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*Systematic Review*

# Advancing Urban Life: A Systematic Review of Emerging Technologies and Artificial Intelligence in Urban Design and Planning

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**Abstract:** The advancement of cutting-edge technologies significantly transforms urban lifestyles and is indispensable in sustainable urban design and planning. This systematic review focuses on the critical role of innovative technologies and digitalization, particularly artificial intelligence (AI), in urban planning through geo-design, aiming to enhance urban life. It begins with exploring the importance of AI and digital tools in revolutionizing contemporary urban planning practices. Through the methodology based on the Systematic Reviews and Meta-Analyses (PRISMA) protocol, this review sifts through relevant literature over the past two decades by categorizing artificial intelligence technologies based on their functionalities. These technologies are examined for their utility in urban planning, environmental modeling, and infrastructure development, highlighting how they contribute to creating smarter and more livable cities. For instance, machine learning techniques like supervised learning excel in forecasting urban trends, whereas artificial neural networks and deep learning are superior in pattern recognition and vital for environmental modeling. This analysis, which refers to the comprehensive evaluation conducted in this Systematic Review, encompasses studies based on diverse data inputs and domains of application, revealing a trend toward leveraging AI for predictive analytics, decision-making improvements, and the automation of complex geospatial tasks in urban areas. The paper also addresses the challenges encountered, including data privacy, ethical issues, and the demand for cross-disciplinary knowledge. The concluding remarks emphasize the transformative potential of innovative technologies and digitalization in urban planning, advocating for their role in fostering better urban life. It also identifies future research avenues and development opportunities. In light of our review findings, this study concludes that AI technologies indeed hold transformative promise for the field of geo-design and urban planning. They have proven instrumental in advancing predictive analytics, refining decision-making, and streamlining complex geospatial tasks. The AI's capacity to process expansive datasets and improve urban planning accuracy has facilitated more sustainable urban development and enhanced the resilience of urban environments.

**Keywords:** artificial intelligence; urban planning and environmental modeling; machine learning applications; sustainable urban development



**Citation:** He, W.; Chen, M. Advancing Urban Life: A Systematic Review of Emerging Technologies and Artificial Intelligence in Urban Design and Planning. *Buildings* **2024**, *14*, 835. https://doi.org/10.3390/buildings14030835

Academic Editor: Haifeng Liao

Received: 29 February 2024
Revised: 17 March 2024
Accepted: 18 March 2024
Published: 20 March 2024



## 1. Introduction

Artificial intelligence (AI), which offers unprecedented opportunities to enhance urban environments, has fundamentally altered urban life and impacted sustainable urban design and planning irreplaceably. This systematic review aims to underscore AI and digital tools' significant role in transforming contemporary urban planning practices through geo-design, delve into the intricacies of AI's application within the realm of urban planning and help understand the historical context and the evolution of this field.

### 1.1. Research Background

Governments worldwide are beginning to tackle the problems caused by urbanization in the 21st century [1]. The sustainable development of cities and nature increasingly depends on the successful planning of urban growth and the geographical planning and design of regions [2]. In the past thirty years since the influential Brundtland Commission Report, humanity still faces the pressing task of altering its behavior to secure a sustainable future [3]. Despite the intricate nature of these challenges, they demand our full technological prowess to devise solutions for both the immediate and distant future. Artificial intelligence (AI) stands out as a significant opportunity in this endeavor, with its capability for machines to "learn from experience, adapt to new information, and carry out tasks similar to those performed by humans" [3].

AI technology presents three primary advantages. Firstly, it automates crucial yet monotonous and time-intensive tasks, freeing up human capacity for more sophisticated endeavors. Secondly, it unlocks insights buried within vast quantities of unstructured data, including video, photo, textual reports, business documents, social media content, and emails, which previously required manual oversight and analysis. Thirdly, AI has the power to harness the capabilities of thousands of computers and additional resources to tackle highly complex challenges. Hence, utilizing AI to explore solutions for the climate crisis is vital. To accomplish this effectively, comprehensive research is required to understand how AI can seamlessly integrate with human emotions, thought processes, social norms, and behaviors.

In this paper, the authors present the case that AI can aid in creating organizational processes and individual practices that are culturally sensitive and reduce the demand for natural resources and energy in human activities. The real significance of AI lies not just in its capacity to help individuals and society lower their consumption of energy, water, and land beyond.

### 1.2. The Wide Application of Artificial Intelligence Technologies

The progress in AI and data science today holds the potential to fundamentally alter business operations. It achieves this by aiding knowledge workers in conveying their analytical findings, backing up evidence, and making informed decisions [4]. Almost every organization is now focused on understanding their business and transforming data into actionable insights. For example, to detect and quantify a water pollution problem, a water quality monitoring network is designed and established through artificial intelligence technology [5]. Large-scale soil regulation and agricultural sustainability can be addressed with geographic information systems [6]. In landscape architecture planning and design, using scientific analysis methods to quantitatively study the law of site change and provide a scientific decision basis for planning has always been an important topic. The emergence of new technologies, such as big data, has rapidly grown the data related to landscape architecture, providing strong support for the quantitative analysis of site laws.

### 1.3. Advances in Artificial Intelligence Technologies and the Interrelation of Urban Planning

In the past, planners would display their data on large, physical maps and employ tracing paper overlays to incorporate stakeholder information. However, the advent of Geographical Information Systems (GIS) revolutionized this approach by substituting the need for transparent maps with digital map layers, which are presented and manipulated within a GIS on a computer screen [7]. The numerical analysis available in GIS is often combined in landscape architecture during the generation of planning and design schemes. The application of artificial intelligence in urban space and architecture began in the 1970s. In the past 10 years, with the great changes brought about by the Internet, artificial intelligence has been applied and explored in many research directions of geographical design and related aspects. With research depth and breadth enhancement, geographical design intelligence has gradually formed. Artificial intelligence in geographic design transforms complex qualitative descriptions in space into quantitative analysis and design models through intelligent mechanisms. The role of artificial intelligence technology in geographical design is mainly reflected in two aspects: (1) Using artificial intelligence algorithms and thinking to calculate and analyze the relevant data in geographical design research efficiently and accurately and mining knowledge and rules from it; (2) Aiming at complex and difficult problems in geospatial research, establish a spatial intelligence model to reveal the internal mechanism behind the phenomenon. Artificial intelligence applied to geographic design mainly refers to "weak artificial intelligence": execution ability is generally better than humans and can formulate and apply digital technology to achieve goals [8]. Its core lies in applying artificial intelligence technology to replace the work handled by the human brain in the past and improve the reliability, validity, and accuracy of geographical planning and design.

Technological change is a key driver of long-term growth in regional planning, design, and management [9]. AI allows humans to devise, strategize, and implement comprehensive solutions to environmental degradation and the climate crisis, moving beyond narrow-minded and self-serving approaches of individuals and small groups [3]. GIS is one of the main tools to realize the application of artificial intelligence in geo-design and planning [10]. There are two main types of artificial intelligence in geo-design and planning applications. One is the "inference type", such as logical reasoning, theorem proving, etc., including the knowledge type and the "learning type", such as deep learning, support vector machine, and so on. The other is according to the type of artificial intelligence algorithm, divided into "symbolism", such as expert systems, knowledge engineering, etc., including "connectionism", such as neural networks; "behaviorism", such as multi-self-agents, cellular automata, and so on [11]. Symbolism is the process of simulating human-like intelligence using logical reasoning to deduce the whole theoretical system [12]. According to the attributes and functions of artificial intelligence technology and the types of geographical design problems that can be solved, the artificial intelligence methods applied in the field in recent years are divided into three categories: artificial life, intelligent random optimization, and machine learning.

