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Mapping the landscape and roadmap of geospatial artificial intelligence (GeoAI) in quantitative human geography: An extensive systematic review

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ABSTRACT

This paper brings a comprehensive systematic review of the application of geospatial artificial intelligence (GeoAI) in quantitative human geography studies, including the subdomains of cultural, economic, political, historical, urban, population, social, health, rural, regional, tourism, behavioural, environmental and transport geography. In this extensive review, we obtain 14,537 papers from the Web of Science in the relevant fields and select 1516 papers that we identify as human geography studies using GeoAI via human scanning conducted by several research groups around the world. We outline the GeoAI applications in human geography by systematically summarising the number of publications over the years, empirical studies across countries, the categories of data sources used in GeoAI applications, and their modelling tasks across different subdomains. We find out that existing human geography studies have limited capacity to monitor complex human behaviour and examine the non-linear relationship between human behaviour and its potential drivers—such limits can be overcome by GeoAI models with the capacity to handle complexity. We elaborate on the current progress and status of GeoAI applications within each subdomain of human geography, point out the issues and challenges, as well as propose

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the directions and research opportunities for using GeoAI in future human geography studies in the context of sustainable and open science, generative AI, and quantum revolution.

1. Introduction

Geospatial artificial intelligence (GeoAI) is an emerging and promising research field that integrates AI with geospatial science to resolve problems and issues of geographic nature (Li and Hsu, 2022). The development of GeoAI brings the advantages of traditional AI studies in computer science to geographic research by empowering its quantitative methods with revolutionary technologies including machine and deep learning, high-performance computing power, and big data mining(Liu and Biljecki, 2022). Such emerging AI-oriented research tendency is particularly important for geographic studies in the era of big data, given more than 80 % of big data contain spatial information (Leszczynski and Crampton, 2016). As the advocacy of the Tobler's first law of geography—"everything is related to everything else, but near things are more related than distant things" (Miller, 2004), GeoAI enables researchers better monitor human behaviours and the surrounding environment which are often spatially dependent and autocorrelated. The recent breakthrough in GeoAI and more specifically deep learning facilitates the growth of a new research paradigm integrating data science and geography to analyse, mine, and visualise large volumes of spatio-temporal data, as well as enables researchers better capture the human-environment relationship given such relationship is complex, multifaceted and non-linear (Li, 2022).

Human geography is the branch of geography that studies spatial relationships between human communities, cultures, economies, and their interactions with the environment (Hoggart, 2002). Whereas physical geography concentrates on spatial and environmental processes that shape the natural world and tends to draw on the natural and physical sciences for its scientific underpinnings and methods of investigation, human geography concentrates on the spatial organization and processes shaping the lives and activities of people, and their interactions with places and nature (Gregory et al., 2011). Human geography consists of a number of sub-disciplinary domains that focus on different elements of human activity and organization (Gregory et al., 2011), mainly including (Fig. 1) *cultural, economic, political, historical, urban, population, social, health, rural, regional, tourism, behavioural, environmental* and *transport geography*. What distinguishes human geography from other related disciplines, such as development, economics, politics, and sociology, are the application of a set of core geographical concepts and notions that the world operates spatially and temporally, and that social relations were thoroughly grounded in and through of place and environment—where the implementation of GeoAI is well positioned and urgently needed. Although a range of review papers give attention to various related topics such as the application of

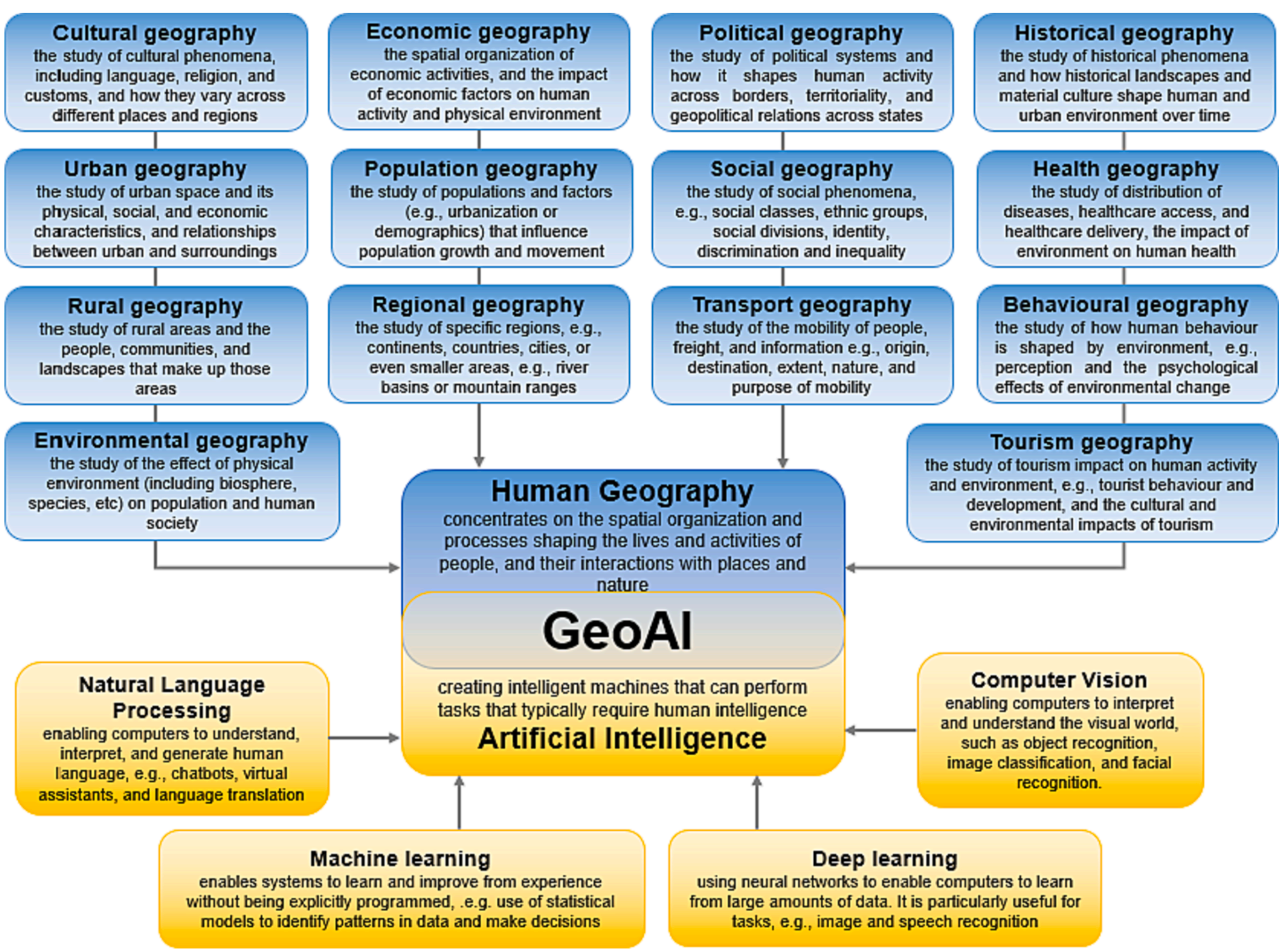

Fig. 1. Conceptual framework to shape the review scope.

deep learning in geography (Li and Hsu, 2022), GeoAI applications in urban planning and development (Alastal and Shaqfa, 2022) and urban geography (Liu and Biljecki, 2022), GeoAI approaches for complex geomatics data (Pierdicca and Paolanti, 2022), unsupervised machine learning in urban studies (Wang and Biljecki, 2022), and more broadly GeoAI in social science from a scoping review perspective (Li, 2022), what is lacking from the current scholarship is a holistic, comprehensive, and systematic understanding of GeoAI application in various domains of human geography—which our study fulfils.

