban traffic surveillance systems [34] and real-time pedestrian flow analysis [35]. Hao et al. [36] argue that big data analytics using AI-based tools could allow for regional perspectives to be modelled at the individual level, to move from static total amounts to dynamic flows, and to reflect the fine-grained scale of regional spatial changes. This approach, with the help of cellular automata and multi-agent systems, was used by Rienow et al. [37] for forecasting urban growth. The emergence of advanced machine learning methods can also provide unprecedented opportunities to model complex processes in shaping the cities of today [38]. Amiri et al. [39] apply machine learning to household transportation energy consumption, while Byon and Liang [40] focus on real-time transportation mode detection. Moreover, numerous studies [38,41,42] confirm that, in various prediction tasks, machine learning models can provide higher accuracy and efficiency than classic statistics. Deep learning, with its artificial neural network algorithms, is often combined with cellular automata, e.g., for spatiotemporal modelling of urban growth [30], or with fuzzy logic, e.g., for urban water consumption estimations [43].

The conducted review shows that the types of AI-based tools that are most widely used in urban planning are those from the evolutionary computing and spatial DNA group: mostly artificial neural network [4,44,45] both of the convolutional [27,46] and recurrent [47] types but also unsupervised machine learning, mainly self-organising maps (SOMs) [48,49]. The next most numerous group contains examples of the Knowledge-based intelligent systems group, where the most important tools are fuzzy logic [29,50] and rough sets [50]. Studies by Varia [51] and Beura and Bhuyan [52] use a genetic algorithm to model the dynamic flow of both cars and bikes. Additionally, artificial life—namely, cellular automata [30,53,54] and agent-based models [55,56], are widely used in studies of urban growth.

3. Methodology

The aim of the paper, i.e., to investigate the possibilities provided by AI-based tools and urban big data to support the design and planning of cities, was addressed by the creation of the conceptual framework to assess the influence of the emergence of these tools on the design and planning. This framework was developed based on an integrative systematic review of the current literature on the use of big data and AI in urban design and planning, which allows for the identification of the relevant criteria for evaluation of the impact of AI-based tools on the design of cities—namely, accessibility and reliability of data, as well as adaptability and replicability of those tools. The synthesis of the recent studies justifies the introduction of classification of six main areas of use of urban big data analytics based on AI-related tools. Further exploratory research analysing the current studies and applications in those categories aiming to support urban change, followed by analyses of the most significant criteria of their evaluation—range of the analyses, type of AI-based tools and data, impact on design and planning, strengths and limitations—were conducted.

This study is based on a systematic review described by Cook, Mulrow, and Haynes [57], aiming to adopt a replicable, scientific process to minimise bias through an exhaustive literature search and by providing an audit trail of procedures and conclusions [48]. Integrative reviews, as the broadest type of research review method, allow for the simultaneous inclusion of experimental and non-experimental research to fully understand the phenomenon of concern [58]. It also allows for combining evidence from the theoretical and empirical literature. A similar type of review was conducted by Hao et al. [36]; however, it was limited only to Chinese studies and concerned only the use of big data, while this study focuses on the worldwide use of AI-based tools for big data analytics. This integrative systematic literature review was based on the following steps presented by Whittemore and Knafl [59]: (1) identification of the problem, (2) literature search, (3) data evaluation, (4) data analysis, and (5) presentation, though the methodology was adjusted to the different field of study.

Identification of the problem was based on seeking an answer to the research questions that were formulated in the introduction. For **literature research**, the author analysed research papers on the application of big data analytics and AI-based tools in urban planning and design. The included papers were sourced from the Web of Science Core Collection using the keywords 'ARTIFICIAL INTELLIGENCE' and 'URBAN/CITY/CITIES' to construct the initial corpus of literature. Those keywords were sought in the titles, the keywords of the papers, and the abstracts. The second literature query was conducted using the terms 'BIG DATA' and 'URBAN/CITY/CITIES' as keywords; thus, as it included many unrelated searches, while the most important sources appear on both of the abovementioned searches, the latter search was abundant. Books and book chapters were excluded from the query. After this search, only papers from the urban studies, regional urban planning, geography, architecture, transportation, and environmental studies categories were included. The resulting database that consists of 134 papers was imported into the Mendeley® software. Further, 54 papers in the seed corpus not fitting the scope were manually removed, e.g., including studies of the use of AI in construction or innovation policy evaluations. This analysis of the abstracts narrowed the study to 82 papers.

In the **data evaluation** phase, this core literature was analysed from multiple perspectives. Due to the diverse representation of primary sources, they were coded according to various criteria relevant to this review: year of publication, research centre, type of paper (theoretical, review, and experimental), type of data, and AI-based tools that were used. This allowed for the identification of publications related to, among others, the most renowned data centres such as Media Lab MIT, Senseable City Lab MIT, Centre for Advanced Spatial Analysis UCL, Future Cities Laboratory, and Urban Big Data Centre. The final sample for this integrative review included empirical studies (64), theoretical papers (4), and reviews (14). Only 9.7% of the papers were published before 2010. The main types of data used are mobile phone data, volunteered geographic information data (including social media data), search engine data, point of interest data, GPS data, sensor data, e.g., urban sensors, drones, and satellites, data from both governmental and civic equipment, and new sources of large volume governmental data.

Data analysis started with the identification of opportunities and barriers to foster or prevent the use of big data and AI in emerging urban practices. Strengths and limitations of the use of different types of urban big data analytics based on AI-based tools were identified in both the review papers and the experimental studies from the literature corpus. This analysis was conducted through the lenses of accessibility and reliability of data, as well as adaptability and replicability of AI-related tools.

With the aid of qualitative content analysis of the literature corpus, the review results were **presented** in the more systematic and comparable form of a typology identifying the major fields of use of urban big data analytics based on AI-based tools. In this step, all experimental studies were coded according to the defined six major fields of use. A synthesis in the form of typology was developed to comprehensively portray the impact of AI-based tools and urban big data analytics on the design and planning of cities. The typology was based on the work of Hao et al. [36] but further developed based on the conducted literature review. Further analyses helped to define the of structure the results tables and to categorise the impacts on the design and planning, strengths, and limitations of each field of use of urban big data analytics based on AI-based tools. At the end of the paper, the main findings are discussed through the lens of the research questions introduced at the beginning of this study: the author identified six major fields where these tools can support the planning process to assess the potential of using urban big data analytics based on AI-related tools in the planning and design of cities and the role of AI-based tools in shaping policies to support urban change. Finally, cognitive conclusions and recommendations for planning practice—defining the main points for big data and AI-based analysis to better reach policymakers and urban stakeholders—were formulated.

4. Urban Big Data Analytics with AI-Based Tools in the Design and Planning of Cities

Recent years mark a rapid expansion of urban studies and planning practices using urban big data and AI-based tools. At the same time, as it is still an emerging field, the impact on the design and planning of cities needs to be further assessed. To this end, based on the introduced assessment framework, the author proposed a typology of the use of big data and AI-based tools in urban planning with regard to their aim and range, types of AI-based tools and data being used, impact on design and planning, as well as strengths and limitations.