### *1.4. The Value of Geographic Design in Regional Spatial Applications*

In recent years, urban areas worldwide have frequently experienced both natural disasters, such as earthquakes, floods, and hurricanes, and man-made accidents, including terrorist attacks, chemical spillages, fires, and explosions. Due to the importance of spatial information to geographical research, the application of artificial intelligence is mainly reflected in social science research, data sorting, disaster prevention, early warning, and other aspects [13]. One of the main advantages of AI technology is that it can explore the ecological challenges that future landscapes may face. Geo-design is a planning and design approach that closely integrates the simulation of the impact of the geographic environment, system cognition, and digital technologies to create design solutions [14,15]. Geographic design provides a comprehensive framework for landscape information processing. In addition, geographic design tends to be applied across disciplines and differs from traditional landscape architecture education. Geo-design is rooted in using digital technologies that integrate information from social and natural systems as a basis for modeling, analyzing, and communicating design and planning effects. Geo-design as a strategy helps planners and designers address pressing urban and landscape issues such as climate change, sustainability, environmental quality, and justice. These problems can be represented, described, and analyzed using geographical information [16].

### *1.5. Research Questions*

This paper aims to comprehensively review AI-related technology applications in urban design and planning. The research questions include: (1) Which AI-based technologies have been used to study this area? (2) What are the trends and research areas of the published literature? (3) What are the key data inputs and analysis themes when applying these technologies?

## 2. Method

In conducting the literature review, researchers adhered to the rigorous standards of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol [17]. PRISMA protocol outlines a transparent and systematic methodology for database searching, selecting relevant literature, and synthesizing gathered information. By following PRISMA, researchers ensured a comprehensive and replicable search strategy, which involved clearly defined criteria for inclusion and exclusion, identifying databases and other sources of relevant studies, and a meticulous documentation process for each step taken.

### *2.1. Search Keywords*

This study developed a list of keywords based on the above research questions. This research utilized a thorough search methodology across the Web of Science. Multiple variations of keyword strings were employed, each specifically adapted to the search functionalities of these databases, ensuring the retrieval of the most pertinent and consistent findings. The time frame for the publications included in this search spanned from January 2003 to June 2023. The search keywords included two groups: (1) Topic-related words: "geo-design", "geo", and "design", "GIS", and "design", "geographic" and "design", "geospatial", and "design"; (2) Method-related words: simulation, parametric, deep learning, big data, social media, remote sensing, neural networks, grasshopper, machine learning, virtual reality, VR, decision model, computing, AR, MR, computer vision, swarm intelligence. Combining topic-related and method-related words generated a total of 85 search terms (Figure 1).

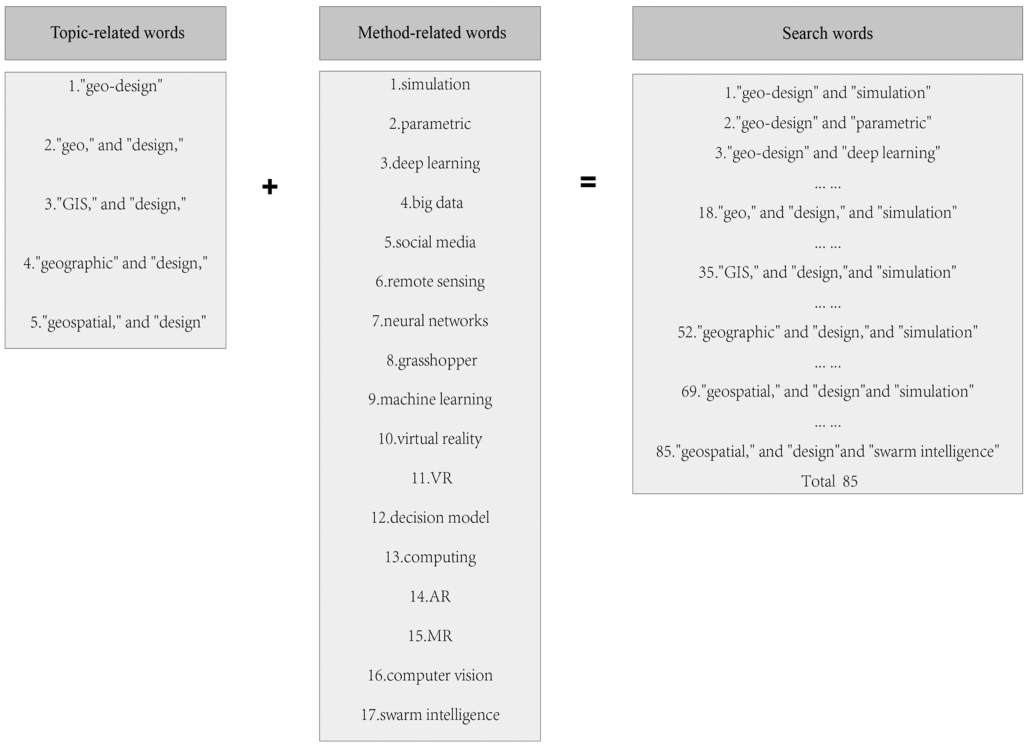


**Figure 1.** Search Words.

### *2.2. Search Strategy*

Using a total of 85 search words, our initial search yielded 25,241 articles from the Web of Science, as visualized in Figure 1. Rigorous deduplication and title screening reduced this to 14,779 articles. A subsequent detailed review of titles based on our inclusion criteria further narrowed the pool to 1400 articles (Figure 2). This involved excluding off-topic articles outside the urban planning and design scope, employed outdated technologies or were not conducted in an urban, outdoor context. Studies were included if they met the following criteria:

1. The study must be conducted in an urban, outdoor context. Studies in rural areas, forests, or natural river environments are excluded.
2. The focus of the study should be on the use of geospatial information in planning and design.
3. The study must incorporate state-of-the-art technologies, with a preference for articles published within the last decade to ensure relevance to recent advancements in artificial intelligence.
4. The study should fall within the disciplinary categories of planning, landscape, geography, or forestry. Articles dedicated to computer science focusing primarily on algorithms or models are excluded.

