AI-Based and Big Data Analytics on Urban Planning

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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.

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

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 article 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 article 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

After the industrial revolution, humankind entered the Anthropocene [10], 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 [11]. Further, the 1990s brought numerous applications of complexity theories to urban planning [12][13][14]. 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 [15][16] 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 [17]. As urban space is a dynamic system, composed of human and commercial activity, flows of energy and matter, and their interactions [18], 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 [19][20][21]. 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 [22]. 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 [23].

Additionally, data-driven city planning based on urban big data analysis, planned and managed in real-time can support those changes. Urban big data [24], also called geo-big data [25], 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 [26] or mapping cultural heritage [27]) but also advancing existing type of analyses (e.g., simulations of urban growth, which allow the study of the complexity of those processes [28][29]). 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][30][31][32]. 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 [33] and real-time pedestrian flow analysis [34]. Hao et al. [35] 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. [36] 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 [37]. Amiri et al. [38] apply machine learning to household transportation energy consumption, while Byon and Liang [39] focus on real-time transportation mode detection. Moreover, numerous studies [37][40][41] 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 [29], or with fuzzy logic, e.g., for urban water consumption estimations [42].

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][43][44] both of the convolutional [26][45] and recurrent [46] types but also unsupervised machine learning, mainly self-organising maps (SOMs) [47][48]. The next most numerous group contains examples of the Knowledge-based intelligent systems group, where the most important tools are fuzzy logic [28][49] and rough sets [49]. Studies by Varia [50] and Beura and Bhuyan [51] use a genetic algorithm to model the dynamic flow of both cars and bikes. Additionally, artificial life—namely, cellular automata [29][52][53] and agent-based models [54][55], 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.

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 entry: 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 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. 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.

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][35][56]. Their frequency and sample size are important features, so in this paper, the author defined, following a study by Hao et al. [35], 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. [56], 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.

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**	[28][34][49][57][58]	**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

Fields of Use	Aim and Range	Research Studies	Types of AI-Based Tools	Impact on Design and Planning
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**	[26][29][52][53][55][57][59][60][61][62][63][64]	**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**	[35][39][43][44][45][51][59][65][66][67][68][69]	**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

Fields of Use	Aim and Range	Research Studies	Types of AI-Based Tools	Impact on Design and Planning
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**	[23][70][71][72][73][74][75]	**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
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**	[34][54][76][77][78][79][80][81]	**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

Fields of Use	Aim and Range	Research Studies	Types of AI-Based Tools	Impact on Design and Planning
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**	[41][46][82][83][84][85][86][87][88][89][90][91][92]	**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

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).

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