4.1. Classification of Data Sources Supporting AI-Based Urban Analysis

Before introducing a framework to analyse urban processes using big data analytics, the full recognition and classification of the data sources are needed [2]. There are various typologies of data sources that can be defined as big data [8,36,60]. Their frequency and sample size are important features, so in this paper, the author defined, following a study by Hao et al. [36], big data as both high-frequency and low-frequency data with large sample sizes. The author proposed a typology of urban big data based on the work of Thakuriah et al. [60], who argue that big data can be both structured and unstructured data generated naturally as a part of transactional, operational, planning, and social activities in the following categories:

- **Sensor systems gathered data** (**infrastructure-based or moving object sensors**)—environmental, water, transportation, building management sensor systems; connected systems; Internet of Things; drone, satellite, and LiDAR data;
- **User-generated content** (‘**social**’ **or** ‘**human**’ **sensors**)—participatory sensing systems, citizen science projects, points of interest (POI), volunteered geographic information (VGI), web use, e.g., search engine data, mobile phone data (MPD), GPS log data from handheld GPS devices, online social networks, and other socially generated data;
- **Administrative (governmental) data (open and confidential microdata)**—open administrative data on taxes and revenue, payments and registrations; confidential personal microdata on employment, health, welfare payments, education records, detailed digital land use data, parcel data, and road network data;
- **Private-sector data (customer and transactions records)**—store cards and business records, smart card data (SCD), fleet management systems, GPS data from floating cars (Taxis), data from application forms; usage data from utilities, and financial institutions;
- **Historical urban data, arts and humanities collections**—repositories of text, images, sound recordings, linguistic data, film, art, and material culture, and digital objects, and other media;
- **Hybrid data (linked and synthetic data)**—linked data including survey—sensor or census—administrative records.

A large number of reviewed studies use social media data to study the opinions of city dwellers [61,62]. These data provide quite precise geo-location and allows researchers to conduct urban analyses where no other data sources are available [27]. New sources of large volume governmental data are used in the majority of cases for analyses of urban growth dynamics [29], environmental conditions [63], and traffic studies [51]. GPS data from floating cars [44], and handheld devices [40] are used in various types of analyses of the flows of people and vehicles. The strengths and limitations of those types of data are described below in Section 4.4.

New sources of data, which have emerged as a result of technological, institutional, social, and business innovations, substantially increase the opportunities for urban researchers and practitioners. Traditional temporal data are often gathered at a one-year scale, while analyses using traditional spatial data often ignore temporal variations, lacking dynamic elasticity or offering a predominantly fragmented picture of a given phenomenon. Those problems could be overcome with the use of new types of urban data of high spatiotemporal refinement such as mobile phone data or GPS data. Additionally, traditional individual attributive data gathered in questionnaires and interviews focus on socio-economic features such as gender or occupation and are not useful to reflect attributes such as preferences or emotions of individuals.

At the same time, new ways of accessing existing sources of data, and innovations in the linkage of data belonging to different owners and domains, which are leading to new connected data systems [60], are of equal importance in the development of this field. The conducted review shows that the need for data integration starts already on the level of a single data source, which often needs to be transformed before a consistent database is created and is even more pronounced in more complex models, which link data of different types and owners.

4.2. Types of AI-Based Tools Used in Urban Planning

Wu et al. [40] propose a classification of AI-based tools used in urban planning, which divides them into the following four groups according to their application and properties:

- **Artificial life**—cellular automata, agent-based model, swarm intelligence;
- **Intelligent stochastic simulation models**—the most important of which are genetic algorithms and simulated annealing;
- **Evolutionary computing and spatial DNA**— the most important of which are artificial neural networks (convolutional and recurrent) and spatial DNA;
- **Knowledge-based intelligent systems**—fuzzy logic, expert systems, heuristics, and reasoning systems.

Artificial intelligence-based tools—namely, artificial neural networks and genetic algorithms or their combinations, are gaining ground for use in the main types of micro-dynamic models such as the microsimulation model, cellular automata, and agent-based microsimulation model [36]. In order to avoid the limitations of the different types of tools, various studies combine two or more of those, such as ANN algorithms with cellular automata for the modelling of urban growth [30] or with fuzzy logic for the risk-based asset management of water piping networks [64].

4.3. Use of Urban Big Data Analytics Based on AI-Related Tools

The use of big data rises technological and methodological challenges, as well as complexities regarding the scientific paradigms and planning trends. In the context of the design and planning of cities, based on the conducted literature review, one can define six major fields of use of AI-based tools and urban big data, as described in Table 1: (1) analyses of regional linkages and polycentric spatial structure; (2) urban spatial structure and dynamic; (3) urban flows; (4) urban morphology and digital urban image; (5) the behaviour and opinions of urban dwellers; (6) urban health, microclimate, and environment. While there are various ways to organise big data analyses for urban research and applications, the grouping here is primarily informed by both the subject and type of analyses, but other factors such as the methods of generation and access to data, together with its strengths and limitations, were also considered. This typology is not mutually exclusive; for example, analyses of spatial mobility patterns might be used to study urban dynamics and the behaviour of urban dwellers.

Table 1. Impact of IA algorithm-based tools in the design and planning of cities.

Fields of Use	Aim and Range	Research Studies	Types of AI-Based Tools	Impact on Design and Planning
Regional linkages and polycentric spatial structure analyses	Analyses of flows of people, goods, capital, and information among regions and cities; various kinds of economic, social, and spatial linkages among cities; urban boundaries and spatial expansion simulation; performance of spatial structures at regional/urban scale	[29,35,50,65,66]	Knowledge-based intelligent systems–(Fuzzy Logic, Rough Sets); Evolutionary computing and spatial DNA–(Artificial Neural Networks); Artificial life–(Cellular Automata, Agent-Based Models)	• Can reflect complex features, e.g., mobility, ambiguity, and spatiotemporal dynamics • Support evolution from the urban hierarchy to modelling urban networks; • Allow the description of urban flows from the individual level, reflecting the fine-scale of regional changes • Allow assessing the spatiotemporal evolution of urban networks
Urban spatial structure and dynamic analyses	Analysing the spatial structure and 'pulse of the city'; study of functional structure based on citizens activities; spatial mobility patterns; recognition of spatial characteristic of commercial centres and public spaces; Point of Interest analysis applied to advanced land-use identification and urban structure analysis	[27,30,53,54,56,65,67–72]	Knowledge-based intelligent systems–(Fuzzy Logic, Rough Sets); Evolutionary computing and spatial DNA–(unsupervised machine learning–SOM, Artificial Neural Networks); Artificial life–(Cellular Automata, Agent-Based Models)	• High-frequency data allow for the study of the growing dynamics and liquidity of the spatial structure of cities • Allow for refinement of spatiotemporal interactions • Can help planning in a data-scarce environment • Could lay a foundation for optimisation of urban land classification standards
Urban flows analyses	Urban traffic analyses and determination of the capacity of transport networks; analyses of transportation connectivity; analysis of jobs-housing balance and commuting corridors; energy planning models	[36,40,44–46,52,67,73–77]	Intelligent stochastic simulation models–(Genetic Algorithms); Evolutionary computing and spatial DNA–(Artificial Neural Networks, reinforced learning)	• Analyses of patterns embedded in the network of MPD interaction and smartphone users' movements can support transport system optimisation and spatial structure improvements • Due to its spatial accuracy, can also support spatial planning and transport organisation at the meso- and community-planning scale
Urban morphology analyses	Analyses of the change of urban form and evaluation of land-use planning; landscape analyses; study the process of formation and transformation of human settlements; digital expression of city image; evaluation of urban form; evaluation of liveability of urban space, e.g., based on urban point of interest data	[24,78–83]	Knowledge-based intelligent systems–(Rough Sets); Intelligent stochastic simulation models–(Genetic Algorithms); Evolutionary computing and spatial DNA–(unsupervised machine learning–self-organising maps, Artificial Neural Networks);	• allow for the evaluation of public spaces and creation of typologies based on large samples • urban image as a kind of human-based data can help to reveal the cityscape at the pedestrian level and assist enhancement of the urban landscape • can reduce the need for extensive fieldwork: interviews, neighbourhood tours, and expert consultation