We conduct a systematic review on the implementation of GeoAI in quantitative human geography including the subdomains listed above to 1) provide a holistic picture of the state-of-the-art GeoAI techniques and applications that have been used in human geography as well as data sources that were used to support GeoAI; 2) outline the future directions for geographers to grasp the AI-oriented opportunities whilst at the same time the future challenges and risks that need us to think critically and

Essential inclusion criteria: human-centred; related to human/society, human AI or human intelligence; focusing on the impact of other phenomena on human society and population.	**Essential exclusion criteria:** non-human-centred; focusing on physical aspects; or techniques centred; without focusing on their impact on human society and population.
Exemplary papers are:	**Exemplary papers are:**
• Quantitative studies (including data, methods, modelling tasks, and results)	• Qualitative summary; outline of study progress; review papers
• To predict or estimate demographic and socioeconomic aspects of populations	• Physical aspects of urban, and neighbourhood features, land use and change
• Social sensing via social media to study human behaviour (e.g., perception, attitude, opinions, mental signals, natural languages, and semantics towards some phenomena)	• Techniques comparisons; methodological oriented (e.g., IoT, 5G, technical resolution, software, etc)
• Public health	• Climate change modelling without considering effects on human and society
• Economic activities (e.g., housing prices, settlement, etc) and sharing economy (e.g., sharing cars, etc)	• Remote sensing only (e.g., object detection, data fusion, etc)
• Political activities (e.g., agents; stakeholders; political economy; legitimation)	• Weather and air pollution prediction without impacts on human
• Urban governance and management; human centred urban planning	• Survey and workshop to educate people to study AI
• Social phenomenon (e.g., migration, gentrification, etc)	• Transport modelling without impacts on human (e.g., system performance, etc)
• Transportation choices and behaviours (e.g., transport sharing, walkability, etc)	
• Human-eye measures (e.g., visual quality, street view, visual greenness, perceived measures, etc)	

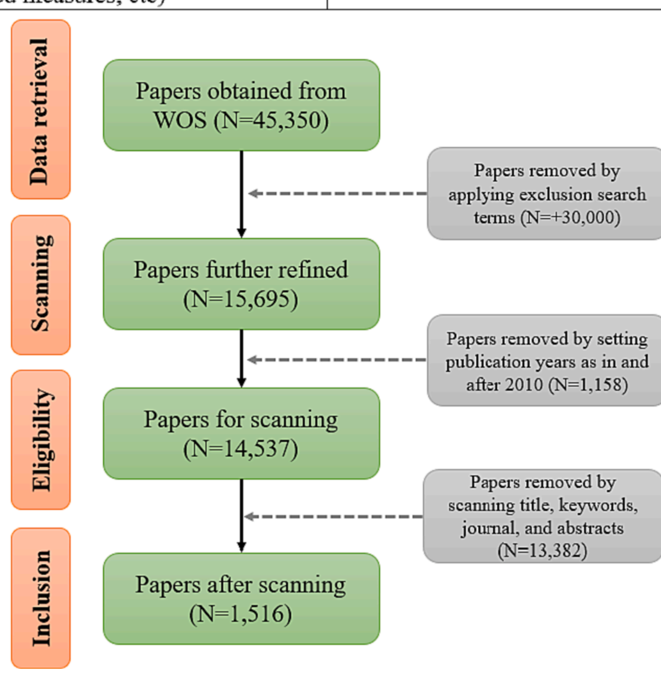

Fig. 2. PRISMA workflow for paper selection.

tackle specifically. Failing to do so could be costly and left behind in the mainstream of science as others leverage insights from the growing data deluge.

2. Review method

2.1. Data retrieval

We employed the standard systematic review methodology (Moher et al., 2010), known as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method (Fig. 2), to collect, scan and select appropriate papers within our research scope (detailed in Section 2.2). Following the existing review work (e.g.,Li and Hsu, 2022; Liu and Biljecki, 2022; Wang and Biljecki, 2022), we obtained papers relevant to GeoAI application in human geography from the Web of Science (WOS), as one of the most popular academic databases, based on several sets of predefined search syntax: 1) paper topics (in the WOS advanced searching engine, these terms were searched through topics which include article titles, abstracts, and keywords) relevant to GeoAI, including “artificial intelligence”, “geospatial artificial intelligence”, “AI”, “GeoAI”, “machine learning”, “deep learning” and “neural network”; 2) paper topics relevant to human geography, including “urban*” (the asterisk expands the search to include variations of the key syntax, such as urbanization), “city*”, “place*”, “human*”, “geo*”, as well as the name of 14 subdomains shown in Fig. 1. Their intersection signifies the focus of our review; 3) article type as “peer-reviewed journal articles” with the language as “English”; 4) disciplines as “environmental studies”, “environmental sciences”, “geography physical”, “geography”, “green sustainable”, “science technology”, “engineering civil”, “urban studies”, “regional & urban planning”, “sociology”, “social sciences”, “interdisciplinary”, “social sciences”, “mathematical methods”, “humanities”, and “multidisciplinary” to further refine the research; 5) publication timespan as “in and after 2010) given AI techniques started to rapidly develop after 2010 with the rise of social media, smartphones, and the internet of things (Van Roy et al., 2020).

With all these settings, the initial search results display 45,350 papers and the majority of such papers were relevant to remote sensing and physical geography without focusing on their impact on human society and population as well as a proportion of these papers fell into other disciplines (e.g., food industry and hydrology) beyond our review scope. Accordingly, we added one more set of search syntax—“remote sensing”—as the exclusion criteria to exclude papers, that are not human/population centred. Finally, the research results by the time of this study, February 1st, 2023, show that 14,537 papers were obtained—a substantial number for a systematic review, but a reasonable one considering the broad scope of the paper and one that can be manageable for human scanning in a large team. The paper list was downloaded with attributes including the publication year, author name, article title, journal, keywords, abstract, and the number of citations by the time of this study.

2.2. Scanning papers with human efforts

It was imperative to select the pre-obtained papers specifically centred around human society, population, and their perception and relationship with the surrounding environment—as the essential notion of human geography that the spatial organization and processes where the lives and activities of population immerse are shaping their interactions with places and nature. Thus, we conducted the paper scanning with human efforts from March 1st to April 1st, 2023 based on the inclusion and exclusion criteria (Table 1). Essentially, papers need to be included if they are quantitative studies in any subdomain of Human Geography, as well as being human-, population- and society-centred within the application of GeoAI; otherwise, they should be excluded.

Table 1
Inclusion and exclusion criteria used in the paper selection through human scanning.

Essential inclusion criteria:	**Essential exclusion criteria:**
human-centred; related to human/ society, human AI or human intelligence; focusing on the impact of other phenomena on human society and population.	non-human-centred; focusing on physical aspects; or techniques centred; without focusing on their impact on human society and population.
Exemplary papers are:	**Exemplary papers are:**
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• To predict or estimate demographic and socioeconomic aspects of populations	• Physical aspects of urban, and neighbourhood features, land use and change
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• Transportation choices and behaviours (e.g., transport sharing, walkability, etc)	
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3. Statistical outline of GeoAI applications in human geography

This section summarises how GeoAI applications have been applied in Human Geography studies across different subdomains in terms of modelling tasks, study areas and data types by using a Sankey diagram (Fig. 3). The full version containing all categories is provided in Supplementary Figure S1. This visualisation shows that 1) the top three subdomains using GeoAI in human geography include urban geography, transport geography and environmental geography (more details provided in Fig. 4); 2) the top three study areas where GeoAI was applied most frequently include China, US and India (more details provided in Fig. 5); 3) the top three data types that were most widely used in GeoAI include remote sensing imageries, street view imageries and transport network (more details provided in Fig. 6); 4) the top three modelling tasks implemented by GeoAI include predication (i.e., the non-linear and linear regression) and image-based classification (more details provided in Fig. 7).

It is evident from Fig. 4 that the usage of GeoAI in human geography has significantly increased since 2018. In 2019, there were 168 papers, which rose to 526 by 2022. Out of the 1512 selected papers, the majority of them, accounting for 29.1 % (440), were related to urban geography. Transport geography followed with 16.4 % (248), environmental geography with 14.1 % (213), and health geography with 10.6 %. Interestingly, the number of papers published in health geography showed a sharp increase from 2020 to 2021, which could be attributed to the COVID-19 pandemic outbreak.

GeoAI has been applied in various study areas, with China leading at 33.3 % (529) followed by the US at 17.6 % (280), India at 4 % (63), multiple countries worldwide at 3.8 % (60), and UK at 3 % (48) (Fig. 5). The subdomain of urban geography is the most popular among all study