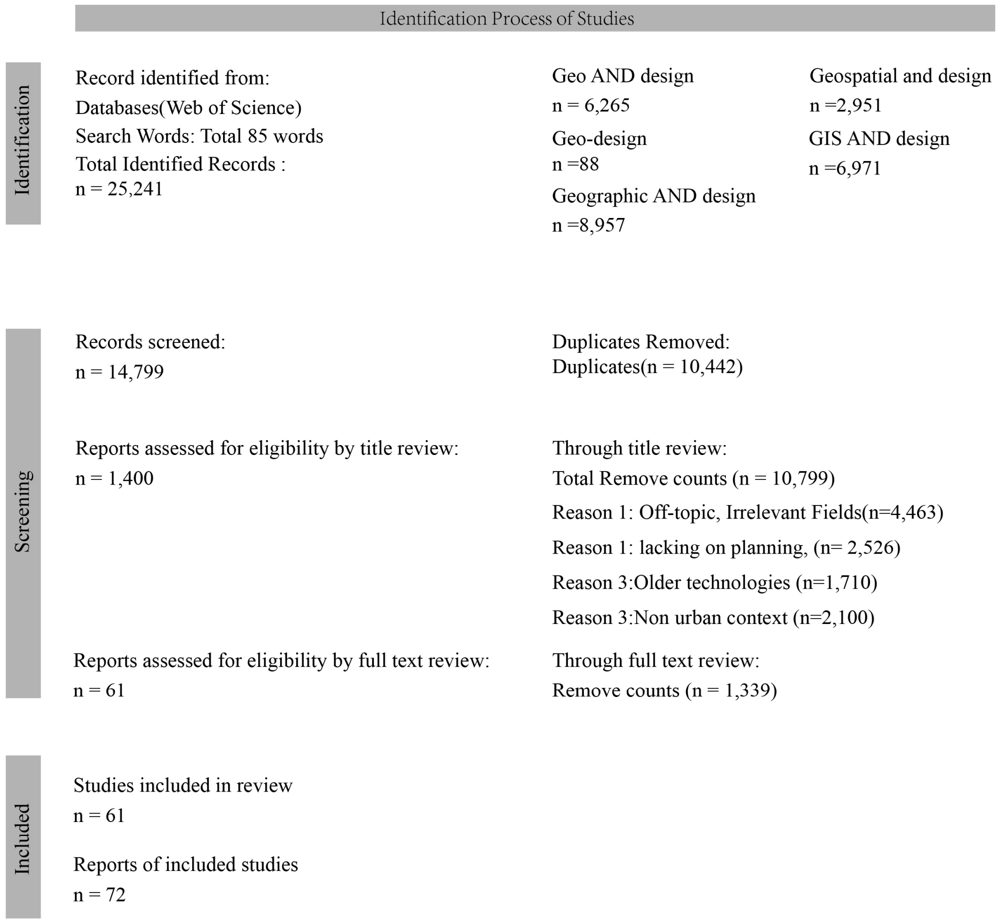


**Figure 2.** The procedure of the review (based on the PRISMA review protocol).

Review papers, conference proceedings, book chapters, and studies that did not meet the above criteria were excluded. Studies focusing on indoor environments or employing traditional monitoring technologies were also excluded. Any disagreements between reviewers were resolved through discussion and consensus. This additional scrutiny led to a final set of 61 articles.

### *2.3. Data Extraction and Synthesis*

For each included article, data were extracted on the study design, vision-based and/or sensor-based technology employed, research themes and areas, and strengths, limitations, and considerations of using these technologies. A data extraction form was developed and piloted to ensure consistency in data extraction across studies. The extracted data were then synthesized using a narrative approach to provide a comprehensive overview of the current state of research in this field. Researchers developed a data extraction sheet, including the parts: basic information (titles, publication year, author, country, and keywords), topic and method (themes, types of data, algorithms, vision/sensor/hybrid, and sample size), and findings (outcome results, strength, and limitations).

## 3. Results

### *3.1. Research Trend*

In the domain of geo-design and planning, a diverse array of scholarly journals has contributed to disseminating research on artificial intelligence applications (Figure 3). The most prolific of these is the *ISPRS Journal of Photogrammetry and Remote Sensing*, which stands out with the most published articles, followed by *Urban Forestry & Urban Greening*, and *Landscape and Urban Planning*. These journals indicate a strong interdisciplinary interest in bridging the gap between technical remote sensing techniques and their practical implications in urban and environmental contexts. The presence of specialized journals such as *Computers, Environment and Urban Systems* and *Transactions in GIS* further emphasizes the technological advancement in the field, focusing on the intersection of computer science and spatial analysis within urban systems.

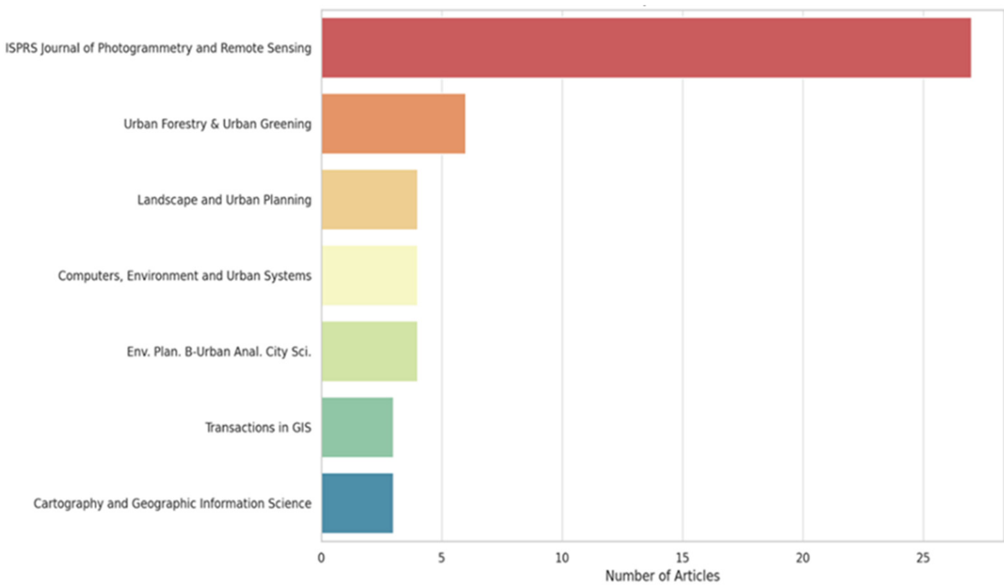


**Figure 3.** Frequency of journal.

Figure 4 compares the distribution of the top 10 research areas. The distribution reveals a comprehensive engagement with geo-design and planning across multiple academic disciplines. 'Physical Geography' precedes the highest volume of published articles, signaling its dominance and centrality in the field. The following closely follow 'Computer Science' and 'Remote Sensing', reflecting the integral role of technological innovation and analytical methods in understanding and managing geographical spaces.

Other key disciplines, such as 'Environmental Sciences & Ecology' and 'Urban Studies' are well-represented, denoting a concerted focus on sustainable development and the intricate dynamics of urban environments. 'Public Administration' also emerges as a crucial area, underscoring the relevance of policy and governance in shaping the landscape of geo-design and planning. The inclusion of 'Plant Sciences', 'Forestry', and 'Engineering' within the top ten research areas further illustrates the multifaceted nature of the field, where biological, ecological, and engineering insights converge to inform comprehensive geo-design strategies. Within the expansive domain of geo-design and planning, the role of 'Urban Ecology and Environmental Sciences' is particularly salient. This field acts as a critical nexus where the imperatives of urban development meet the principles of ecological sustainability. As cities expand and transform, urban ecology provides essential insights into the complex interplay between urban growth and the natural environment, informing approaches prioritizing biodiversity, ecosystem services, and resilience in urban design.