Table 1. *Cont.*

Fields of Use	Aim and Range	Research Studies	Types of AI-Based Tools	Impact on Design and Planning
Analyses of the behaviour and opinion of urban dwellers	Study of the spatial pattern of behaviour of individuals, visualisation of social networks; recognition and simulation of individual mobility; simulation of the behaviour characteristics of both residents and visitors as well as their trajectories; analysis of sentiments	[35,55,61,62,84–87]	Knowledge-based intelligent systems—(fuzzy logic); evolutionary computing and spatial DNA; machine learning artificial neural networks; artificial life (cellular automata)	• Reflect dynamic attributes at the spatiotemporal scale: preference, emotions, and satisfaction of individuals • Allow for new types of analyses based on specific behavioural patterns and as such can provide more reasonable and accurate explanations for evolution mechanisms of complex systems
Urban health, microclimate, and environment analyses	Analyses of the resilience of urban structures; analyses of urban microclimate and urban heat islands; analyses of major environmental threats, e.g., flooding, heat or air quality; participatory sensing of urban space	[42,47,63,64,88–96]	Knowledge-based intelligent systems–(Fuzzy Logic); Intelligent stochastic simulation models–(Genetic Algorithms); Evolutionary computing and spatial DNA–(reinforced machine learning, Artificial Neural Networks)	• By the inclusion of user-generated content, and data from participatory action research, more detailed analyses of the resilience of urban structures can be supported • Can help to measure ecological behaviour and support urban planning practices that promote such behaviour • If based on regular image acquisitions, can be especially valuable to track temporal changes

4.4. Impact of AI and Urban Big Data Analysis

Those analyses mainly measure individual behaviour data at different spatiotemporal scales using spatial, temporal, and individual attributive data. To assess the impact of those technologies, it is vital to define different scales of intervention of new AI and urban big data analysis starting from local fine-grained analyses of urban spaces such as street and plaza (possible due to geolocation) through the neighbourhood, and up to the city or even regional scale (allowing to study functional connections).

Regional linkages and polycentric spatial structure analyses can help to reflect complex features such as mobility and ambiguity and to illustrate spatiotemporal dynamics. They can support evolution from the urban hierarchy analyses to modelling urban networks, from static total amounts to dynamic flows, by allowing the description of those flows from the individual level and reflecting the fine-scale of regional changes. Analyses of this kind assess the spatiotemporal evolution of urban networks; they are not limited to administrative unit boundaries but allow for analysing functional areas.

Urban spatial structure and dynamic analyses using data with high-frequency allow for the study of the growing dynamic and liquidity of the spatial structure of cities and, at the same time, allow for a refinement of spatiotemporal interactions such as individual user trajectories. New data sources can help planning in a data-scarce environment, where traditional data sources are not available, and lay a foundation for optimisation of urban land classification standards.

Urban flows analyses allow the study of patterns embedded in the network of MPD interaction and mobile phone holders' movements and, due to their massive volume and high frequency of data, can support transport system optimisation and spatial structure improvements. Their spatial accuracy can provide support to spatial planning and transport organisation at the meso- and community-planning scales.

Analyses of urban morphology can reduce the need for extensive fieldwork, e.g., interviews, neighbourhood tours, and expert consultation, as analyses of large volumes of data (e.g., images, with AI algorithms) allow for the evaluation of public spaces and the creation of typologies based on very large samples. Urban image as a kind of human-based data can reveal the cityscape at the pedestrian level and assist the enhancement of the urban landscape.

Analyses of the behaviour and opinion of urban dwellers could help in reflecting fixed features, e.g., age, gender, occupation, but also other attributes that are dynamic at the spatiotemporal scale: preference, emotion, and satisfaction of individuals. Such analyses allow the study of specific behavioural patterns using, e.g., agent-based microsimulation models. They could provide more reasonable and accurate explanations for evolution mechanisms of complex systems and help to identify concerns, emotions, and preferences among citizens, particularly in response to the changing conditions such as urban operation disruptions and policy changes.

Urban health, microclimate, and environment analyses, through the extension of traditional data sources to include user-generated content and data from participatory action research, can support the transition into more resilient urban structures. Analyses of this kind measure ecological behaviour and support urban planning practices that enhance such behaviour. As sensor systems are now likely to be wirelessly connected, mobile, and significantly more embedded and distributed, when those analyses rely on sensor data from regular image acquisitions, they can serve as a valuable source of information for tracking temporal changes.

The new tools have **significant** strengths (see Table 1); conducted review supports Allam and Dhunny's [9] claim that the primary advantage of AI in big data analysis is that it supports the heterogeneity and commonality principles which are at the core of big data analytics [56,73]. They enable planners and design practitioners to understand the place from afar. If the studies are performed with scientific rigour combined with traditional planning analysis and validated by those, e.g., using triangulation, such analyses can enrich the results obtained from fieldwork such as interviews, neighbourhood tours, and expert consultation [78,97]. Mobile phone data or social media data can cover a relatively large area and, due to the volume of the sample, build up a relatively comprehensive picture. Studies are not limited to the administrative unit in which data are traditionally gathered. Many posts contain geographic coordinates, allowing researchers to geotag the samples with high precision [21]. New data sources, due to their high volume and frequency, help to reflect complex features such as mobility, ambiguity, and spatiotemporal dynamics. Additionally, classic techniques such as regression analysis, mathematical programming, and input–output analysis do not perform that well in modelling the complex, dynamic and nonlinear factors inherent in urban systems or subsystems [47,85,88,89]. AI-based tools make it possible to answer some of the challenges that emerge in urban modelling, shifting it from macro to micro, from static to dynamic, from linear to nonlinear, from structure to process, from space to space–time [98].

Big data and AI-based tools have significant potential for developing new types of analysis; however, there are also important **limitations** of each type of analysis, which need to be identified in order to assess their effectiveness. The assessment includes identification of the challenges that appear while implementing AI-based tools in spatial analyses, including the aspect of the reliability and accessibility of the data, followed by evaluation of the usability of those tools to support data-driven urban planning (details in Table 2). Big data can add to the complexity of data reliance [9]. Bari [99] stresses that the availability of big data poses various challenges including scaling, spanning, preparation, analysis, and storage bottlenecks. Another important aspect is the limited access to some sources of big data, e.g., social media data, due to personal security purposes or the unstructured nature of the data gathered [24]. To respond to a lack of integration of data limits its usability, Neves et al. [100] propose the introduction of an open data policy, which could foster new types of studies and have the potential to enhance innovations. At the same time, such policies need to be assessed through the lenses of confidentiality and ethics. Solving the problem of the unstructured nature of data and their integration regarding all four phases of acquisition, storage, calculation, and distribution calls for the emergence of urban data platforms.

Moreover, sceptics of social media data contend that activities in the virtual world may not reflect real life, e.g., Rost et al. [101], arguing that social media users tend to represent the population groups that are young, technology savvy, and male. Distortion can also be caused by political campaigns and large public events. This bias requires careful filtration of volunteered geographic information, including social media data, and is the problem that needs to be solved for big data applications. In the current literature, there are two main solutions for this problem: (1) combining big data with traditional data sources, e.g., small data used for model construction, and big data are applied to simulate and verify the established model ([102], as cited in [36]); (2) verifying the reliability of big data with recognised theories and models [36,97,103]. As far as AI-based analytics tools are concerned, while big data call for large sample size [104], one has to take into consideration possible problems of noise accumulation, spurious correlations, measurement errors, and incidental endogeneity, which may impact the results or at least prologue the time of the studies [9].

Table 2. Use of urban big data in design and planning of cities.