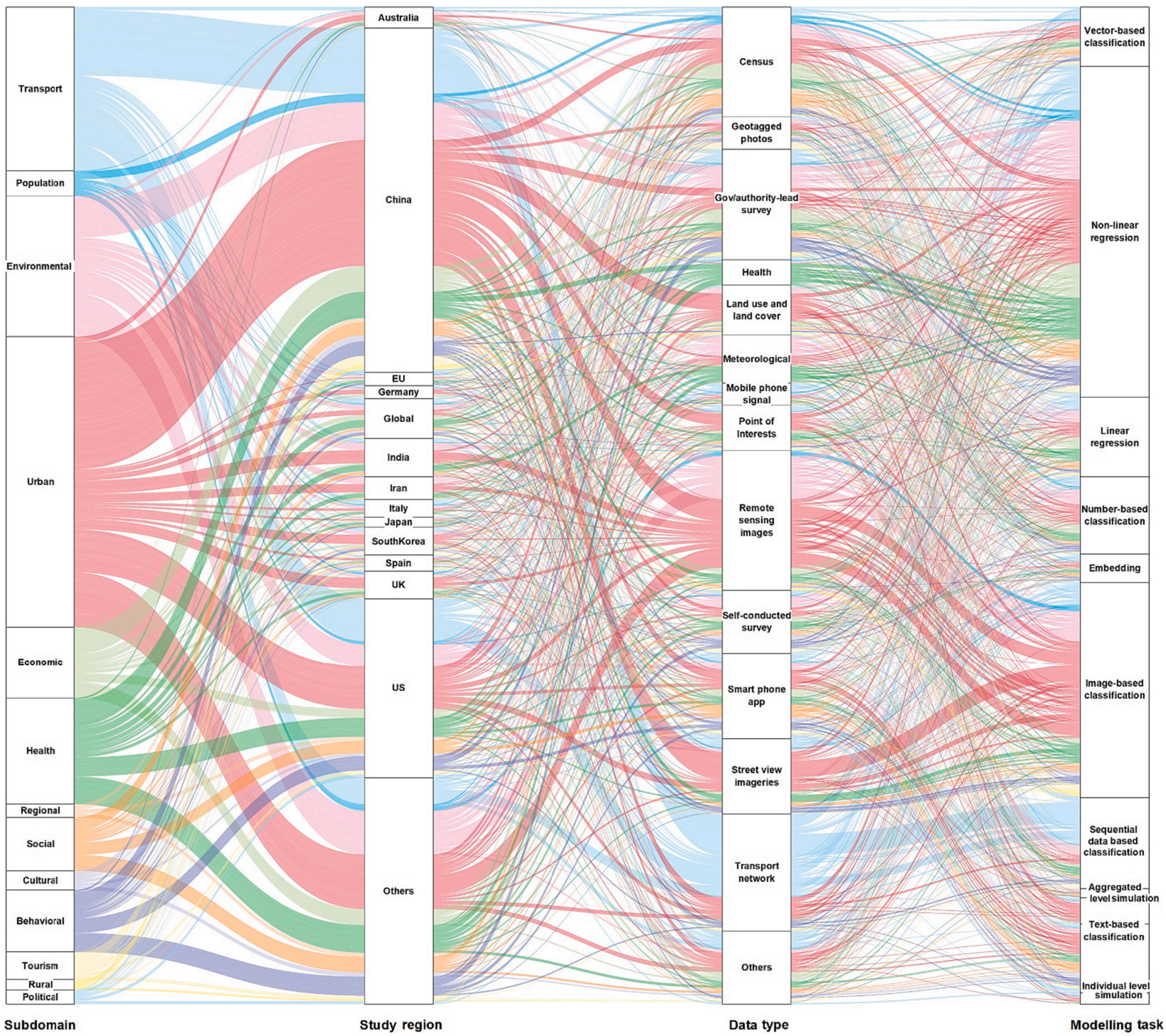

Fig. 3. Sankey diagram showing the distribution of study areas, data types and modelling tasks GeoAI achieved in each subdomain of human geography (top 15 categories included); the full version containing all categories is provided in Supplementary Fig. S1.

areas where GeoAI has been applied. For example, 36.9 % of 529 papers in China and 23.6 % of 280 papers in the US are in the domain of urban geography. The second and third most popular study areas where GeoAI has been applied are transport geography and environmental geography, respectively.

The types of data that have been used in GeoAI applications in Human Geography are classified into broad and secondary categories (Fig. 6) including 1) raster-based imageries (e.g., remote sensing images, street view images, and geotagged photos); 2) vector-based spatial data (e.g., points of interest, building, built environment, land use and land cover maps, and 3D point clouds); 3) vector-based spatiotemporal flow data (e.g., transport network, call records, mobile phone signals, smartphone apps, credit card transactions and traffic records); 4) official data provided by government or other sectors (e.g., census, government/authority-lead survey, health, economic data, tourists, crime, meteorological data, and other official statistics); 5) sound, video and texts; and 6) self-conducted survey. More details of the data classifications are provided in Table 2. The data types used in GeoAI are varying across subdomains.

The modelling tasks that have been implemented by GeoAI applications in Human Geography studies are classified into broad and secondary categories (Fig. 7) including 1) classification (e.g., image-based, vector-based, sequential-data-based, number-based, and text-based); 2) prediction (e.g., linear and non-linear regression); 3) simulation (e.g., at the aggregated and individual level); 4) embedding (i.e., the reduction of data dimensions; feature extraction); and 5) geolocating (i.e., geoparsing). More details of the modelling tasks are provided in Table 3. We can observe some common patterns of GeoAI modelling tasks across various subdomains of human geography—prediction (particularly non-linear regression) and classification (particularly image-based classification) have been widely employed in different subdomains of human geography, regardless of the number of published papers. GeoAI in urban geography also conducted a range of simulation tasks, in particular the aggregated level simulation (e.g., using cellular automata, deep neural network, and deep enforcement learning models).

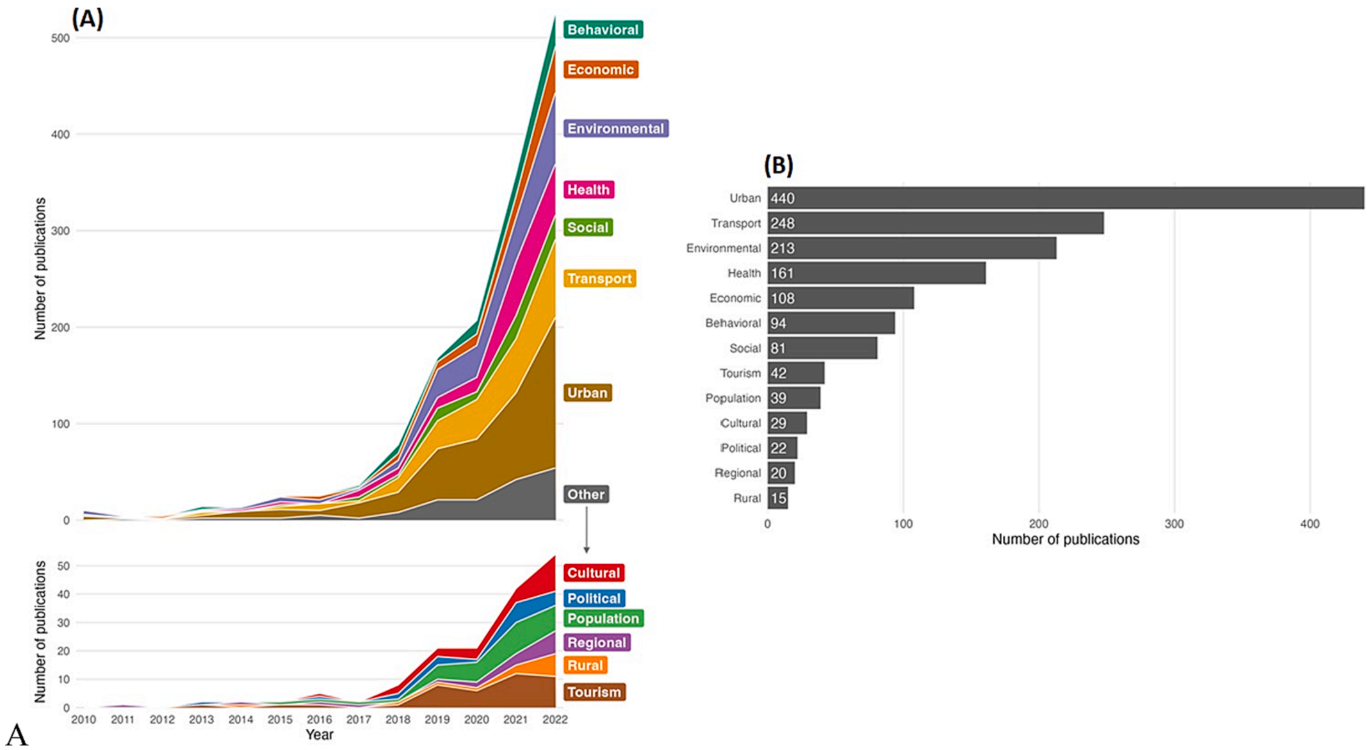

Fig. 4. **(A)** The number of papers published over the years and in each subdomain by accounting for the primary subdomain (the statistics accounting for both the primary and secondary subdomains are provided in Supplementary Table S1. The less common subdomains are plotted separately due to their minor share. The year 2023 is included in the review but not in this plot since it was not complete at the time of the writing.; **(B)** the total number of papers published in each subdomain from 2010 to 2023.