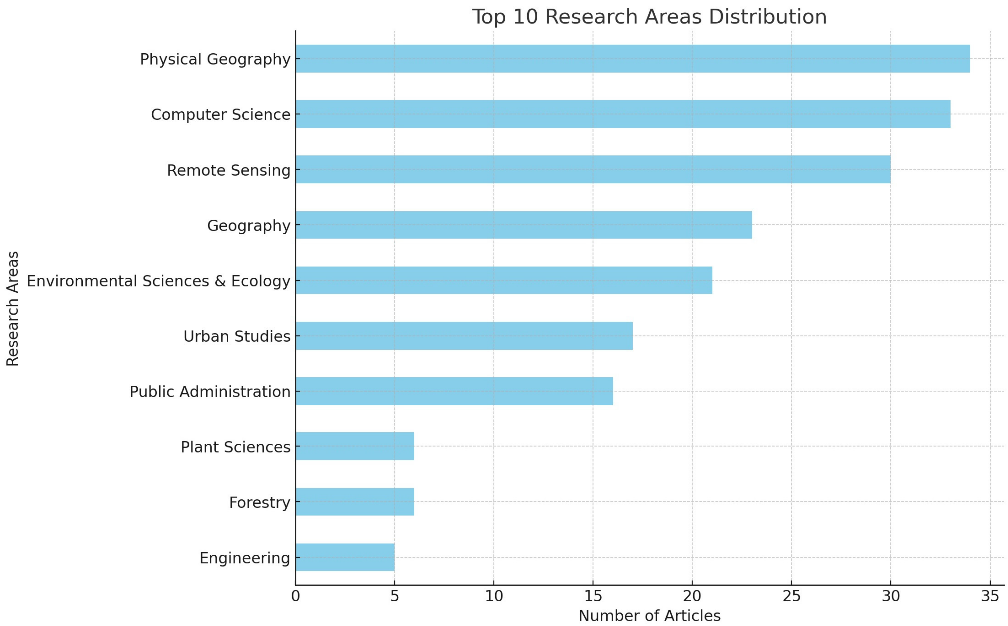


**Figure 4.** Top 10 research area distribution.

The trend of publications over the years reveals a growing interest and increasing research output in the field of AI in geo-design and planning (Table 1). Starting from 2016, there has been a noticeable upsurge in the number of articles, reaching a peak in 2022. This uptick reflects the accelerating integration of AI technologies in geospatial studies and the heightened recognition of their potential to address complex urban and environmental challenges. Although there is a slight decrease in 2023, the overall trajectory remains upward, suggesting a sustained and expanding engagement with AI research within the geo-design and planning disciplines. This pattern underscores the evolving nature of the field and the continual advancements in AI technologies and their applications. The observed decrease in publication rates in 2021 may be primarily due to the lagged effects of the pandemic, wherein the delayed impacts of disruptions in research activities persisted in influencing publication outputs. Additionally, the subsequent year saw a notable advancement in AI-assisted tools, such as GPT, which enhanced research efficiency. This development allowed researchers to swiftly pivot to applying AI tools within their fields, further impacting publication trends.

**Table 1.** Publications by years (percentage).

| **2016** | **2017** | **2018** |
|---|---|---|
| 2<br>(3.28%) | 1<br>(1.64%) | 3<br>(4.92%) |
| **2019** | **2020** | **2021** |
| 7<br>(11.48%) | 11<br>(18.03%) | 10<br>(16.39%) |
| **2022** | **2023** | **total** |
| 16<br>(26.23%) | 11<br>(18.03%) | 61<br>100% |

Analyzing the interconnectivity of concepts within the literature on AI in geo-design and planning, a prominent thematic cluster can be observed around "machine learning", a central node linking various sub-themes and technologies (Figure 5). The prominence of "machine learning" signifies its fundamental role in advancing geo-design and planning methodologies. Adjacent to this core, "street view" and "live images" are significant, illustrating the emphasis on real-time data processing and visualization in urban studies. Another noteworthy cluster centers around "urban occupation", "phone data", and "activity space", highlighting the growing interest in human dynamics and mobile data utilization for urban planning. The intricate network of these themes showcases the multidisciplinary approach in the field, integrating advanced computational techniques with practical applications such as urban street network analysis, occupancy modeling, and real-time environmental monitoring. This complex web of interconnected terms reflects the current research landscape and underscores the synergy between AI technologies and their practical deployment in shaping the urban spaces of tomorrow (Figure 6 and Table 1).

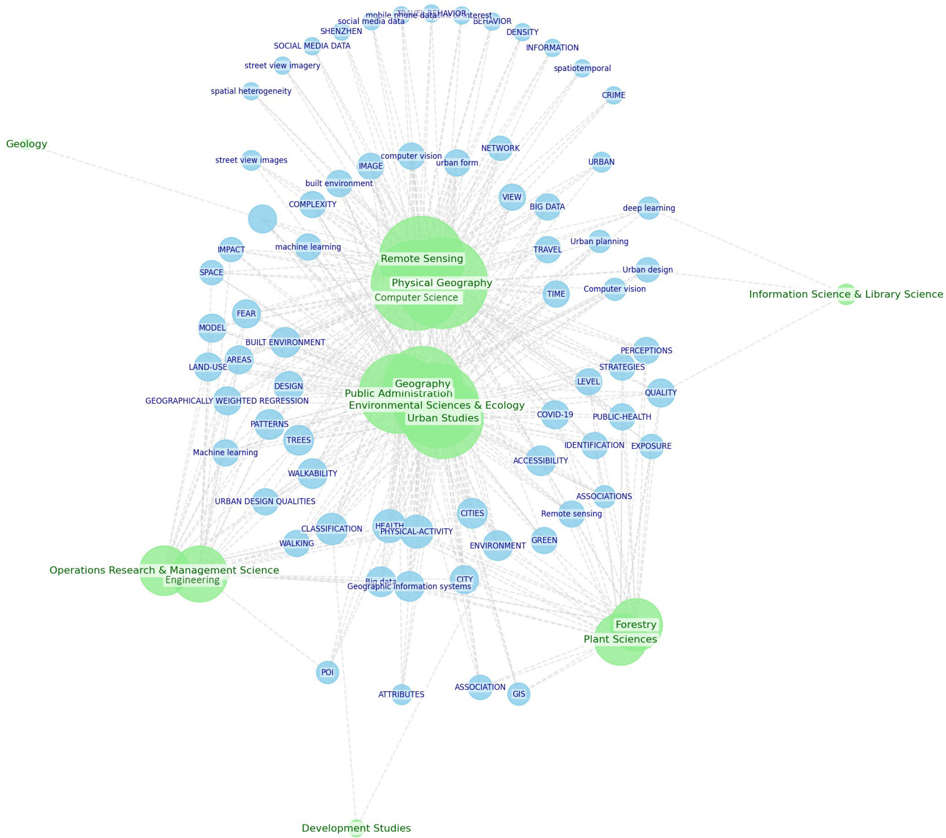


**Figure 5.** Research area network visualization.

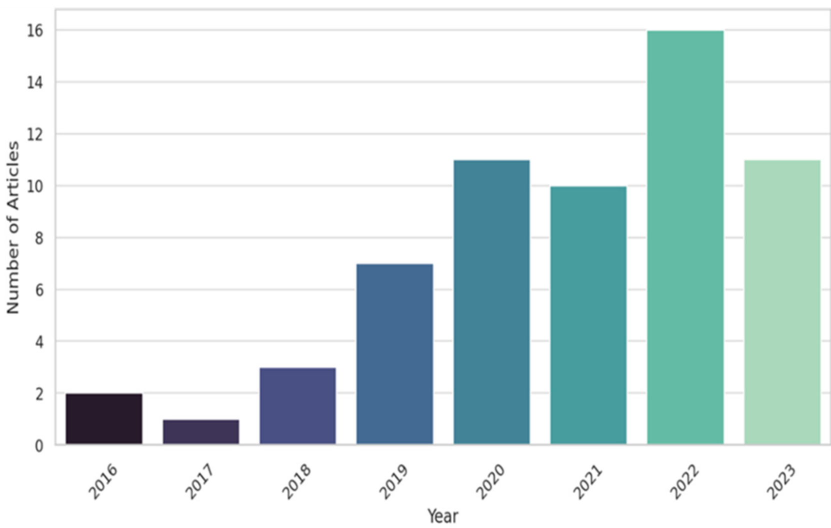


**Figure 6.** Publications by years.

### 3.2. Methodological Approaches

The systematic review comprehensively analyzed the data types utilized in geo-design technologies, identifying a multifaceted array of sources that underscore the breadth and depth of information employed in the field (Table 2). Image-based data sources, including satellite imagery, Normalized Difference Vegetation Index (NDVI), and Digital Elevation Model (DEM) data, form a critical foundation for high-resolution spatial analysis, allowing for detailed landscape assessments and vegetative indexing. Furthermore, street view images and map data provide granular details of urban fabric essential for meticulous urban planning.