Fields of Use	Main Types of Big Data	Strengths	Limitations
Regional linkages and polycentric spatial structure analyses	Mobile phone data, volunteered geographic information data (incl. social media data), search engine data, new sources of large volume governmental data	High spatiotemporal precision; large sample size; mass coverage; no need for extra equipment; for volunteered geographic information and search engine data: relatively easy to obtain; for new sources of large volume governmental data: relatively cheap, potentially less intrusive, but comprehensive	Possible information bias; for volunteered geographic information and search engine data: the threat of duplicate and invalid information, uncertain source; for mobile phone data: failing to obtain individual attributes, missing information may not be compensated
Urban spatial structure and dynamic analyses	Mobile phone data, handheld GPS devices data, point of interest data; new sources of large volume governmental data; volunteered geographic information data (incl. social media data)	High spatiotemporal precision; allow for obtaining overall picture; for mobile phone data and volunteered geographic information: no need for extra equipment; for mobile phone data: large sample size; for handheld GPS devices: collected in real time	Failing to obtain individual attributes (for mobile phone data: missing information may not be compensated, for handheld GPS devices: may be partly supplemented by surveys and interviews; for handheld GPS devices: relatively small sample size and the need of equipment; for MPD: information bias
Urban flows analyses	Mobile phone data; gps data from floating cars; volunteered geographic information data (incl. social media data)	high spatiotemporal precision; for GPS from float cars: collected in real time; for mobile phone data: no need for extra equipment, large sample size	information bias (for GPS data smaller than social media data); for gps from floating car data: does not show all trips, smaller sample size, instability; for mobile phone data: missing information may not be compensated, failing to obtain individual attributes
Urban morphology analyses	Social media data; new sources of large volume governmental data; point of interest data; volunteered geographic information	Due to their geolocation, allow fine-grained analyses; high degree of automation; large samples securing higher objectivity; for social media data: relatively easily accessible; high spatiotemporal precision	Information bias (virtual world activities may not reflect real life); for new sources of large volume governmental data: databases are often in different formats or even unstructured; for social media data: the need for capacity to analyse voluminous data such as images; for POI: relatively difficult to collect in real time
Analyses of the behaviour and opinion of urban dwellers	Social media data; volunteered geographic information; mobile phone data	For volunteered geographic information: allows for obtaining individual attributive information through text information mining, such as preference, emotion, motivation, and satisfaction of individuals; for social media data: can cover a relatively large area and due to the volume of the sample; for mobile phone data: helps to model detailed individual attributes	Information bias; even if it can ease the amount of fieldwork, it is still time consuming—both in terms of the procedure and data preparation standards; for volunteered geographic information: smaller sample size than, e.g., mobile phone data; refinement of individual attributive data lacks high precision
Urban health, microclimate, and environment analyses	sensor data, e.g., urban sensors, drones, and satellites, from both governmental and civic equipment; new sources of large volume governmental data	Realise refinement of individual attributive data; enable conducting simulations of traditional, data-scarce environments; if archived over long periods, can be used to study environmental changes; possibility to collect massive amounts of high temporal- and high spatial resolution data	Need for specific and, in some cases, costly equipment; requirement of regular maintenance (if used over a long period); very diverse access and data governance conditions, as sensor systems might be government or privately owned; while frequently covering long time frames, seldom have large-scale spatial coverage

5. Results

Although the use of big data and AI-based tools in urban planning is still in the development phase, the current research shows numerous applications of those instruments in various fields of planning. While assessing the **potential of using urban big data analytics based on AI-related tools to support the planning and design of cities**, based on this literature review, the author identified six major fields where these tools can support the planning process, which include the following:

- **Large-scale urban modelling—**the use of urban big data analytics AI-based tools such as artificial neural networks allows analyses to be conducted using very large volumes of data both in terms of the number of observations and their size (e.g., interpretation of images). One can observe the increasing popularity of complex systems approaches using individual attributive data, e.g., agent-based models [37];
- **High velocity and frequency—**create conditions to capture urban processes such as rapid urbanisation without waiting for the periodic publication of data from official administrative sources but to conduct nearly real-time observation, which helps to define urban change [35,50,73];
- **Functional, often a fluid definition of the study area—**the boundaries between regions and areas are often blurred, and the emergence of 'soft spaces' prevents analyses that are limited to administrator boundaries from capturing different phenomena such as mobility or common labour markets. Urban big data can support various strategies prepared for 'soft spaces' in between the formal, statutory scales of government [66], from area masterplans to multiregional growth strategies [24];
- **High granularity—**Big data have functions beyond enabling quantitative analyses of urban morphology of higher accuracy and granularity, as the data are often geo coded [6,61]. They permit in-depth analyses but also provide a wider perspective to reveal the dynamics behind complex urban processes and structural patterns.
- **Collaboratively Sensing the City—**User-generated content, especially volunteered geographic information, is becoming an important source of information for urban participatory practice to gather information, generate ideas, and even generate solutions to the diagnosed problems [62,68];
- **Empirical Urban Research—**use of big data and AI allows for widening the scope of possible analyses to find a way to measure, and as result make an evidence-based decision, such phenomena as spatial quality and urban image [55,65]. It helps to effectively combine quantitative studies with a qualitative approach, and even to quantify behaviours, sentiments, or happiness [97].

The studies introduced in this paper confirm that **urban big data and AI-based tools can help in shaping urban policies to support urban change**. Indeed, the spectrum of possible analyses is broadened, and methods previously associated with other disciplines can now be used to analyse and improve the built environment, e.g., quantifying urban elements (e.g., cars, trees) through image detection can be a tool to assess and further improve the quality of the public realm. Additionally, the use of new data sources such as points of interest, volunteered geographic information, mobile phone data, and GPS Log data enables researchers to conduct much deeper studies of, e.g., the 'pulse of the city'. The linkage of existing data sources such as mobile phone data with social media data can further broaden the scope of analyses. Data-based urbanism allows for dynamic resource management of urban assets and infrastructure, to support the planning of more resilient urban structures and social inclusion in mobility. As some sources of big data are collected in real time and not limited to the boundaries of administrative units, there is the possibility to introduce a new approach to planning metropolitan areas based on functional connections, as analyses do not need to be limited to statistical office data, which are released twice a year and aggregated to administrative units. Additionally, obtaining geo-coded data allows for fine-grained analyses of the built environment, which, in turn, enables better identification of users' needs. Urban big data and AI-based tools support the creation of plans that, instead of introducing the final vision, show possible scenarios of development and evaluations that allow the assessment of and design for urban change.

The conducted literature mapping confirms that big data analytics based on AI-related tools applied in the planning of cities can, in many cases better, describe the complexity of a city's functional and spatial structure and help successfully manage urban change, because AI-based tools allow for more precise research of urban dynamics, which is a base to analyse the city as flows of people, goods and energy, not as a planned static structure. Geo-located data allow the study of the heterogeneity of space and provides fine-grained urban analyses specific enough to show how urban change was accomplished. AI-based tools for big data analytics allow for a higher degree of refinement and more accurate empirical studies. They can increase the accuracy and precision of traditional spatial planning analyses but can also assist in dynamic, even real-time evaluation. Additionally, the frequency of data plays a significant role in defining the possible use of their different types. A particular tension of the opposed temporalities between high-frequency data and the long-term structural urban challenges can be observed, as the strategic value of big data for cities helps to bridge fundamentally different temporal scales of urban dynamics: the short-term scale of fast dynamics and the long-term, of much slower dynamics of traditional urban planning and policy [8]. Those features bring big data analytics much closer to the notions of urban change and the complexity of city structures. Therefore, big data analytics based on AI-related tools can support traditional planning techniques, which are based mostly on static data and often ignore temporal variations.

At the same time, even though the technologies associated with artificial intelligence and big data have the potential to render numerous positives to the urban fabric, they should not be blindly adopted. Technology needs to be integrated into the societal fabric [9] and be developed to answer the needs of urban dwellers. Moreover, given the representation bias of social media data, mobile phone data, and volunteered geographic information, these techniques cannot substitute for classic urban analyses. In order to enable a holistic approach to design and planning, there is a need to integrate those data sources and combine them with other more traditional methods of urban assessment. At the same time, there are still various concerns about big data analytics based on AI-related tools connected, for example, with the accessibility to and accuracy of big data, as well as the limitations of different types of AI-based tools which do not permit this kind of analytics to fully replace traditional urban planning analyses. In terms of technological change, the application of big data in design and planning may greatly support traditional planning methods and provide conditions for innovation; however, due to its limitations, it can only enrich but in no way replace traditional urban studies.