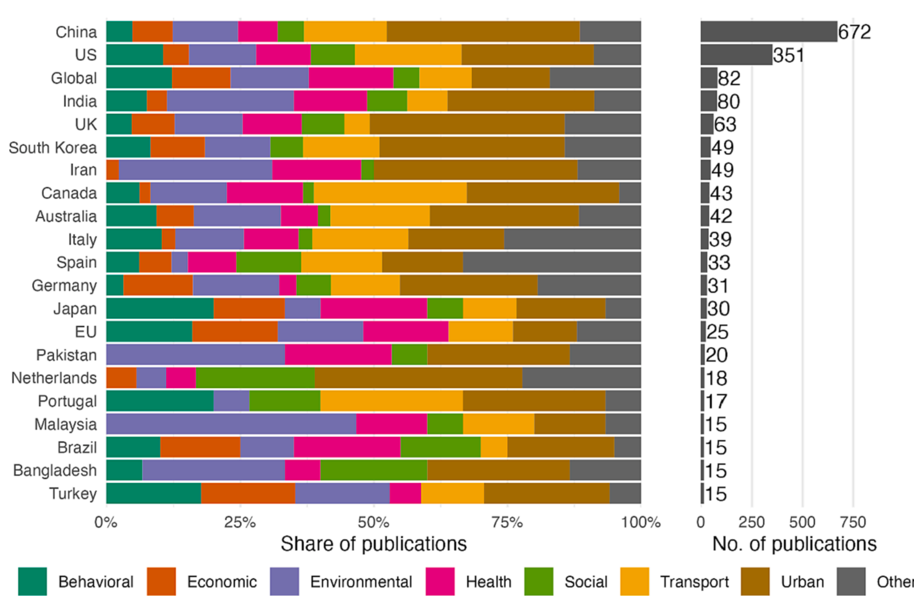

Fig. 5. A number of papers with empirical studies focusing on different regions, and the share of their categories. Note: there are a total of 100 countries studied in our selected papers; this bar chart only includes the top score of regions most frequently studied and the full list of them is provided in Supplementary Table S2.

4. How GeoAI enhances each subdomain of human geography

This section systematically and comprehensively summarises how GeoAI has been applied to 13 subdomains of Human Geography and advanced the current studies in terms of analytical approaches, emerging data, and research scopes.

4.1. Urban geography

GeoAI plays a pivotal role in Urban Geography, analyzing urbanization, urban changes, and hazards. Advancements in GeoAI include integrating CA with machine learning methods ((e.g.,Azari et al., 2016; Kafy et al., 2021; Rienow and Goetzke, 2015; Zhang and Xia, 2022; Zhang, Liu, et al., 2019) and neural networks (He et al., 2018; Ullah et al., 2019; Yang et al., 2019), using varied data sources like satellite

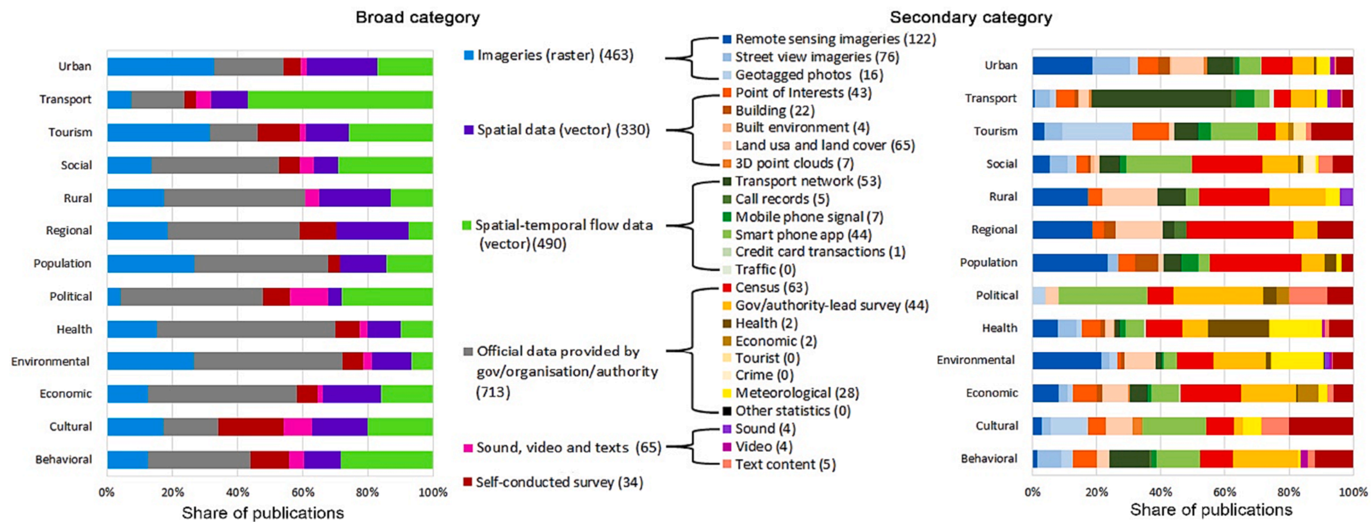

Fig. 6. Data types are classified into the broad and secondary category.

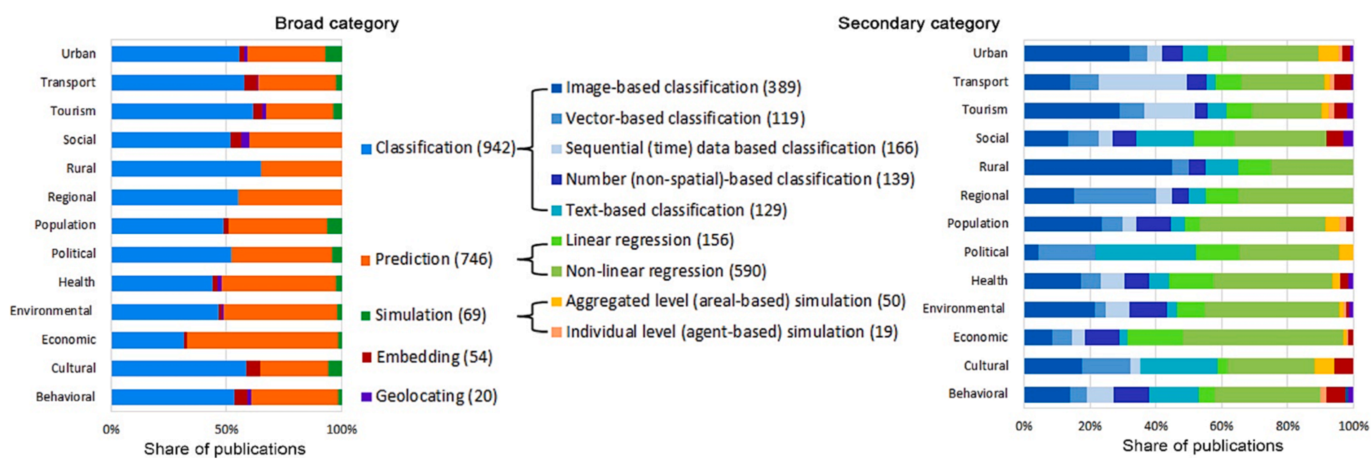

Fig. 7. Modelling tasks are classified into the broad and secondary categories.

images (Qian et al., 2020; Wu et al., 2010) and census data (Feng et al., 2019; Wu et al., 2010) to support precise and high-resolution simulations in the cities. Beyond CA, other methods, such as CNNs (e.g., Chen et al., 2020b) and generative models (e.g., Ibrahim et al., 2021), also show their potential to model the spatial and spatiotemporal interactions of urban objects in the phases of urbanisation. To study urban places and functions, with the development of smart urban infrastructures (e.g., smart cards for transportation), human-sensing data (e.g., geo-tagged text and images) and digital platforms (e.g., OpenStreetMap, Mapillary), intelligent computational models, such as natural language processing and computer vision-based (e.g., CNNs) analytical frameworks have massively contributed to the understanding of urban places (e.g., Andrade et al., 2020; Kim, 2019; Luo et al., 2022a; Wu et al., 2023; Zhang et al., 2023; Zhu et al., 2020) and supporting urban functional zones planning (e.g., Jiang et al., 2015; Zhai et al., 2019; Zhang et al., 2019a). Urban hazards cover a wide range of topics, such as flooding, heat waves, and fire emergencies. Tools developed based on CNNs with bird's eye-level remote sensing and human eye-level street view images (e.g., Bao et al., 2019; Feng and Sester, 2018; Li et al., 2022a) are adopted to support hazard detection and urban reconstructions. With the help of smart devices and social media platforms, natural language processing methods, such as geo-referencing (e.g., Zhang et al., 2021) and content analysis (e.g., Agonafir et al., 2022), are exclusively developed to support hazards localisation and severity analysis. As evidenced by the paper collection, thanks to the rapid enrichment of multiple data sources, we have witnessed a clear trend in exploring deep learning and its combination of machine learning and statistical methods in studying urban issues and discovering new patterns of cities that facilitate decision-making or assist downstream analytics.

4.2. Transport geography

The application of GeoAI in transport geography is a rapidly evolving field that has gained significant attention in recent years. The use of machine learning and AI techniques has the potential to improve transportation systems while providing insights into human travel behaviour. To date, numerous articles have focused on specific modes of transportation such as urban rail transit (e.g., Wang et al., 2021a; Zhang et al., 2020b) bike-sharing (e.g., Fontes et al., 2022; Yang et al., 2018), and ride-hailing services (e.g., Huang et al., 2021; Niu et al., 2019), while others have addressed broader topics such as traffic forecasting (e.g., Zhang et al., 2019c; Zhang et al., 2020f), crash prediction (e.g., Hu et al., 2022; Wei et al., 2022), and mobility pattern recognition (e.g., Heredia et al., 2021; Lv et al., 2021). Of particular interest is the growing trend in exploring the use of deep learning models for analysing images (e.g., street views and user-generated pictures), and other sensor data (e.g., traffic sensors, GPS pins, and environmental sensors), to understand

Table 2
Type of data that have been used in GeoAI related Human Geography studies.