**Table 2.** Data types of the geo-design technologies.

| Data Type | Crowdsourced Data Source |
| --- | --- |
| Image | Satellite imagery<br>Normalized Difference Vegetation Index (NDVI) data<br>Street view images<br>Map data |
| Spatial Distribution | Land use data<br>Crop production data<br>Ecosystem services<br>Soil property data<br>Point of Interest (POI) |
| Spatiotemporal | Tracks<br>Road network data<br>Location coordinates<br>GPS Location data |
| Numeric | Socioeconomic data<br>Population numbers<br>Mobile Phone Data<br>Building and housing data<br>Data for ridership |
| Social media data | Crowdsourced data |
| Emotion and empirical data | Emotion and empirical data |

In the spatial distribution category, land use, crop production, and ecosystem services data contribute to a holistic understanding of land management practices and environmental stewardship. Soil property data enhances the precision of environmental modeling, while Points of Interest (POI) and tracks offer insights into urban dynamics and mobility patterns. The integration of spatiotemporal data like road network data, location coordinates, and GPS data facilitates advanced modeling of movement and urban growth patterns, providing a temporal dimension to spatial configurations.

Numerical data types, including socioeconomic datasets, population numbers, and mobile phone data, enrich the analytic capabilities by introducing demographic and behavioral dimensions. These datasets are pivotal in understanding and predicting urban occupation patterns and infrastructure needs. Building and ridership data contribute to a more nuanced view of urban utilization and transport dynamics. Lastly, the review identified the emergence of social media data as a potent tool for gauging public sentiment and emotional landscapes, offering a new frontier in geo-design that incorporates human-centric data. Including such diverse data types enhances the accuracy and applicability of geo-design technologies and points to the potential for creating more responsive and adaptive urban environments.

### 3.3. Application Theme

As AI technology continues to evolve, the field of geo-design is increasingly incorporating AI to address various challenges. Based on an analysis of 61 articles, this review section explores different themes of AI applications in geo-design. This study categorized these into four main themes: Transportation and Context, Built Environment and Perception, Data-Driven Approach, and Urban Region. Under these four primary themes, researchers have further classified the applications into 28 specific categories, offering a detailed exploration of AI's diverse roles in geo-design (Table 3).

#### 3.3.1. Transportation and Context

The "Transportation and Context" theme primarily focuses on the interplay between human mobility and transportation systems within urban environments. This theme delves into optimizing transport, analyzing traffic patterns, and understanding the broader context of transportation operations. Based on a review of 11 papers in this field, it can be categorized into five distinct areas: TOD Planning, Traffic Flow Analysis, Transportation Management, Transportation Safety, Transportation Decision and Simulation.

Contrasts with traditional 3D TOD designs that typically rely on linear functions. Dong et al. [18] advanced TOD (Transit-Oriented Development) planning by implementing a multi-objective optimization design with a nondominated sorting genetic algorithm III with an ensemble learning method. Their approach demonstrated superiority regarding ridership objectives, achieving better optima and convergence than linear models. This signifies a notable improvement in the efficiency and effectiveness of the Math method in TOD planning methodologies.

In addition, traffic flow analysis forms a foundational pillar in urban transportation optimization. Tang et al. [19] and Semanjski et al. [20] advanced travel time and transport mode detection based on traditional GIS and mobile-sensed spatiotemporal GPS data. However, reliance on traditional ways may limit adaptability in dynamic urban environments. Following this, deep learning methods like SVM, KNN, PCA, RT, and Faster R-CNN have gained prominence in traffic flow analysis. Golej et al. [21] utilized these techniques alongside high-resolution satellite imagery for vehicle detection.

Furthermore, deep learning technology in the field of image classification can also be used to automatically identify parallel lines in images and high-visibility crosswalks in the field of traffic safety [22]. Complementarily, Chen et al. [23] used machine learning techniques, such as the LDCF algorithm, for pedestrian volume assessment via street view images. Nadarajan and Sivanraj [24] further developed traffic forecasting with the ANST model, integrating LSTM networks and attention mechanisms, significantly enhancing traffic prediction by considering spatiotemporal dynamics and environmental factors.

Finally, AI tech can address issues related to transportation decision-making and simulation in addition to the above scenarios. Advancements in urban data research have demonstrated the effectiveness of deep learning methods in evaluating active mobility potential for urban environments. Yap et al. [25] integrated street view imagery and urban networks to evaluate active mobility, using deep learning to assess traffic environment factors impacting subjective decisions. Unlike traditional GPS resources, Chen and Yang [26] combined social media signals with pedestrian simulation technologies in historic neighborhoods, addressing conflicts between tourists and locals and enhancing urban planning. These studies underscore the value of diverse data and visual elements in urban design.

The research in the "Transportation and Context" theme offers valuable insights for urban management. AI enables precise traffic flow analysis, aiding cities in implementing effective congestion reduction measures and identifying signalized intersections and crosswalks, thus enhancing pedestrian safety in urban areas in a geo-design framework. Additionally, integrating AI and geographical data supports data-driven decisions in transportation planning and urban development, promoting a more complex system.

#### 3.3.2. Built Environment and Perception

The "Built Environment and Perception" theme in geo-design research focuses on how built environments affect human perception and activity. This theme encompasses studies that utilize AI tech and big data to analyze and improve human interactions with urban spaces. Key research areas include optimizing urban safety, understanding emotional responses to urban environments, and the impact of visual and socioeconomic elements on human perception. Additionally, this theme explores the assessment of urban space quality, linking street view imagery, social media data, and economic factors to urban planning and design. These studies collectively highlight the critical role of AI in creating more livable, efficient, and engaging urban environments. This part is based on a review of 22 papers in this field; it can be categorized into two main distinct areas: Human Perception and Activity (12 papers) and Building Environment Assessment (10 papers).

In Human Perception and Activity, techniques such as urban network analysis and image processing have been extensively utilized. Recent studies typically integrate various sensor data and socioeconomic survey data to objectively assess perception and the physical environment, exploring their impact on human activities and emotional responses. For instance, Li et al. [27] introduced an emotion-tracking technique based on Geographic Information System (GIS), quantifying the relationship between people's emotional responses and urban spatial characteristics through spatial analysis and logistic regression. This method evaluated the impact of multiple urban features on emotional responses, including architectural shapes and textures, façade parameters, visual entropy, and visual fractals.

AI technology in geo-design is primarily employed for data analysis and mining data related to humans and their environment, aiding in establishing the relationship between urban environments and human activity perception. Liu et al. (2020) explored urban vitality, spatial patterns and driving mechanisms using multi-source big data, including mobile location data, geospatial big data, and shared internet data. Huang et al. [28] analyzed city images on social media through text mining and image annotation, introducing "Instagram ability" and "Twitter ability" as new urban image indicators. Gong et al. [29] developed an algorithm to identify patterns of human activities by analyzing mobile data and spatial analysis techniques.

Moreover, in Building Environment Assessment research, technologies such as Convolutional Neural Networks (CNN) automate the analysis of images, extracting data from Google Street View images and pictures from social media platforms like Flickr. Yang et al. [30] utilized the VGG-16 deep learning architecture, while Wang et al. [31] employed the DeepLabv3 model to learn about the physical environment, extracting semantic information from street view images to quantify the built environment.