6. Discussion

6.1. Cognitive Conclusions

The analyses of urban systems are theoretically underpinned by economic, social, behavioural, biological, and physical principles that allow for the simulation of complex interactions, flows, movements, and diffusion patterns, while the emerging field of data science often relies on a strictly empirical approach without reference to the social, psychological, economic, and regional planning theories [60] that frame urban research. At the intersection of those two approaches, the use of urban big data and AI-based tools allows for analyses of detected patterns, knowledge discovery, empirical explanation, and hypothesis generation regarding urban phenomena and trends. As this study confirms [64], to make this happen, there is a need to retrieve and extract information from unstructured or very voluminous streams of data, and further to reconfigure and structure big data through data preparation techniques for it to meet the input requirements of existing or emerging urban modelling approaches.

Kandt and Batty [8] stress the importance of the theoretical underpinning of big data analyses, as the room for discretion in the interpretation of big data and AI analyses is much larger than in, e.g., survey data. Thus, theoretical reasoning and contextualisation play a much greater yet even more elusive role in the practice of big data analytics [8]. The reviewed papers [97,103] confirm the importance of the cognitive processes that are involved in interpreting the patterns found in big data. Additionally, promoting open science aspects and deeper integration between disciplines [104] may ensure higher recognition of the potential use of big data and AI-based research in urban planning.

6.2. Recommendations for the Planning Practice and Future Application Trends

The emergence of big data raises a range of concerns in line with issues regarding confidentiality and ethics [9], and this study confirms [6] that these concerns are also present while using these tools in the field of urban planning. As user-generated content is often gathered without the consent of its subjects, it is vital to introduce regulations that will protect their privacy and safety, while in this case, the contributors are even not conscious if and how the data are used, volunteered geographic information is gathered in a contributory, collaborative, or co-creative process [105]. Using sensors or social media, and other socially generated information resulting from their participation in social, economic, or civic activities, citizens are turning from being passive subjects of survey and research studies to being active generators of information [60]. De Mauro et al. [106] stress the impact of the advancement of big data analytics on society, and other reviews [29,30] support this claim, as such analytics can shift the way we analyse the information that is used as a base of the data-driven transformation of urban space. At the same time, technological factors need to be weighed with respect to societal integration and the focus on liveability, as technology needs to be used to improve urban life in terms of both performance and efficiency.

On the other hand, open data initiatives have the potential to enhance innovations [107]. A conducted review [24] confirms Gurstein's [108] claim that if wisely adopted, such initiatives can address the needs of the disadvantaged groups. At the same time, open data initiatives, although they present many opportunities, can face challenges for a number of reasons including privacy legislation and limitations in data quality that prohibit their publication or limited user-friendliness [109]. Another important aspect is the introduction of urban data platforms which could provide seamless integration of data acquisition, storage, calculation, and distribution. On the conditions identified above, big data and AI-based tools can support the current urban design and planning of cities and regions.

In view of the study conducted, we can identify possible application trends for the use of urban big data analytics based on AI-based tools in urban design and planning. With the increase in the processing and computational power and wider access to pre-trained ANN algorithms, deep learning models could become a more mainstream tool for urban analytics. Additionally, cloud-based services, which allow easier access to data, in some cases, at a fraction of the cost and availability of computer system resources, especially the data storage and computing power, can enhance this trend. One can expect that the technologies currently applied in other fields may have the potential to become more widely used in urban planning; thus, we are likely to observe a greater variety of types of AI-based tools used in urban analytics. This may concern, for example, reinforcement learning models which can be used for optimal decision making in complex environments, even though till now the majority of models in evolutionary computing used in urban planning are applications of unsupervised and supervised learning. We can expect further development of digital-twins technologies and their increasing role in urban management as well as urban planning; thus, using predictive models for interdependency modelling based on accurate input data can improve longer-term scenario planning. AI-based tools will not solve urban planning problems by themselves; however, emerging technologies can be integrated into existing information systems and, as such, provide more intelligent and effective solutions to urban problems.

While taking into consideration already risen concerns about security and safety of data, we can also predict that the issue of ethical responsibility and regulation will be even more pronounced and new networks, protocols, and systems for increased security will be introduced. At the same time, the majority of current models focus on single sector domains such as transport or pollution which call for an introduction of integrated tools that interlink different urban layers through the sharing of data and introduction of models allowing for higher interoperability of the systems.

6.3. Contribution and Future Directions of Studies

The proposed framework can be of help for both planning practitioners interested in AI-based tools for urban big data analytics and for urban theorists working on new methods of assessing urban change, as it identifies the main areas of their use in recent studies. This paper provides a conceptual contribution that discusses the role of urban big data analytics based on AI-based tools in modelling urban change. While analysing the uses of urban big data and AI-based tools, this study, by showing general trends, strengths and limitations, can form a base for future comparative studies between regions and cities showing what the main barriers are impeding the use of those kinds of tools in the regional context. Access to the data varies between countries or even cities; thus, it is worth conducting studies that take into consideration regional specificities in the possibilities of the use of big data. Such a study can help to identify the variety of both different approaches and especially place-specific policies connected with data acquisition, storage, management, and distribution.

The next vital aspect is to study the potential to use urban big data analytics based on AI-related tools to model the resilience of urban structures and support the regenerative design and planning of cities, which could be an important direction of future studies. Intelligent systems can add to the optimisation of the use of resources in the urban environment but in order to do so, there is a need to identify ecologically sounded indicators which allows for continuous monitoring of the built environment, allowing to tap into the potential of big data analytics based on AI-related tools.

As the majority of revised papers focus on sectoral solutions or analyses, there is a need to assess the potential of AI-based tools to support decision making in chosen sectors such as energy or transport but also to deal with more complex issues such as the above-mentioned resilience or well-being of urban dwellers. Such an approach could surely help to assess the usability and reliability of urban big data analytics and AI-related tools for multidisciplinary research and urban planning practice, as AI can be an important tool to model the dynamics and heterogeneity of urban space, which, in turn, helps to model urban change.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declares no conflict of interest.

Abbreviations

ANN	Artificial neural network
DNA	Deoxyribonucleic acid
MPD	Mobile phone data
POIs	Points of Interest
SCD	Smart card data
SOM	Self-organisation Map
VGI	Volunteered geographic information