Broad category	Secondary category	Exemplary data sources
Imageries (raster)	Remote sensing imageries	Land use and land cover raster maps, night-time data, LIDAR, MODIS
	Street view imageries	User/vehicle-generated imageries, Google/Baidu street view imageries
	Geotagged photos	Geotagged (social media) photos such as Flickr
Spatial data (vector)	Points of Interest	Location of public facilities, parks, and bus stops
	Building	Cadastral maps/building footprints
	Built environment	Measures of road density, distance to the nearest stations
	Land use and land cover	Polygon layers of land use and land cover
	3D point clouds	3D point clouds data including vertical dimension
Spatial-temporal flow data (vector)	Transport network	Mobility network, road network, smart card-generated data, flight tickets
	Call records	911 hotline calls, municipal complaint records
	Mobile phone signal	Safegraph
	Smartphone app	Social media app/website-generated data (e.g., Baidu/Google/Facebook mobility data), tweets/geotagged tweets, online bike-sharing information
	Credit card transactions	Credit card records with spatial–temporal information
	Traffic	Traffic crashes, bike usage, accident records, and emergency events.
Official data provided by gov/organisation/authority	Census	Census data provided by the government
	Gov/authority-lead survey	Disaster evacuation data in the US, HILDA data in Australia
	Health	Clinic/patient data, healthcare facilities
	Economic	Housing, insurance, sale and retail records, tax assessment, residential settlement
	Tourist	Tourist statistics
	Crime	Crime records
	Meteorological	Weather station-generated data (e.g., wind, rainfall, humidity)
	Other statistics	Bio environment (e.g., species)
Sound, video and texts	Sound	Voice, sound records
	Video	Traffic video
	Text content	Texts without spatiotemporal information
	Photo	Static photos without spatiotemporal information
Self-conducted survey	—	Primary data collected via online/offline interviews, questionnaires

the built environment's impact on travel behaviour (e.g., Li et al., 2023a; Li et al., 2023b; Liu et al., 2022). Additionally, researchers are increasingly interested in the application of intelligent algorithms (e.g., tree-structure models, graph neural networks, and recurrent neural networks) for predicting travel patterns, including mode choice (e.g., Zhang et al., 2020a), passenger flow (e.g., Zhang et al., 2020a), and traffic volume (Zheng et al., 2021). To support transportation planning efforts, various tools have been developed, such as a planning support tool for street network design (Fang et al., 2022). Moreover, there is a surge of research activities proposing novel approaches to transportation-related challenges, such as detecting traffic incidents using social media data (e.g., Chang et al., 2022), identifying critical transfer zones for coordinating transit (e.g., Qiu et al., 2022), and predicting the demand for bike-sharing and ride-hailing services (e.g., Chen et al., 2020a; Zhang and Zhao, 2022). These approaches have the

Table 3
Modelling tasks and methods that have been implemented in GeoAI related Human Geography studies.

Broad category	Secondary category	Exemplary models and algorithms
Classification	Image-based	• Convolutional Neural Networks (CNNs) (LeNet, AlexNet, ResNet, VGG, Inception, EfficientNet, DenseNet, MobileNet) • Artificial Neural Network • Support vector machine (SVM) and one-class SVM • Gradient Boosting algorithms (GBM) (e.g., XGBoost, LightGBM, Catboost) • K-Nearest Neighbour • Naïve Bayes Algorithm • Deep Belief Networks (DBNs) • Autoencoder (AE) • Siamese networks • Isolation forest • Local outlier factor • Angle-based outlier detector • Histogram-based outlier detection • Autoencoders (variational types) • Hidden Markov models • Fuzzy logic-based outlier detection • Deep-learning based methods (Conditional neural network, RNN) • YoLo model family • R-CNN model family (R-CNN, Fast R-CNN, Mask R-CNN, R-FCN, Cascade R-CNN) • CenterNet model family (Single Shot Detector (SSD), DSSD, RON, CornerNet) • Histogram of Oriented Gradients (HOG) • Region-Based Segmentation • Edge Segmentation • K-Means • Convolutional Encoder-Decoder Architecture (e.g. SegNet, U-Net, Fully Convolutional Networks (FCN) • Multi-Scale and Pyramid Network Based Models (FPN) • Pyramid Scene Parsing Network (PSPNet), Mask R-CNN, Fast R-CNN) • Dilated Convolutional Models and DeepLab Family
	Vector-based	• Spatially constrained multivariate clustering • Multivariate clustering • Density-based clustering • Image segmentation • Hot spot analysis • Cluster and outlier analysis • Space-time pattern mining • Hierarchical clustering analysis (HCA) • Density-based spatial clustering of applications with noise (DBSCAN) • Spectral clustering • Affinity propagation (AP) • Gaussian mixture model (GMM)
	Sequential (time) data-based	• Hidden Markov Models • Long Short-Term Memory networks (LSTM) • Recurrent Neural Networks (RNN) • Conditional Random Fields • Distance-based (e.g., KNN, dynamic warping) • Interval-based (e.g., time-series forest) • Dictionary-based (e.g., Bag of SFA Symbols (BOSS)) • Frequency-based (Random Interval Specteal Ensemble (RISE)) • Shapelet-based (e.g., shapelet transform)
	Number (non-spatial)-based	• Support vector machine (SVM) • Gradient Boosting algorithms (GBM) (e.g., XGBoost, lightGBM, CatBoost) • Decision tree / Random Forest

(continued on next page)

Table 3 (*continued*)

Broad category	Secondary category	Exemplary models and algorithms
		• Means algorithm • Fuzzy logic-based algorithms • DBSCAN • Spectral clustering • Hierarchical clustering • Affinity Propagation
	Text-based	• Latent Dirichlet allocation (LDA) / RNN • Word2Vec • Doc2Vec • Bag-of-words model • n-gram model • Transformers-based methods (BERT, XLM, GPT, RoBERTa, XLNet, DistilBERT etc) • ELMo • RNN • LSTM • Word2Vec • Doc2Vec • Bag-of-words model • n-gram model • Transformers-based methods (BERT, XLM, GPT, RoBERTa, XLNet, DistilBERT etc) • ELMo
Prediction	Linear	• Generalized linear model (GLM), including Lasso regression, Ridge regression, Polynomial Regression, Bayesian linear regression; Logistic regression, Gamma regression, Poisson regression, Bernoulli regression, Binomial regression, Multinomial regression, Exponential regression, (Inverse) Gaussian regression
	Non-linear	• Support vector machine • Artificially Neural Network (ANN) • Gradient Boosting algorithms (GBM) (e.g., XGBoost, lightGBM, CatBoost) • Empirical Bayesian Kriging regression prediction • Forest based prediction (random forest, decision tree) • Graph Convolutional Neural Network • Generalised additive model (GAM) and GeoGAM • Bayesian hierarchical model (BHM) • Second-dimension spatial association • Geographically optimal similarity model
Simulation	Aggregated level (areal-based)	• Cellular Automata • Deep neural network • Deep enforcement learning • Tabular Q-learning
	Individual level (agent-based)	• Agent based modelling
Embedding	—	• Principal component analysis (PCA) • Independent Component Analysis (ICA) • Linear Discriminant Analysis (LDA) • Locally Linear Embedding (LLE) • t-distributed Stochastic Neighbour Embedding (t-SNE) • Auto-encoder model family • enerative adversarial network (GAN) • Isomap • Hessian Eigenmapping • Spectral embedding • Multi-dimensional Scaling (MDS) • Kernel PCA • Graph Neural Networks (GraphSAGE, GCN)
Geolocating	—	• Geoparsing models

potential to transform the way transportation systems are planned, designed, and managed. Overall, we observe that GeoAI has emerged as a highly promising avenue for transforming the transportation industry. Nevertheless, as many scholars have pointed out, the potential challenges that must be overcome include integrating disparate data sources, addressing privacy concerns, and devising efficient algorithms that can process immense quantities of transportation data in real time. Nonetheless, the commendable progress achieved thus far has laid the groundwork for sustained research in the GeoAI domain of Transport Geography, thereby facilitating continued improvements in transportation systems.