Applying AI technologies like these is crucial in geo-design, offering diverse methods to analyze, understand, and quantify urban environments. Using social media and big data, researchers acquire valuable insights into urban dwellers' perceptions and needs, informing policy-making aligning with public interest. Automated image analysis in environmental assessments provides real-time, precise data essential for adapting to rapid urban changes.

#### 3.3.3. Data-Driven Approach

The "Data-Driven Approach" theme of geo-design research focuses on leveraging AI and advanced data management tools for geo-design or combining multiple frames to achieve multidimensional data visualization. Based on a review of seven papers in this field, it can be categorized into two main distinct areas: Data Visualization (four papers) and Geospatial Data Management (three papers).

The data visualization field has enhanced the richness and clarity of maps through innovations in GIS systems and spatial analysis processes. Schiewe [32] optimized the accurate representation of geographic information through task-oriented data classification, integrating steps like interval selection and spatial unit aggregation, but was mainly limited to desktop GIS systems. To broaden understanding, geographic data visualization has evolved from 2D to more immersive 3D and 4D, with corresponding web interface designs. Lafrance et al. [33] enhanced public engagement and understanding of urban planning through web-based multidimensional visualization and interactive tools like timelines and animations. Deep learning technologies, such as GAN-based segmentation, effectively enhance the realism and precision of data visualization. Benita et al. [34] advanced the field with deep learning methods like SIDE and GANs, pushing forward automated and detailed reconstruction of building facades.

Furthermore, Geospatial Data Management focuses on the underlying logic and code of database construction to suit large-scale data processing. Burini et al. [35] proposed the J-CO framework based on JSON format. At the same time, Bareche and Xia [36] developed the VeST indexing technique, and Wang et al. [37] implemented the STR method, all contributing to more precise and dynamic analysis of urban spatial data. These techniques allow for more accurate and efficient processing of larger-scale and complex urban spatial data in geo-design.

#### 3.3.4. Urban Region

The "Urban Region" focuses on studies that contribute to our understanding of geo-design, how to use it in urban function, the health impacts of urban environments, and how urbanization affects ecosystem services, providing valuable insights for sustainable urban development and planning. Based on a review of 15 papers in this field, it can be categorized into three main distinct areas: urban function classification (7 papers), public health (3 papers), and urban ecosystem services (5 papers).

In urban function classification, prime studies like Luo et al.'s [38] leveraged POI data and kernel density analysis to identify urban functional areas based on special analysis tools with machine learning. Zhai et al. [39] introduced the Place2vec model, an advancement over conventional semantic models, for effectively identifying urban functional regions using POIs and K-means clustering. Xu et al. [40] and Zhao et al. [41] applied deep learning and graph neural networks for building function classification and pattern recognition in urban areas.

For public health, research like that of Peng et al. [42] and Benita and Tunçer [43] examined the impact of urban features on physiological stress responses, employing techniques like environmental monitoring and machine learning. Li et al. [44] explored how urban park features and psychological factors affect perceived restoration using methods like PPGIS and deep learning. Further, it underscored the transformative role of Geo AI in enhancing urban pattern recognition and building function classification.

**Table 3.** Analysis of themes and categories.

| Analysis Theme | Category | Description | Citation |
|---|---|---|---|
| Transportation and Context | TOD Planning | Multi-objective optimization design based on nondominated sorting genetic algorithm III | [18] |
| | Traffic Flow Analysis | Uses machine learning, including SVM, KNN, PCA, RT, and Faster R-CNN, for vehicle detection. | [21] |
| | | The ANST model combines LSTM and attention mechanisms for traffic forecasting. | [24] |
| | | Using spatial context mining and a support vector machine model to identify transport modes from big data. | [20] |
| | | Estimates urban intersection travel times using low-frequency GPS data, analyzing traffic patterns, and applying fuzzy fitting to calculate flow speed and delay. | [19] |
| | | Using LDCF machine learning algorithm to automatically assess pedestrian volumes in urban areas. | [23] |
| | Transportation Management | Using a two-step method of spatiotemporal pattern extraction and Gaussian modeling for precise urban transport management. | [45] |
| | | Combines road network analysis, street view images, and deep learning to efficiently identify signalized intersections. | [46] |
| | Transportation Safety | This study employs imagery and a deep learning-based model to detect marked crosswalks. | [22] |
| | Transportation Decision and Simulation | Enhances active mobility planning using deep learning DeepLabV3 segmentation trained on a WideResNet-38 model analyzing street imagery. | [25] |
| | | Uses big data, pedestrian simulation, and AnyLogic to identify facility gaps and traffic issues. | [26] |

**Table 3.** *Cont.*

| Analysis Theme | Category | Description | Citation |
|---|---|---|---|
| Built Environment and Perception | Human Perception and Activity | Using multi-source big data and data mining to analyze influencing factors to optimize unsafe urban areas. | [47] |
| | | Uses deep learning and random-forest algorithms to analyze human perceptions of urban spaces. | [48] |
| | | Uses deep learning to explore how urban space characteristics influence people's emotional responses | [44] |
| | | Analyses urban vitality's spatial patterns and driving factors using multi-source big data. | [49] |
| | | Analyzes the built environment's impact on occupational diversity using GeoDetector-based indicators for in-depth analysis. | [1] |
| | | Employs deep learning for image segmentation and NDVI to measure urban greenness. | [50] |
| | | Utilizes a mix of text mining, image processing, clustering, kernel density estimation, and sentiment analysis to assess urban perceptions. | [28] |
| | | Uses multiple linear regressions to analyze three types of urban residents' activity spaces at multiple geographic scales. | [29] |
| | | Develops an analytical framework using mobile phone data to assess occupational diversity in urban areas. | [51] |
| | | Uses machine learning to predict urban street running intensity. | [52] |
| | | Analyses Dhaka's travel patterns using household diaries, artificial neural networks, and regression. | [53] |
| | | Evaluating human perceptions of streetscapes using integrating PSPNET, attention mechanisms, and transfer learning. | [54] |
| | Building Environment Assessment | Develop a framework for assessing urban street quality using the DeepLabv3 model. | [31] |
| | | Examines the Street commercial pedestrian block characteristics using Isovist_App software simulation and spatial analysis. | [55] |
| | | This study employs machine learning and a Fully Convolutional Network (FCN) for image segmentation to improve street quality. | [31] |
| | | Conducts a deep learning-based classification analysis of public space images. | [30] |
| | | Leveraging semantic segmentation and information entropy models for assessing visual perceptual information in urban street spaces. | [56] |
| | | Introduces a deep learning approach to comprehensively analyze the spatial ratios of streets. | [57] |
| | | Employs GIS, deep learning DeepLab-v3 +model, and sensors to assess urban walkability. | [58] |
| | | Examines how street greenery affects older adults' walking behavior using global (linear regression, Box–Cox) and local (geographically weighted regression) models. | [59] |
| | | Utilizes deep convolutional neural networks to classify urban street frontages. | [60] |
| | | Employs a multiscale analysis method and Multiscale Geographically Weighted Regression (MGWR) to explore the impact of environmental features on crime. | [61] |