References

1. Goodchild, M. Citizens as Sensors: The World of Volunteered Geography. *GeoJournal* **2007**, *69*, 211–221. [CrossRef]
2. Kamrowska-Załuska, D.; Obracht-Prondzyńska, H. The Use of Big Data in Regenerative Planning. *Sustainability* **2018**, *10*, 3668. [CrossRef]
3. Drożdż, W. Moje miasto, wspólne plany. In *Regionalny Thinkletter Idee dla Pomorza, 1/2020*; Partnerzy Wydawca: Warszawa, Poland, 2020.
4. Wu, N.; Silva, E.A. Artificial intelligence solutions for urban land dynamics: A review. *J. Plan. Lit.* **2010**, *24*, 246–265.
5. Abduljabbar, R.; Dia, H.; Liyanage, S.; Bagloee, S.A. Applications of artificial intelligence in transport: An overview. *Sustainability* **2019**, *11*, 189. [CrossRef]
6. Yigitcanlar, T.; Kankanamge, N.; Vella, K. How Are Smart City Concepts and Technologies Perceived and Utilized? A Systematic Geo-Twitter Analysis of Smart Cities in Australia. *J. Urban Technol.* **2021**, *28*, 135–154. [CrossRef]
7. Raimbault, J. Cities as They Could Be: Artificial Life and Urban Systems. *arXiv* **2020**, arXiv:2002.12926.
8. Kandt, J.; Batty, M. Smart cities, Big Data and urban policy: Towards urban analytics for the long run. *Cities* **2021**, *109*, 102992. [CrossRef]
9. Allam, Z.; Dhunny, Z.A. On Big Data, artificial intelligence and smart cities. *Cities* **2019**, *89*, 80–91. [CrossRef]
10. Dempsey, N.; Bramley, G.; Power, S.; Brown, C. The social dimension of sustainable development: Defining urban social sustainability. *Sustain. Dev.* **2009**, *19*, 289–300. [CrossRef]
11. Crutzen, P.J. The "Anthropocene". In *Earth System Science in the Anthropocene*; Ehlers, E., Krafft, T., Eds.; Springer: Berlin/Heidelberg, Germany, 2006; pp. 13–18.
12. Batty, M. *The New Science of Cities*; MIT Press: Cambridge, MA, USA, 2013.
13. Allen, P.M. Cities and regions as evolutionary complex systems. *Geogr. Syst.* **1997**, *4*, 103–130.
14. Portugali, J. *Self-Organization and the City*; Springer: Berlin, Germany, 1999.
15. Batty, M. *Cities and Complexity: Understanding Cities with Cellular Automata, Agent-Based Models, and Fractals*; MIT Press: Cambridge, MA, USA, 2005.
16. Hopkins, L.D. *Urban Development: The Logic of Making Plans*; Island Press: Washington, DC, USA, 2001; Volume 166.
17. Brindley, T.; Rydin, Y.; Stoker, G. *Remaking Planning: The Politics of Urban Change*; Routledge: Oxfordshire, UK, 2005.
18. Inam, A. *Designing Urban Transformation*; Routledge: Oxfordshire, UK, 2013.
19. Liu, Z.; Cao, J.; Yang, J.; Wang, Q. Discovering Dynamic Patterns of Urban Space via Semi-Nonnegative Matrix Factorization. In Proceedings of the 2017 IEEE International Conference on Big Data, Boston, MA, USA, 11–14 December 2017; pp. 3447–3453.
20. Cranshaw, J.; Schwartz, R.; Hong, J.I.; Sadeh, N. The Livehoods Project: Understanding Collective Activity Patterns of a City from Social Media. In Proceedings of the 6th International AAAI Conference on Weblogs and Social Media, Dublin, Ireland, 4–7 June 2012; pp. 58–65.
21. Bertrand, K.; Bialik, M.; Virdee, K.; Gros, A.; Bar-Yam, Y. Sentiment in New York City: A High Resolution Spatial and Temporal View. NECSI Report. *arXiv* **2013**, arXiv:1308.5010.
22. Quercia, D.; Hare, N.O.; Cramer, H. Aesthetic Capital: What Makes London Look Beautiful, Quiet, and Happy? In Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing, Baltimore, MD, USA, 15–19 February 2014; pp. 945–955.
23. Shi, Q.; Abdel-Aty, M. Big Data applications in real-time traffic operation and safety monitoring and improvement on urban expressways. *Transp. Res. Part C Emerg. Technol.* **2015**, *58*, 380–394. [CrossRef]
24. Allmendinger, P.; Haughton, G. Soft spaces, fuzzy boundaries, and metagovernance: The new spatial planning in the Thames Gateway. *Environ. Plan. A* **2009**, *41*, 617–633. [CrossRef]
25. Kitchin, R. The real-time city? Big Data and smart urbanism. *GeoJournal* **2014**, *79*, 1–14. [CrossRef]
26. Gao, S.; Li, L.; Li, W.; Janowicz, K.; Zhang, Y. Constructing gazetteers from volunteered big geo-data based on hadoop. *Comput. Environ. Urban Syst.* **2017**, *61*, 172–186. [CrossRef]
27. Ibrahim, M.R.; Haworth, J.; Cheng, T. URBAN-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision. *Environ. Plan. B Urban Anal. City Sci.* **2021**, *48*, 76–93. [CrossRef]
28. Mager, T.; Hein, C. Digital excavation of mediatized urban heritage: Automated recognition of buildings in image sources. *Urban Plan.* **2020**, *5*, 24–34. [CrossRef]
29. Grekousis, G.; Manetos, P.; Photis, Y.N. Modeling urban evolution using neural networks, fuzzy logic and GIS: The case of the Athens metropolitan area. *Cities* **2013**, *30*, 193–203. [CrossRef]
30. Soltani, A.; Karimzadeh, D. The spatio-temporal modeling of urban growth case study: Mahabad, Iran. *TEMA J. Land Use Mobil. Environ.* **2013**, *6*, 189–200.
31. Townsend, A.M. *Smart Cities: Big Data, Civic Hackers, and the Quest for a New Utopia*; W. W. Norton & Company: New York, NY, USA, 2013.
32. Kourtit, K.; Nijkamp, P.; Steenbruggen, J. The significance of digital data systems for smart city policy. *Socio-Econ. Plan. Sci.* **2017**, *58*, 13–21. [CrossRef]
33. Batty, M. Urban analytics defined. *Environ. Plan. B Urban Anal. City Sci.* **2019**, *46*, 403–405. [CrossRef]
34. Yan, Z.J.; Li, B.; Li, Q.Q.; Yang, M. An efficient multiple access control protocol for directional dense urban traffic surveillance system. *J. Intell. Transp. Syst.* **2020**, *24*, 237–253. [CrossRef]