4.3. *Environmental geography*

Environmental geography has gained significant importance in recent years due to pressing global environmental challenges, such as climate change, population growth and urbanization, environmental pollution, and an increasing number of natural disasters. By leveraging the power of advanced machine learning and artificial intelligence techniques, GeoAI enables the processing and analysis of large and complex environmental data with the integration of diverse data sources (e.g., Ning et al., 2020), remote sensing imagery, street view images (Wu et al., 2020), social media posts (Ning et al., 2020), and census, real-time monitoring, and enhanced predictive capabilities. For example, GeoAI techniques have been employed for land use and land cover changes detection and prediction (e.g., Apollonio et al., 2016; Handayanto et al., 2017), climate change modelling and forecasting (e.g., Logan et al., 2020; Shen et al., 2020), disaster management and risk assessment (e.g., Bui et al., 2019; Feng and Sester, 2018; Talukdar et al., 2020), water resource management (e.g., Obringer and White, 2023; Zhang et al., 2018), environmental pollution monitoring (e.g., Acheampong and Boateng, 2019; Cole et al., 2020), and urban planning and sustainable development (e.g., Richards and Tunçer, 2018; Wu et al., 2020). As GeoAI continues to evolve, it holds the potential to significantly improve our understanding of environmental geography and provide essential insights for effective decision-making to address pressing environmental issues.

4.4. *Health geography*

The implementation of GeoAI can be easily identified in many health-related areas, including infectious epidemiology, social media analysis, built environment, and environmental epidemiology. GeoAI has been used to identify and forecast the spread of infectious diseases (Guo et al., 2017), but the booming of this application was not until the hit of the COVID-19 pandemic that various models have been developed and used for COVID-19 prediction (Ghahramani and Pilla, 2021; Guo and He, 2021; Tomar and Gupta, 2020), especially at the early stage of the pandemic. Other application related to COVID-19 includes measuring the association between mitigation policies and COVID-19 transmission (Zhang et al., 2020c), maximizing the assessed population in the shortest possible time for mobile assessment agents (Simsek and Kantarci, 2020), and monitoring social distancing using video sequences (Ahmed et al., 2021). GeoAI has also been applied to analyse social media data to help with the early detection of the distribution of COVID-19 (Golder et al., 2020). It has also been widely used to understand the distribution and public opinion of other diseases, including estimating obesity prevalence (Cesare et al., 2019), understanding autism-related antivaccine beliefs (Tomeny et al., 2017), monitoring the well-being of transit riders (Tran et al., 2023), and measuring urban-regional disparities of mental health signals (Wang et al., 2022b). GeoAi was mainly used to identify tweets and to measure emotions within a body of text. There has been a long-term interest in applying GeoAI to better evaluate built environment (e.g., cities, buildings, and greenspace) (Larkin and Hystad, 2019) and measure its association with other health outcomes, including COVID-19 transmission (Kawlra and

Sakamoto, 2021), mental health status (Helbich et al., 2021; Wang et al., 2019a), the well-being of elderly (Wang et al., 2019b), and pedestrian emotion (Xiang et al., 2021). Most of this work applies GeoAI to identify the features of the built environment through analysing street view images. GeoAI has also been advancing modelling technics in environmental epidemiology in accessing air pollution and measuring its impact on health. Recent applications include predicting PM2.5 concentration during the pandemic (Yang et al., 2022b), generating daily surface concentration maps for PM2.5 and O-3 during a wildfire (Reid et al., 2019), and predicting air quality (Xiao et al., 2021). It also helps to model the association between air pollution exposure and early cognitive skills among children (Stingone et al., 2017).

4.5. Economic geography

The GeoAI applications in economic geography have largely crossed over urban geography, in particular, land use and land change (e.g., Hu et al., 2016a; Levers et al., 2018), given land provides space for economic activities and relevant costs occurring along the process of land changes link to economic development and evaluation. GeoAI models, especially non-linear models, have been widely employed to predict and estimate sale prices of real estate properties (Čeh et al., 2018; Rafiei and Adeli, 2016) and income levels (Ivan et al., 2020); to generate a wide range of socioeconomic indicators based on other data sources (e.g., remote sensing imageries, open street maps and social media data) (Feldmeyer et al., 2020; Roumiani and Mofidi, 2022); to explore the potential driving factors for housing and rental prices(Ma et al., 2020; Yoo et al., 2012) or economic consumptions and activities across different industries (e.g., electric appliances, retail industry)(AL-Musaylh et al., 2021; Rao and Ummel, 2017); or to evaluate the relationship between management and organizational performance (Lin et al., 2022). Those relationships among economic activities and their potential factors are complex, non-linear and mingling with various confounders, where GeoAI provides advanced approaches to generalise such interrelationships. In addition, GeoAI helps to develop planning and decision support system (Demetriou et al., 2012), urban renewal policy analysis based on a wide range of crowdsourcing data (Auerbach et al., 2020) or to simulate housing rentals (Chen et al., 2016) with the advantages of visualising its spatiotemporal patterns—these end-user applications and policy implications can readily benefit government, public sectors and authorities on economic planning and policy making.

4.6. Behavioural geography

One cutting-edge advance of GeoAI is to quantify the behaviour of human beings which could be difficult to achieve by other approaches. Such human behaviours include human perception (e.g., the sense of safety, anxiety, depression, beauty, and happiness) to the visual features of the built environment (e.g., green and blue space) and natural environment (Choi et al., 2022; Ramírez et al., 2021; Rossetti et al., 2019; Zhang et al., 2018)as well as certain social phenomena, events and crises (e.g., COVID-19; disease treatment-seeking behaviours) (Kim et al., 2022). GeoAI has also been widely applied to explore the relationship between environment and human decisions on travel (e.g., active commuting, walkability, bikeability, and transport demand) (Ding et al., 2018; Ki and Lee, 2021; Molina-García et al., 2019; Rossi et al., 2019; Tran et al., 2020), linguistic and semantic expressions (Wirz et al., 2018), spatiotemporal trajectory (Torrens et al., 2011), and consumers' behaviours (Dias et al., 2021): such human-environment relationships are confounding, complex which can be rarely captured by linear models. The prediction of crime (criminal rates, locations and patterns) and social lifestyles (Ben Zion and Lerner, 2018; Kadar and Pletikosa, 2018) is another stream of GeoAI applications in behavioural geography. Since the outbreak of COVID-19, GeoAI become popular to capture people's altitude, opinion, mental reaction and connection to the global pandemic (e.g., Wang et al., 2022b), although such studies have been largely categorised into the subdomain of health geography.

4.7. Social geography

Studies in social geography are largely mingling with other subdomains of human geography, including behavioural geography, urban geography and environmental geography. GeoAI empowers the methods that were used in the traditionally sociological/urban studies to examine the relationship between urban built/natural environment and the observed social phenomenon, including gentrification and community deprivation (Alizadeh et al., 2018; Li et al., 2019b; Reades et al., 2019; Talukdar et al., 2021); to evaluate the impacts of social events via large-scale spatiotemporal crowdsourcing data (e.g., geo-tagged social media data (Zhu et al., 2018); to address some unique social problems such as modern slavery (Lavelle-Hill et al., 2021); to visualise the urban social change of neighbourhoods (Lee and Rinner, 2015); to identify poverty and urban slums (Yin et al., 2020) and explore the potential driving factors of poverty (Luo et al., 2022b); to quantify neighbourhood mixing (Hipp et al., 2017); to evaluate social justice (Debnath et al., 2021), housing inequality (Knaap, 2017), and social inequality in the selection of transport modes (Zhou et al., 2019); and to monitor social wellbeing of different social groups (Brown et al., 2021). GeoAI also has implications for the management of social organisations and public policy via examining social network (Choudhury et al., 2022) and organizational geosocial network (Zhao et al., 2022), as well as to facilitate citizen engagement in urban governance (Siyam et al., 2020) and to predict the socioeconomic status of urban neighbourhoods (Diou et al., 2018). Similar to some studies in behavioural geography, GeoAI has been also used to track and predict neighbourhood crime (Amiruzzaman et al., 2021) and examine how it links to neighbourhood visual appearance (Reier Forradellas et al., 2020) and the socioeconomic attributes of locations (Doi et al., 2021). Lastly, GeoAI helps to generate new datasets from the perspective of social science, including the social vulnerability index (Alizadeh et al., 2018) and livelihood vulnerability index (Talukdar et al., 2021), which can be further used in cross-disciplinary studies.

4.8. Tourism geography

The application of Geo AI in tourism geography has significantly advanced the field by providing insights into various aspects of tourism dynamics and management. Key areas of focus include analysing tourist behaviour and movement patterns (e.g., Chang et al., 2019; Zhang et al., 2019b), understanding visitor experiences (e.g., Song et al., 2021; Zhang et al., 2020d), building an attraction evaluation and recommendation system (Giglio et al., 2019; Sun et al., 2015), evaluating sustainability (e.g., D'Uva and Rolando, 2023; Roumiani et al., 2023), assessing the quality of public spaces (e.g., Ghahramani et al., 2021a; Li et al., 2022b), and monitoring environmental impacts (e.g., Furgała-Selezniow et al., 2021). These studies use various data sources including surveys (such as Hou et al., 2021), geotagged photos (such as Zhang et al., 2019b), points of interest (such as Zhang et al., 2020d), smartphone apps and signals (such as Crivellari and Beinat, 2020; Song et al., 2021), transport networks (such as Nuzzolo and Comi, 2016), remote sensing imagery (such as Sun et al., 2021), street view images (such as Kruse et al., 2021), and text content from social media (such as Zhang et al., 2020d). Accordingly, the GeoAI methods used in tourism geography mainly include text-based techniques like topic modelling (van Weerdenburg et al., 2019), and sentiment analysis (Ghahramani et al., 2021b), computer vision models such as deep learning models (Kang et al., 2021), other machine learning techniques like random forest (Li et al., 2019a) and XGBoost (Kang et al., 2022), as well as spatial clustering models like density-based clustering method (DBSCAN) (Sun et al., 2015). Overall, GeoAI has been widely used to provide insights for policy decisions, improve tourism management, and contribute to a better understanding of human behaviour and perception of urban spaces and travel experiences. However, some scholars point out that the application of AI technology may affect turnover intention (Li et al., 2019a).