**Table 3.** *Cont.*

| Analysis Theme | Category | Description | Citation |
|---|---|---|---|
| Data-Driven Approach | Data Visualization | Develops a task-oriented approach. The method enhances geo-design maps for change analysis by integrating spatial data preprocessing, local extreme value preservation, and context-aware classification techniques. | [32] |
| | | Introduces a novel 3D-4D interface that combines GIS, geo-located data, high-resolution 3D models, and multimedia for immersive visualization of large space-time datasets in smart cities. | [34] |
| | | Develops a deep learning method with GANs and Single image depth estimation for 3D reconstruction of building façades. | [62] |
| | | Enhancing citizen engagement in urban planning, using dynamic, immersive tools for visualizing city evolution. | [33] |
| | Geospatial Data Management | Introduces VeST, a novel indexing model for efficient CKNN queries on moving objects in a distributed environment. | [36] |
| | | Introduces STR, a multivariate hierarchical regionalization method for uncovering spatiotemporal patterns, focusing on spatial, temporal contiguity, and attribute similarity. | [37] |
| | | Introducing the J-CO framework for analyzing JSON-formatted data sets to improve urban planning in regeneration and mobility. | [35] |
| Urban Region | Function Classification | Applied POI data from an online map service and kernel density analysis in various grid sizes to identify urban functional areas. | [38] |
| | | Develop a machine learning approach with Random Forest, Support Vector Machine, and Naive Bayes algorithms to identify rural residential land. | [63] |
| | | This study introduces and validates the Place2vec model for effectively identifying urban functional regions using Points of Interest (POIs) and K-means clustering. | [39] |
| | | Focuses on classifying building functions in urban areas using deep learning techniques, specifically Graph Convolutional Networks (GCNs). | [40] |
| | | The study introduces a novel deep neural network based on graph convolutions, designed to automatically identify patterns in building groups with arbitrary forms. | [41] |
| | | This study introduces a method to identify and analyze influential urban regions using spatial interaction networks based on human movement data. | [64] |
| | | This research proposes the Spatial Vector Deep Neural Network (SVDNN) model to measure the Multidimensional Poverty Index (MPI). | [65] |
| | Public Health | Examines the commercial pedestrian block characteristics using Isovist_App software simulation, big data statistics, and spatial. | [42] |
| | | Utilizing environmental monitoring, machine learning explores the impact of urban features and environmental factors on physiological stress responses. | [43] |
| | | Uses PPGIS, Deep Learning, and PLS methods to analyze how urban park features and psychological factors affect college students' perceived restoration. | [44] |
| | Urban Ecosystem Services | Investigate the relationship between urban spatial patterns and ecosystem services using spatial metrics and the Geographically Weighted Regression (GWR) model. | [66] |
| | | Based on remote sensing and spatial analysis, the spatial and temporal changes of green space distribution and spatial and temporal patterns of green space distribution index were analyzed. | [67] |
| | | Bivariate Moran's I and multiple regression are adopted to explore the equity of urban green space accessibility. | [68] |
| | | This study uses land use regression to assess urban greening's impact on air pollution. | [69] |
| | | Combines including rainfall simulation, remote sensing analysis, and semantic information analytics to identify flooded roads. | [70] |

## 4. Discussion

### *4.1. Methodological Approaches*

Image data types serve as a cornerstone in geo-design, enabling a wide spectrum of analyses that significantly enhance urban planning and environmental management. Tasks such as urban spatial patterns analysis and vehicle detection leverage high-resolution imagery to discern and quantify intricate urban layouts and vehicular presence, respectively. This data is pivotal in analyzing urban green space distribution, coupled with the quantification of ecosystem services, which provides a detailed understanding of environmental assets within urban settings. Studies focusing on the spatial association of urban greenness with dockless bike-sharing usage demonstrate the potential of image data to reveal correlations between environmental features and urban mobility patterns. Further, image data is instrumental in assessing street safety and evaluating the impact of built environment features on public health and crime occurrence. The Visual Perception Information Quantity of Street Space task underscores the ability to assess urban streetscapes' aesthetic and functional aspects. Beyond structural analysis, image data facilitates active mobility planning by enhancing urban walkability, contributing to healthier and more sustainable urban environments. In summary, image data underpins a diverse array of tasks within geo-design and planning and enriches the decision-making process by providing a multifaceted view of urban ecosystems and human-environment interactions.

Spatial distribution data encompasses information regarding geographical patterns and distributions. Land use data [18,63,69] aided in transit-oriented development planning, vulnerability identification, and urban green cover status assessment. Crop production data [63,65,66] contributed to quantifying ecosystem service, vulnerability, and measuring poverty. Ecosystem services, including water yield, soil conservation, carbon storage, and crop production, were evaluated using meteorological and soil property data [63,66]. Points of Interest (POI) analysis [37,39,47] facilitated diverse assessments such as street safety, urban functional region identification, and street space quality evaluation. Spatial distribution data aids urban planning, environmental conservation, and resource allocation. It enabled efficient land management and resource utilization. However, challenges may include data accuracy issues, evolving land use patterns, and the need for continuous updates to maintain relevance.

Spatiotemporal data encapsulates various information sets crucial for understanding spatial and temporal aspects of urban dynamics. Tracking data involving crowdsourced trajectory and check-in information [52] facilitated calculating road running intensity, offering insights into urban road movement patterns and utilization. Road network data analysis [31,47] aided in assessing street safety, diagnosing strategies for urban street space, and contributing significantly to urban planning and safety assessments.

Location coordinates sourced from diverse data sets such as China Mobile signaling data [59], dockless bike sharing records [50], cell phone location data [49], and travel location points (Sharmeen et al. 2020) offered insights into residents' distribution, spatial usage patterns, transport mode recognition, and understanding travel behaviors. GPS location data analysis [19,47,70] contributed to street safety assessments, estimating intersection travel times and providing valuable spatiotemporal insights crucial for urban planning, transportation management, and safety analysis. Spatiotemporal data involves information related to both space and time. GPS location data tracks positions at specific times, while road network data outlines connectivity and routes. Tracking data records movement paths aids in understanding mobility patterns.

Spatiotemporal data enables real-time tracking, navigation, and route optimization. It assists in transportation planning, disaster management, and logistics. However, challenges include data privacy concerns, accuracy issues in dense urban areas or mountainous regions, and the need for substantial storage and computational resources.

Numeric data encompasses quantitative information pivotal to demographic, economic, and infrastructure aspects. Socioeconomic data include indicators like urbanization rate, labor income per capita, and sown area per capita [63], providing insights into local development levels. Factors like the secondary industry proportion, per capita fiscal expenditure, night light index, healthcare facilities, and phone access ratios aided in poverty measurement [65]. Population data and investigating population changes [61] elucidated the correlation between street-built environments and crime occurrence. Mobile phone data revealed patterns in population demographics, exploring urban spatial features related to COVID-19 transmission [42]. It also aided in understanding residents' activity space, occupation assessment, transport mode recognition, and modeling human movement [20,29,35,51,64]. Building and house data encompassing information on location, number of floors, house prices, and structural attributes played pivotal roles in assessing street safety, evaluating occupation mixture mechanisms, understanding street greenery's effects, urban image classification, and analyzing urban vitality [15,47–49,59,60,68]. Data for ridership, involving smart card data, residents' travel behavior, traffic flow, and environmental data, contributed to transit-oriented development, understanding street greenery's impacts on walking time, evaluating street walkability, and urban street planning [18,22,59]. Numeric data, spanning demographics to infrastructure, supports policymaking, urban planning, and resource allocation. It aids in understanding societal trends and transportation patterns. Challenges include data accuracy maintenance, ensuring representativeness in sampled populations, and privacy concerns related to demographic and ridership data.