35. Hwang, S.; Lee, Z.; Kim, J. Real-Time Pedestrian Flow Analysis Using Networked Sensors for a Smart Subway System. *Sustainability* **2019**, *11*, 6560. [CrossRef]
36. Hao, J.; Zhu, J.; Zhong, R. The rise of Big Data on urban studies and planning practices in China: Review and open research issues. *J. Urban Manag.* **2015**, *4*, 92–124. [CrossRef]
37. Rienow, A.; Stenger, D.; Menz, G. Sprawling cities and shrinking regions-forecasting urban growth in the ruhr for 2025 by coupling cells and agents. *Erdkunde* **2014**, *68*, 85–107. [CrossRef]
38. Kang, Y.; Zhang, F.; Peng, W.; Gao, S.; Rao, J.; Duarte, F.; Ratti, C. Understanding house price appreciation using multi-source big geo-data and machine learning. *Land Use Policy* **2020**, 104919. [CrossRef]
39. Amiri, S.S.; Mottahedi, S.; Lee, E.R.; Hoque, S. Peeking inside the black-box: Explainable machine learning applied to household transportation energy consumption. *Comput. Environ. Urban Syst.* **2021**, *88*, 101647. [CrossRef]
40. Byon, Y.J.; Liang, S. Real-Time Transportation Mode Detection Using Smartphones and Artificial Neural Networks: Performance Comparisons Between Smartphones and Conventional Global Positioning System Sensors. *J. Intell. Transp. Syst.* **2014**, *18*, 264–272. [CrossRef]
41. Natekin, A.; Knoll, A. Gradient boosting machines, a tutorial. *Front. Neurorobot.* **2013**, *7*, 21. [CrossRef] [PubMed]
42. Zhang, F.; Zhou, B.; Liu, L.; Liu, Y.; Fung, H.H.; Lin, H.; Ratti, C. Measuring human perceptions of a large-scale urban region using machine learning. *Landsc. Urban Plan.* **2018**, *180*, 148–160. [CrossRef]
43. Surendra, H.J.; Deka, P.C. Urban Water Consumption Estimation Using Artificial Intelligence Techniques. In *Urban Hydrology, Watershed Management and Socio-Economic Aspects*; Sarma, A.K., Singh, V.P., Kartha, S.A., Bhattacharjya, R.K., Eds.; Springer International Publishing: New York, NY, USA, 2016; Volume 73, pp. 277–285.
44. Cheng, X.M.; Wang, J.Y.; Li, H.F.; Zhang, Y.; Wu, L.; Liu, Y. A method to evaluate task-specific importance of spatio-temporal units based on explainable artificial intelligence. *Int. J. Geogr. Inf. Sci.* **2020**, *35*, 10. [CrossRef]
45. Gilmore, J.F.; Abe, N. Neural-network models for traffic control and congestion prediction. *J. Intell. Transp. Syst.* **1995**, *2*, 231–252. [CrossRef]
46. Hou, Y.; Edara, P. Network Scale Travel Time Prediction using Deep Learning. *Transp. Res. Rec.* **2018**, *2672*, 115–123. [CrossRef]
47. Stajkowski, S.; Kumar, D.; Samui, P.; Bonakdari, H.; Gharabaghi, B. Genetic-Algorithm-Optimized Sequential Model for Water Temperature Prediction. *Sustainability* **2020**, *12*, 5374. [CrossRef]
48. Abarca-Alvarez, F.J.; Campos-Sanchez, F.S.; Osuna-Perez, F. Urban Shape and Built Density Metrics through the Analysis of European Urban Fabrics Using Artificial Intelligence. *Sustainability* **2019**, *11*, 6622. [CrossRef]
49. Kourtit, K.; Nijkamp, P.; Arribas-Bel, D. Migrant Entrepreneurs as Urban "Health Angels"-Contrasts in Growth Strategies. *Int. Plan. Stud.* **2015**, *20*, 71–86. [CrossRef]
50. Baeza, R.A. A methodology for urban sustainability indicator design. *TEMA J. Land Use Mobil. Environ.* **2018**, *11*, 285–303.
51. Varia, H.R.; Gundaliya, P.J.; Dhingra, S.L. Application of genetic algorithms for joint optimization of signal setting parameters and dynamic traffic assignment for the real network data. *Res. Transp. Econ.* **2013**, *38*, 35–44. [CrossRef]
52. Beura, S.K.; Bhuyan, P.K. Quality of Bicycle Traffic Management at Urban Road Links and Signalized Intersections Operating under Mixed Traffic Conditions. *Transp. Res. Rec.* **2018**, *2672*, 145–156. [CrossRef]
53. Liao, J.F.; Tang, L.N.; Shao, G.F.; Qiu, Q.Y.; Wang, C.P.; Zheng, S.N.; Su, X.D. A neighbor decay cellular automata approach for simulating urban expansion based on particle swarm intelligence. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 720–738. [CrossRef]
54. Chen, W.Z.; Zhao, L.; Kang, Q.; Di, F. Systematizing heterogeneous expert knowledge, scenarios and goals via a goal-reasoning artificial intelligence agent for democratic urban land use planning. *Cities* **2020**, *101*, 102703. [CrossRef]
55. Bazzan, A.L.C.; Do Amarante, M.D.; Da Costa, F.B. Management of Demand and Routing in Autonomous Personal Transportation. *J. Intell. Transp. Syst.* **2012**, *16*, 1–11. [CrossRef]
56. O'Sullivan, D.; Haklay, M. Agent-based models and individualism: Is the world agent-based? *Environ. Plan. A Econ. Space* **2000**, *32*, 1409–1425. [CrossRef]
57. Cook, D.J.; Mulrow, C.D.; Haynes, R.B. Systematic Reviews: Synthesis of Best Evidence for Clinical Decisions. *Ann. Intern. Med.* **1997**, *126*, 376–380. [CrossRef] [PubMed]
58. Tranfield, D.; Denyer, D.; Smart, P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
59. Whittemore, R.; Knafl, K. The integrative review: Updated methodology. *J. Adv. Nurs.* **2005**, *52*, 546–553. [CrossRef] [PubMed]
60. Thakuriah, P.; Tilahun, N.; Zellner, M. Big Data and Urban Informatics: Innovations and Challenges to Urban Planning and Knowledge Discovery. In Proceedings of the NSF Workshop on Big Data and Urban Informatics, Chicago, IL, USA, 11–12 August 2014; pp. 4–32.
61. Sun, Y.; Shao, Y.W. Measuring visitor satisfaction toward peri-urban green and open spaces based on Social Media Data. *Urban For. Urban Green.* **2020**, *53*, 126709. [CrossRef]
62. Ghahramani, M.; Galle, N.J.; Duarte, F.; Ratti, C.; Pilla, F. Leveraging artificial intelligence to analyze citizens' opinions on urban green space. *City Environ. Interact.* **2021**, *10*, 100058. [CrossRef]
63. Orun, A.; Elizondo, D.; Goodyer, E.; Paluszczyszyn, D. Use of Bayesian inference method to model vehicular air pollution in local urban areas. *Transp. Res. Part D Transp. Environ.* **2018**, *63*, 236–243. [CrossRef]
64. Christodoulou, S.; Deligianni, A.; Aslani, P.; Agathokleous, A. Risk-based asset management of water piping networks using neurofuzzy systems. *Comput. Environ. Urban Syst.* **2009**, *33*, 138–149. [CrossRef]