4.9. Population geography

The application of GeoAI in population geography focuses on predicting population growth and population movement (e.g., Chen et al., 2018; Ullah et al., 2019), disaggregating population counts based on other data sources to generate fine-grained population data that can be used for other research purposes (e.g., Khan et al., 2021; Monteiro et al., 2019; Ye et al., 2019), measuring and characterising human activities (Hu et al., 2016b), delineating human settlement in the exposure to natural hazards (Herfort et al., 2019), forecasting the mortality of populations (Perla et al., 2021) and exploring its potential driving factors (Boumezoued and Elfassihi, 2021), tracking human trajectories and mobility (Hu, 2020), and inferring people's demographic and socioeconomic status (Zhang et al., 2020e). Such studies predominantly utilise machine learning models (e.g., random forest, gradient boosting models) to predict the non-linear relationship between population (e.g., counts, their demographic and socioeconomic characteristics) and other phenomena (e.g., urbanisation, land use change, green space, and climate change). The applications of more advanced deep learning models are employed to derive measures from diverse data sources (e.g., classification based on remote sensing imageries or official data) that can be further used for the disaggregation or prediction of population data at different spatial scales. Common findings from these studies include that GeoAI provides sufficient approaches with sound modelling performance to capture the complex relationship between human and the environment and to produce reliable population data that can be calibrated and validated by other data sources.

4.10. Cultural geography

GeoAI has been used to advance the methodology used in the cultural geography studies which are traditionally rooted in qualitative investigation. For example, GoeAI is applied to processing and analysing geotagged photos and street-level images to assess ecosystem cultural services (nonmaterial benefits people obtain from ecosystems that affect their physical and mental states(Cardoso et al., 2022; Fish et al., 2016; Marine et al., 2022; Richards and Tunçer, 2018) and to understand the spatiotemporal pattern of linguistic variations in one community (Hong, 2020). The approach of GeoAI makes the analysis more efficient by reducing the error and time from previous manual labour work. GeoAI has also helped to understand the development of linguistics by recognizing handwritten words from Bangla word images (Das et al., 2020) and post-correcting Optical Character Recognition in Hebrew (Suissa et al., 2022). These approaches create a stable and generalized system for word recognition and correction and obtained a high accuracy rate. Many studies also use social media data to understand cultural practices and beliefs, including measuring food cultural differences (Zhang et al., 2020c), detecting changes in perception towards smart cities (Yue et al., 2022), recognizing human daily activity (Gong et al., 2019), and measuring social-spatial boundaries (Rahimi et al., 2018). GoeAI is used for data extraction, text pre-processing, and sentimental analysis in those studies.

4.11. Political geography

Compared to other subdomains, the application of GeoAI in political geography is relatively limited, possibly due to the nature of political geographic studies being more qualitative. In very recent years, there are also some GeoAI applications, predominantly natural language processing models, that have been used to process the contents of policies, newspapers, and planning documents (Brinkley and Stahmer, 2021); to monitor people's perception towards political initiatives (e.g., smart city concepts) (Yigitcanlar et al., 2021); to forecast corruption and presidential election based on social media data (Ghahari et al., 2021; Liu et al., 2021b); to explore the political tendency towards certain phenomena or in certain domains (e.g., Brexit, AI, data science, and organic waste flows) (Bastos and Mercea, 2018; Folgado and Sanz, 2022; Morone et al., 2021); to address political issues including the radical right (Jambrina-Canseco, 2023); and to visualize or predict political activities (e.g., protect incidents and terrorism incidents) (Bekker, 2022; Hao et al., 2019). Although such applications are largely limited to coping with texts and qualitative contents, it showcases the great potential of GeoAI in the political implications and helps government hear the voice of the 'silent majority' which was usually difficult to be monitored via qualitative methods.

4.12. Regional geography

The application of GeoAI in regional geography is relatively limited given the aim of regional geography is to study the interaction of different cultural and natural geofactors in a specific land or regional landscape and compare such differences across regions—it largely overlaps with studies in other subdomains, leading to a few papers that fall into this category as the primary subdomain. Despite the nature of mixture in regional geographic studies, the GeoAI applications have been used to evaluate regional carrying capacity (Chen et al., 2011), the inequality and neighbourhood mixing across metropolitan areas (Kane and Hipp, 2019), contrasting landscapes (Hernandez-Moreno et al., 2021), regional sustainability across metropolitan areas (Liu et al., 2021a), regional development (Lai et al., 2022), and regional inequality of neighbourhood typologies (Lynge et al., 2022). Findings from these studies show that GeoAI applications provide highly accurate modelling results to explore the non-linear relationship among regional characteristics and dependent phenomena and to reveal its great potential to be used in comparative studies across different geographic contexts.

4.13. Rural geography

GeoAI is increasingly becoming a vital technique in rural geography, offering innovative solutions to the unique challenges faced by rural areas. One of its key applications is agricultural land use and crop monitoring, where it leverages artificial intelligence technologies for ensuring food security (Yang et al., 2022a) and optimising urban-agricultural-ecological space (Wang et al., 2022a; Zeng et al., 2022). GeoAI also plays a crucial role in rural infrastructure planning and development by assessing and prioritizing infrastructure needs, such as demand for public transportation (Bakdur et al., 2021), the severity of accidents prediction (Habibzadeh et al., 2022), and policy guarantee mechanism assessment (Jin et al., 2021). This contributes to more equitable and sustainable rural development. In addition, advanced machine learning algorithms are employed to model and predict rural economic development (Khalaf et al., 2022; Qin et al., 2020; Xie et al., 2022) and rural population dynamics (Grossman et al., 2022; Lee, 2022). Furthermore, GeoAI has shown remarkable success in identifying land use and land cover changes in rural areas that might be overlooked by traditional remote sensing methods (Killeen et al., 2022; Saha et al., 2022; Xu et al., 2019). These insights guide rural development policies and strategies, helping address key challenges in rural areas. Overall, the integration of GeoAI in rural geography has the potential to revolutionize the field, offering new perspectives and data-driven approaches for the sustainable development of rural communities.

5. Discussion: Future directions and challenges

5.1. Cross-disciplinary research opportunities and beyond

Human geography has been revolutionised to be increasingly supported by spatiotemporal big data, more robust in research design to address the non-linear complex relationship between human society and its potential drivers, more diverse in empirical studies and in turn to advance theoretical foundations. We have observed that the field of GeoAI presents numerous cross-disciplinary research opportunities to link human geography to public health, environmental science, medical science, decision and policy-making, and industrial practices more broadly. In particular, human geography subdomains that were deeply rooted in social science in the past, including cultural, historical and political geography, have been empowered by GeoAI and spatiotemporal big data and crowdsourcing data (e.g., social media data) to broaden its research impact and the coverage of empirical contexts—that can be rarely achieved by using small data (e.g., questionnaires) and qualitative methods. Besides, there is still so much potential to be realized by leveraging the power of GeoAI in conjunction with broader fields in social science such as psychology, sociology, and anthropology to analyse and predict human behaviour—additionally, to enhance the studies on human-environment interactions given human behaviour was thought to be mediated through the surrounding environment where they reside (e.g., urban built environment and natural environment) (Wang et al., 2023; Wang et al., 2021b). On the practical end, GeoAI helps to achieve decision-making and evaluate different scenarios of policies in the initiatives of smart and healthy cities as well as citizen participation in urban planning and design—where public sectors and authorities could rely on the quantitative results simulated by GeoAI to optimise policy implementation and reduce social and financial costs. The possibilities for cross-disciplinary research are endless, and the potential benefits are significant with the invention of new technology such as generative AI, digital twins, knowledge graphs, 5G, and the Internet of Things (Zhang et al., 2022) to help both researchers and policymakers gain a deeper understanding of complex urban systems and make more informed decisions that positively link the academic outcomes to the real world.