Social media data comprises information from various online platforms, reflecting user-generated content and interactions. It includes textual, visual, or multimedia content shared by users across social networks. These data sources offer insights into various urban aspects. For instance, Huang et al. [28] leveraged Instagram and Twitter data to construct the social media image of cities. Gong et al. [29] utilized geo-tagged images and texts to identify residents' activity spaces. Peng et al. [42] and Wang et al. (2022) utilized Weibo data to explore spatial features of COVID-19 transmission and assess street space quality, respectively. Flickr data analysis aids in understanding urban public spaces [30], while WeChat data is utilized for historic neighborhood design [23]. The Baidu Search Index measures residents' mental well-being [71], and general search data is used to gauge city connectivity reflected in different languages [72]. Social media data offers real-time insights into public sentiment, trends, and user behavior. It aids in marketing strategies, trend analysis, and understanding public opinion. However, limitations involve data privacy concerns, data authenticity verification, and the dynamic nature of social media content.

Emotion data and environmental data are pivotal in understanding the emotional urban environments' practical aspects of the urban environment, encompassing physiological responses and perceptual variables, and provide insights into how urban settings influence human emotions and well-being. On the other hand, empirical data involves practical, observed, and experimental evidence, guiding evidence-based decision-making and policy formulation in urban studies. Emotion data, encompassing body skin temperature, electrodermal Activity (EDA), Health Stress Index, and the Wet Bulb Globe Temperature (WBGT), as studied by Li et al. [27] and Benita and Tuncer [43], provided insights into assessing essential qualities of urban spaces and understanding the impact of urban features and immediate environments on human physiological responses. Additionally, Li et al. [58] analyzed the perceptual variables questionnaire data, exploring the influence of urban park characteristics and psychological factors on the perceived restoration of college students, shedding light on the emotional and psychological impacts of urban environments on individuals. On the other hand, empirical data analyzed by Dong et al. [18] contributed to transit-oriented development and land use planning, providing practical, observational, and experimental evidence for urban planning strategies centered around transit-oriented development. Research such as that of Turhan et al. introduced an innovative "Mood State Correction Factor" (MSCF) for adjusting thermal environments to occupants' mood states, extending this approach to outdoor settings for pedestrian comfort [72]. Fan et al. also integrated machine learning with energy management to optimize consumption without sacrificing comfort [73]. This convergence of AI, psychology, and environmental science signifies a shift towards creating energy-efficient urban spaces attuned to the emotional well-being of inhabitants, illustrating the potential for AI to foster more livable and responsive cities.

Emotion data and empirical data collectively offer a holistic view of urban dynamics. Emotion data provide direct insights into the emotional impact of urban settings, aiding tailored urban planning. Advantages include tangible physiological insights and evidence-based decision-making. However, interpretation complexities and subjective perceptions pose limitations. Empirical data's advantages lie in its factual basis for decisions, while limitations include biases, generalizability concerns, and the need for ongoing data collection and analysis in ever-evolving urban landscapes.

### *4.2. Strengths, Limitations, and Implications*

Methodological approaches encompassed in urban planning and environmental management draw upon an extensive range of data types. Each data type serves a unique purpose, facilitating detailed analyses of urban layouts, green space distribution, mobility patterns, socioeconomic trends, and the emotional impact of urban environments on individuals. The strengths of these approaches lie in their ability to provide a comprehensive and nuanced understanding of urban ecosystems through the integration of sources. High-resolution imagery and spatial analyses enable precise assessments of urban features and dynamics, while socioeconomic and emotional data contribute insights into the human aspects of urban living.

However, these methodological approaches are not without their limitations. Data quality issues, privacy concerns, and the need for continuous updates pose significant challenges. The dynamic nature of urban environments, characterized by evolving land use patterns and shifting population demographics, requires adaptable and responsive research methods. Furthermore, the interpretation of emotional data and the subjective nature of some analyses highlight the complexity of understanding urban spaces through these lenses.

Despite these limitations, the implications of adopting such varied methodological approaches are profound. They enrich the decision-making process in urban planning and environmental management, facilitating the development of more livable, sustainable, and tailored urban environments. By leveraging the strengths of these diverse data sources while navigating their limitations, urban researchers and planners can enhance their strategies, ultimately contributing to healthier and more resilient urban ecosystems.

### *4.3. Comparative Analysis*

Across these themes, AI technologies play a crucial role in enhancing the capabilities of geo-design and planning. While each theme focuses on different aspects of urban environments, they collectively demonstrate the versatility and impact of AI in addressing complex urban challenges. The transition from traditional methods to AI-based approaches signifies a paradigm shift in geo-design, offering more efficient, accurate, and comprehensive analyses of urban systems.

AI's integration into geo-design promotes a holistic understanding of urban dynamics, from transportation systems to human-environment interactions. The methodologies highlighted in these themes, including deep learning, machine learning, and data visualization techniques, illustrate the diversity of AI applications in urban planning. This systematic review underscores the transformative potential of AI in geo-design and planning, paving the way for more resilient, sustainable, and human-centric urban environments.

By comparing these themes, it is evident that while the applications of AI in geo-design are varied, the overarching goal remains the same: to leverage technology to create more efficient, sustainable, and livable urban spaces. The detailed categorization and analysis of AI applications within each theme provide a foundation for future research and development in geo-design, highlighting areas of growth and potential for further innovation.

### 4.4. Future Directions

Following the trends, it can be seen that data from various sources are popular data sources for a currently good AI model, or analysis requires strong data to back it, vis-a-vis good predictions and insights that can only be guaranteed by a good AI model. Keeping this fact in mind, the research highlights the use of crowdsourced data, which is prone to noise, outliers, and incomplete or unstructured data. It can also be unethical as the people reporting their data might not be consciously aware that their data will be used for studies. Considering these keys and disclaimers while collecting such data would be more ethical and ensure more clean data is collected. In the future, integrating large language models (LLMs), a state-of-the-art text-based and multimodal analysis technology, will be useful. Once again, its predictions and insights can be different every time, so a good framework for research might help structure the study.

## 5. Conclusions

This systematic review has elucidated the diverse and profound ways in which AI technologies are transforming the field of geo-design and planning. Researchers categorized these technologies into analysis themes and analyzed the literature trends and data inputs. Our extensive analysis of the literature from the past two decades reveals a marked trend toward integrating AI in various aspects of geo-design, including urban planning, environmental modeling, and infrastructure development. Adopting AI technologies, such as machine learning, neural networks, and spatial data analysis, has significantly enhanced predictive analysis, decision-making processes, and the automation of complex geospatial tasks.

The transformative potential of AI in geo-design and planning is evident in its ability to analyze vast and complex datasets, automate and optimize planning processes, and provide more accurate predictions and insights into urban and environmental dynamics. These advancements have enabled a more efficient and effective approach to urban planning and environmental management, leading to more sustainable and resilient urban environments.

However, the integration of AI in geo-design also presents several challenges. Concerns about data privacy, ethical considerations, and the need for interdisciplinary expertise are critical issues that must be addressed to ensure the responsible and effective use of AI in this field. The complexity and novelty of AI technologies require a comprehensive understanding of their application's technical aspects and societal implications in geo-design.

In conclusion, AI technologies hold immense promise for revolutionizing geo-design and planning. They offer new opportunities for addressing the complex challenges of urbanization, environmental management, and sustainable development. However, to fully realize this potential, addressing the accompanying challenges and fostering an interdisciplinary approach that combines technical expertise with an understanding of geo-design's social, ethical, and environmental dimensions is imperative. Future research should focus on exploring these interdisciplinary aspects, developing ethical guidelines for AI application in geo-design, and advancing AI technologies to meet the specific needs of this field. This will ensure that AI enhances geo-design and planning practices and contributes positively to creating sustainable, equitable, and resilient urban environments.

**Author Contributions:** Conceptualization, methodology, investigation, and visualization, M.C.; writing—original draft preparation, data curation, W.H. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Data available in a publicly accessible repository. The data presented in this study are openly available in Web of Science.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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