65. Allam, Z.; Allam, Z. Urban Chaos and the AI Messiah. In *Cities and the Digital Revolution: Aligning Technology and Humanity*; Springer Nature: Basingstoke, UK, 2019; pp. 31–60.
66. Van Geenhuizen, M.; Nijkamp, P. Cities and footlooseness: In search of place-bound companies and effective location policies. *Environ. Plan. C Gov. Policy* **2007**, *25*, 692–708. [CrossRef]
67. Fathi, S.; Srinivasan, R.S.; Kibert, C.J.; Steiner, R.L.; Demirezen, E. AI-Based Campus Energy Use Prediction for Assessing the Effects of Climate Change. *Sustainability* **2020**, *12*, 3223. [CrossRef]
68. Haqbeen, J.; Sahab, S.; Ito, T.; Rizzi, P. Using Decision Support System to Enable Crowd Identify Neighborhood Issues and Its Solutions for Policy Makers: An Online Experiment at Kabul Municipal Level. *Sustainability* **2021**, *13*, 5453. [CrossRef]
69. Intrator, K.; Shivdikar, K. Missing Middle Scenarios: Uncovering Nuanced Conditions in Latin America's Housing Crisis. *Cityscape* **2017**, *19*, 31–43.
70. Jena, S.; Chakraborty, A.; Bhuyan, P.K. Performance Assessment of Urban Streets Addressing Improvement Issues for Automobile Mode of Transport. *Transp. Res. Rec.* **2018**, *2672*, 232–241. [CrossRef]
71. Kourtit, K.; Nijkamp, P.; Van Leeuwen, E. New Entrepreneurship in Urban Diasporas in our Modern World. *J. Urban Manag.* **2013**, *2*, 25–47. [CrossRef]
72. Shen, Z.J.; Kawakami, M.; Kawamura, I. Geosimulation model using geographic automata for simulating land-use patterns in urban partitions. *Environ. Plan. B Plan. Des.* **2009**, *36*, 802–823. [CrossRef]
73. Aschwanden, G.; Wijnands, J.S.; Thompson, J.; Nice, K.A.; Zhao, H.F.; Stevenson, M. Learning to walk: Modeling transportation mode choice distribution through neural networks. *Environ. Plan. B Urban Anal. City Sci.* **2021**, *48*, 186–199. [CrossRef]
74. Arndt, L.T.; Philips, J.W.; Cordeiro, A.D.; Romano, C.A.; Catai, R.E. Domain ontology for urban land management. *Proc. Inst. Civ. Eng. Urban Des. Plan.* **2014**, *167*, 58–68. [CrossRef]
75. Jacob, C.; Abdulhai, B. Machine learning for multi jurisdictional optimal traffic corridor control. *Transp. Res. Part A Policy Pract.* **2010**, *44*, 53–64. [CrossRef]
76. Sheng, Q.; Zhou, C.; Karimi, K.; Lu, A.H.; Shao, M. The application of space syntax modeling in data-based urban design—-An example of Chaoyang square renewal in Jilin city. *Landsc. Archit. Front.* **2018**, *6*, 103–113. [CrossRef]
77. Stathopoulos, A.; Karlaftis, M.G.; Dimitriou, L. Fuzzy Rule-Based System Approach to Combining Traffic Count Forecasts. *Transp. Res. Rec.* **2010**, *2183*, 120–128. [CrossRef]
78. Huang, J.; Obracht-Prondzynska, H.; Kamrowska-Zaluska, D.; Sun, Y.; Li, L. The image of the City on social media: A comparative study using "Big Data" and "Small Data" methods in the Tri-City Region in Poland. *Landsc. Urban Plan.* **2021**, *206*, 103977. [CrossRef]
79. Abarca Alvarez, F.J.; Osuna Perez, F. Semantic mapping though neural networks: The self-organizing maps (SOM) as representation of patterns and fields. *Rev. Expr. Graf. Arquit.* **2013**, *22*, 154–163.
80. Li, X.J.; Cai, B.Y.; Ratti, C. Using street-level images and deep learning for urban landscape studies. *Landsc. Archit. Front.* **2018**, *6*, 20–29. [CrossRef]
81. Quan, S.J.; Park, J.; Economou, A.; Lee, S. Artificial intelligence-aided design: Smart Design for sustainable city development. *Environ. Plan. B Urban Anal. City Sci.* **2019**, *46*, 1581–1599. [CrossRef]
82. Rong, H.H.; Tu, W.; Duarte, F.; Ratti, C. Employing waterborne autonomous vehicles for museum visits: A case study in Amsterdam. *Eur. Transp. Res. Rev.* **2020**, *12*, 1–13. [CrossRef]
83. Wang, W.J.; Wang, W.; Namgung, M. Linking people's perceptions and physical components of sidewalk environments-an application of rough sets theory. *Environ. Plan. B Plan. Des.* **2010**, *37*, 234–247. [CrossRef]
84. Anagnostopoulos, T. A Predictive Vehicle Ride Sharing Recommendation System for Smart Cities Commuting. *Smart Cities* **2021**, *4*, 177–191. [CrossRef]
85. Assi, K.J.; Shafiullah, M.; Nahiduzzaman, K.M.; Mansoor, U. Travel-To-School Mode Choice Modelling Employing Artificial Intelligence Techniques: A Comparative Study. *Sustainability* **2019**, *11*, 4484. [CrossRef]
86. Kedia, A.S.; Sowjanya, D.; Salini, P.S.; Jabeena, M.; Katti, B.K. Transit Shift Response Analysis Through Fuzzy Rule Based-Choice Model: A Case Study of Indian Metropolitan City. *Transp. Dev. Econ.* **2017**, *3*, 8. [CrossRef]
87. Rosa, L.; Silva, F.; Analide, C. Mobile Networks and Internet of Things Infrastructures to Characterize Smart Human Mobility. *Smart Cities* **2021**, *4*, 894–918. [CrossRef]
88. Markose, L.P.; Deka, P.C. ANN and ANFIS Modeling of Failure Trend Analysis in Urban Water Distribution Network. In *Urban Hydrology, Watershed Management and Socio-Economic Aspects*; Sarma, A.K., Singh, V.P., Kartha, S.A., Bhattacharjya, R.K., Eds.; Springer International Publishing: New York, NY, USA, 2016; Volume 73, pp. 255–264.
89. Pirouz, B.; Haghshenas, S.S.; Haghshenas, S.S.; Piro, P. Investigating a Serious Challenge in the Sustainable Development Process: Analysis of Confirmed cases of COVID-19 (New Type of Coronavirus) Through a Binary Classification Using Artificial Intelligence and Regression Analysis. *Sustainability* **2020**, *12*, 2427. [CrossRef]
90. Hsueh, S.L.; Sun, Y.; Yan, M.R. Conceptualization and Development of a DFuzzy Model for Low-Carbon Ecocities. *Sustainability* **2019**, *11*, 5833. [CrossRef]
91. Jung, S.M.; Park, S.; Jung, S.W.; Hwang, E. Monthly Electric Load Forecasting Using Transfer Learning for Smart Cities. *Sustainability* **2020**, *12*, 6364. [CrossRef]
92. Vidana-Vila, E.; Duboc, L.; Alsina-Pages, R.M.; Polls, F.; Vargas, H. BCNDataset: Description and Analysis of an Annotated Night Urban Leisure Sound Dataset. *Sustainability* **2020**, *12*, 8140. [CrossRef]

93. Vogiatzaki, M.; Zerefos, S.; Tania, M.H. Enhancing City Sustainability through Smart Technologies: A Framework for Automatic Pre-Emptive Action to Promote Safety and Security Using Lighting and ICT-Based Surveillance. *Sustainability* **2020**, *12*, 6142. [CrossRef]
94. Wang, L.; Zhao, Q.J.; Wen, Z.M.; Qu, J.M. RAFFIA: Short-term Forest Fire Danger Rating Prediction via Multiclass Logistic Regression. *Sustainability* **2018**, *10*, 4620. [CrossRef]
95. Xiang, X.J.; Li, Q.; Khan, S.; Khalaf, O.I. Urban water resource management for sustainable environment planning using artificial intelligence techniques. *Environ. Impact Assess. Rev.* **2021**, *86*, 106515. [CrossRef]
96. Yin, X.Z.; Li, J.H.; Kadry, S.N.; Sanz-Prieto, I. Artificial intelligence assisted intelligent planning framework for environmental restoration of terrestrial ecosystems. *Environ. Impact Assess. Rev.* **2021**, *86*, 106493. [CrossRef]
97. Filomena, G.; Verstegen, J.A.; Manley, E. A computational approach to 'The Image of the City'. *Cities* **2019**, *89*, 14–25. [CrossRef]
98. Payal Jain, K. A Review Study on Urban Planning & Artificial Intelligence International. *J. Soft Comput. Eng.* **2011**, *1*, 5.
99. Bari, A. *Working with Big Data: Scaling Data Discovery*; Abdallah Bari: Westmouth, QC, Canada, 2017.
100. Neves, F.T.; De Castro Neto, M.; Aparicio, M. The impacts of open data initiatives on smart cities: A framework for evaluation and monitoring. *Cities* **2020**, *106*, 102860. [CrossRef]
101. Rost, M.; Barkhuus, L.; Cramer, H.; Brown, B. Representation and Communication: Challenges in Interpreting Large Social Media Datasets. In Proceedings of the 2013 Conference on Computer Supported Cooperative Work, San Antonio, TX, USA, 23–27 February 2013; pp. 1–6.
102. Sung, H.; Lee, S.; Cheon, S. Operationalizing Jane Jacobs' urban design theory: Empirical verification from the Great City of Seoul, Korea. *J. Plan. Educ. Res.* **2015**, *35*, 117–130. [CrossRef]
103. Fan, J.; Han, F.; Liu, H. Challenges of big data analysis. *Natl. Sci. Rev.* **2014**, *1*, 293–314. [CrossRef] [PubMed]
104. Wellmann, T.; Lausch, A.; Andersson, E.; Knapp, S.; Cortinovis, C.; Jache, J.; Scheuera, S.; Kremerg, P.; Mascarenhasa, A.; Kraemera, R.; et al. Remote sensing in urban planning: Contributions towards ecologically sound policies? *Landsc. Urban Plan.* **2020**, *204*, 103921. [CrossRef]
105. Bonney, R.; Cooper, C.B.; Dickinson, J.; Kelling, S.; Phillips, T.; Rosenberg, K.V.; Shirk, J. Citizen Science: A Developing Tool for Expanding Science Knowledge and Scientific Literacy. *BioScience* **2009**, *59*, 977–984. [CrossRef]
106. De Mauro, A.; Greco, M.; Grimaldi, M. A formal definition of Big Data based on its essential features. *Libr. Rev.* **2016**, *65*, 122–135. [CrossRef]
107. Thorhildur, J.; Avital, M.; Bjørn-Andersen, N. The Generative Mechanisms of Open Government Data, paper, 179. In Proceedings of the 21st European Conference on Information Systems, Utrecht, the Netherlands, 6–8 June 2013.
108. Gurstein, M. Open data: Empowering the empowered or effective data use for everyone? *First Monday* **2011**, *16*. [CrossRef]
109. Huijboom, N.; Van den Broek, T. Open data: An international comparison of strategies. *Eur. J. ePractice* **2011**, *12*, 4–16.