5.2. Emerging spatiotemporal data, and its issues and challenges

Our review finds out that human geography studies have been much advanced by emerging spatiotemporal big data that enables geographers to track, monitor, and quantify complex human behaviors in a large spatial and temporal scale. It further indicates that the AI's extensive role in human geography, yet highlights the limited interpretability of current models, a concern raised in recent studies (Hsu and Li, 2023; Liu et al., 2023; Xing and Sieber, 2023). This issue, along with the potential bias in GeoAI models, is crucial for future research. For instance, models predicting human perceptions from imagery, often developed through broad surveys, may not suit specific geographic needs (Kang et al., 2023). Additionally, these models typically require substantial, region-specific data, presenting challenges in data availability and application across different areas. Addressing these data limitations and biases in GeoAI is vital for advancing the field. Our review (Fig. 6) has further found that the used data spans a variety of types and comes from a variety of sources, e.g. authoritative data from governments to crowdsourced instances. This matter requires attention, as it has implications for the quality and downstream analyses. Much of the data used in the reviewed papers are obtained from OpenStreetMap, the freely editable map of the world, which in some geographies offers suitable data for some of the use cases covered in this review. However, data remains highly heterogeneous (Biljecki et al., 2023) and in some locations, it may not be sufficient or even detrimental for analyses. We call attention to pay attention to the quality of the data, especially those derived from a crowdsourced provenance. Further, a potential research direction is consideration of the impact of the propagation of errors on the outcome of an analysis. Spatial data quality, a topic often ignored in human geography, regards multiple elements such as completeness, positional accuracy, and thematic accuracy (Hou and Biljecki, 2022). The quality of each of these elements impacts different use cases in different ways, and it would require extensive research on understanding the reliability of an analysis based on the input dataset.

5.3. Sustainable GeoAI: repeatable, reproducible and expandable

GeoAI is crucial for environmental and sustainability issues, processing geospatial data efficiently. Its solutions must be repeatable, reproducible, and expandable for consistent, transferable, and scalable methodologies. Repeatability requires GeoAI to provide consistent results with the same data and methods, calling for well-documented algorithms and transparent workflows. Reproducibility, achieved through varied data sets or environments, benefits from open-source platforms, standardized data, and shared code, enhancing collaboration and progress. Expandability enables adaptation to larger or new data sets and evolving queries, utilizing modular designs, cloud computing, and advanced algorithms for big data, ensuring GeoAI solutions remain flexible and applicable. In addition, the complexity of GeoAI methods and their execution environments affects their repeatability, reproducibility, and expandability. Three main approaches for developing and executing GeoAI models include 1) using existing GIS or analysis software like Geoda, ArcGIS, and others, which is user-friendly but less reproducible and scalable; 2) developing and executing complex models through code, which enhances reproducibility and scalability, especially with Jupyter Notebooks. However, Trisovic et al. (2022) conduct a large-scale study on research code quality and execution, and found that 74 % of data science research code failed execution tests (3) utilizing visual programming tools like ArcGIS's Model Builder, QGIS, Knime, Orange3, and Alteryx to develop and execute GeoAI models in an executable workflow, reducing the burden on researchers and improving understandability, it provides a promising idea to improve repeatability, reproducibility, and expandability of GeoAI modes. However, there are still relatively few applications for this at present. Sustainable GeoAI requires a holistic approach to ensure solutions are repeatable, reproducible, and expandable. By focusing on these aspects, the GeoAI community can foster long-term, impactful, and collaborative work, contributing to a more sustainable future.

5.4. Human-centred GeoAI in the era of artificial generative intelligence

AI has witnessed significant advancement with the emergence of Artificial General Intelligence (AGI) representing AI system's capable of performing intellectual tasks better that a human, and sometimes exceeding human intelligence (e.g., ChatGPT). Leveraging AGI in human-centered GeoAI has the potential to deliver substantial advantages, including bolstering decision-making processes, optimizing resource management, and enhancing disaster response and recovery efforts. The active involvement of stakeholders in the design and development of AI solutions is anticipated to enhance trust and acceptance among the community, guaranteeing that the developed solutions are customized to cater to their specific interests and requirements. This approach fosters inclusivity, allowing for a sense of ownership among the stakeholders, thus creating a collaborative atmosphere conducive to developing efficient AI solutions. The integration of AGI in geospatial analysis raises concerns about privacy violations and deepening inequalities. Geospatial data, potentially misused by public or private entities, may infringe on privacy and liberty. AGI, relying on historical data, might perpetuate biases and discrimination, aggravating societal inequalities and marginalizing communities. We argue that human-centered GeoAI must focus on transparency and accountability, allowing stakeholders complete access to AGI-related information. It's vital that AGI be inclusive and equitable, avoiding the reinforcement of existing biases in geospatial analysis. Achieving this involves fair data practices and actively reducing data biases, thus building trust and contributing to a more equitable, sustainable future through transparent, accountable, and inclusive AGI solutions.

5.5. Computational capacity subject to the quantum revolution

GeoAI has experienced rapid growth in recent years, yet it still faces several geo-computation challenges that must be tackled to ensure its long-term success. One significant challenge is scalable, efficient, and cost-effective data storage solutions for the large volumes of high-resolution and real-time geospatial data generated by remote sensing platforms, IoT devices, social media sources, and more. In addition to traditional distributed and cloud-based solutions, edge cloud-based storage system provides an innovative way to improve the performance, efficiency, and scalability of geospatial big data storage by reducing latency, improving bandwidth utilization, and providing high scalability. With the development of blockchain (Zheng et al., 2018), Geochain has the potential to significantly impact geospatial data storage by offering a decentralized, secure, and transparent solution for managing geospatial data (Kamel Boulos et al., 2018; Mao and Golab, 2023). Analysing large geospatial datasets can be computationally intensive, particularly when using advanced machine learning algorithms that require significant processing power. Developing scalable processing techniques that can handle large datasets without compromising accuracy is crucial. This may involve parallel processing, distributed computing, or leveraging specialized hardware, such as GPUs, to improve the efficiency of GeoAI applications. Quantum computing (Steane, 1998), an emerging technology that exploits the principles of quantum mechanics, has the potential to revolutionize various fields, including GeoAI. Although still in its early stages, quantum computing could offer significant advantages by enhancing computational power, processing real-time geospatial big data, improving machine learning algorithms (Riedel et al., 2021), and solving complex optimization problems (e.g., NP-hard problems) (Werner, 2019).

6. Conclusion

Human geography has undergone a transformative shift, increasingly relying on spatiotemporal big data to enhance research design and address the intricate, non-linear relationships between human society and its potential drivers. This evolution is marked by a greater diversity in empirical studies, contributing to the advancement of theoretical foundations. Our review reveals that the integration of emerging spatiotemporal big data has significantly propelled human geography studies, allowing geographers to track, monitor, and quantify complex human behaviors on a large spatial and temporal scale. The intersection of GeoAI with quantum computing is poised to revolutionize human geography studies further, providing advanced tools to simulate spatial phenomena and enhance predictions related to the environment and population dynamics. This integration will empower researchers to process and analyze extensive datasets at an unprecedented speed, enabling a more detailed exploration of spatial relationships. It is essential, however, to approach the development and use of GeoAI responsibly and ethically, considering the potential social and environmental impacts of its implementation. We advocate for collaborative efforts across disciplines and sectors, involving government entities, public and private authorities, and academia. These concerted actions will contribute to enriching the roadmap of GeoAI in human geography, extending its application to broader geographic paradigms. This, in turn, will empower our geographers to seize research opportunities and leverage insights from the emerging data and AI deluge.

CRediT authorship contribution statement

Siqin Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Xiao Huang:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Pengyuan Liu:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Mengxi Zhang:** Writing – review & editing, Writing – original draft, Resources, Investigation, Data curation. **Filip Biljecki:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization. **Tao Hu:** Writing – review & editing, Writing – original draft, Data curation. **Xiaokang Fu:** Writing – review & editing, Writing – original draft, Data curation. **Lingbo Liu:** Writing – review & editing, Writing – original draft, Data curation. **Xintao Liu:** Writing – review & editing, Writing – original draft, Data curation. **Ruomei Wang:** Resources, Data curation. **Yuanyuan Huang:** Resources, Data curation. **Jingjing Yan:** Resources, Data curation. **Jinghan Jiang:** Resources, Data curation. **Michaelmary Chukwu:** Resources, Data curation. **Seyed Reza Naghedi:** Resources, Data curation. **Moein Hemmati:** Resources, Data curation. **Yaxiong Shao:** Resources, Data curation. **Nan Jia:** Resources, Data curation. **Zhiyang Xiao:** Resources, Data curation. **Tian Tian:** Resources, Data curation. **Yaxin Hu:** Resources, Data curation. **Lixiaona Yu:** Resources, Data curation. **Winston Yap:** Resources, Data curation. **Edgardo Macatulad:** Resources, Data curation. **Zhuo Chen:** Resources, Data curation. **Yunhe Cui:** Resources, Data curation. **Koichi Ito:** Resources, Data curation. **Mengbi Ye:** Resources, Data curation. **Zicheng Fan:** Resources, Data curation. **Binyu Lei:** Resources, Data curation. **Shuming Bao:** Resources, Data curation.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary material

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