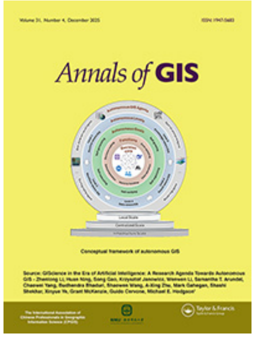

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REVIEW

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GeoAI enabled urban computing: status and challenges

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ABSTRACT

Geospatial Artificial Intelligence (GeoAI), an interdisciplinary field integrating geographic information science with artificial intelligence (AI), has emerged as a transformative force in advancing urban computing technologies and applications. By synergizing the inherent spatiotemporal characteristics of geospatial data with AI's advanced inferential capabilities, GeoAI provides innovative methodologies for addressing multifaceted urban challenges. Therefore, we first systematically examined the core technological components of GeoAI, encompassing geospatial data representation, spatiotemporal interpolation and prediction, geo-related knowledge graphs and pretrained spatiotemporal foundation models. Then, we analysed GeoAI's implementation in urban computing through four representative domains, including including intelligent transportation systems, environmental surveillance, public safety enhancement, and sustainable urban development. Finally, we concluded key challenges in GeoAI-enabled urban computing, emphasizing the integration of deep learning and knowledge graph, interdisciplinary collaboration for intelligent solutions, risk mitigation of deceptive spatiotemporal data, and the incorporation of human-centric principles in GeoAI technologies.

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KEYWORDS
GeoAI; urban computing; advances; challenges

1. Introduction

Smart cities have become an essential goal of urban development around the world. Geographic Information Systems (GIS), with the exclusive capabilities in geo-spatial data management and analysis, have become a core component of the smart city operating systems. With the widespread sensor networks and mobile positioning technologies, vast amounts of geo-spatial data from urban systems are collected and processed, involving human behaviour, traffic, public infrastructure, environment, economic activities and resource consumption. It stimulates a great deal of requirements in comprehensive urban data analysis and leads to the emergence of urban computing concept. More specifically, urban computing is an interdisciplinary paradigm that integrates heterogeneous urban data streams, advanced computational models, and spatiotemporal analytics to unravel complex urban dynamics, ultimately facilitating data-driven decision-making for sustainable and resilient city management (Zheng et al. 2014).

Although the exponential growth of spatiotemporal data availability offers unprecedented opportunities for urban computing, conventional data processing frameworks have failed to achieve commensurate advancements in analytical inference and predictive performance. Many so-called smart city platforms, such as 'City Brain', still exhibit limited data comprehension and processing capabilities. Therefore, effectively harnessing the value of vast spatiotemporal data, designing more accurate data analysis models, and extracting potential knowledge and patterns has become a critical issue in current urban computing researches.

With the rapid development of artificial intelligence (AI), particularly modern machine learning methods, computers can identify patterns from vast datasets and construct predictive or descriptive models based on these patterns (Abiodun et al. 2019). The integration of AI and GIS is increasingly becoming a mainstream requirement in industry applications. In this context, Geospatial Artificial Intelligence (GeoAI) has emerged as

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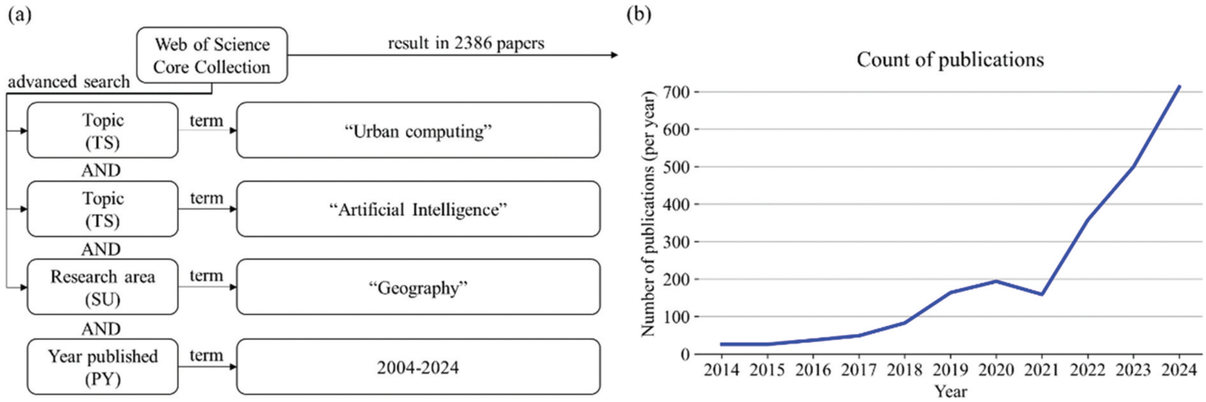

Figure 1. Search process and results of publications from 2004 to 2024. (a) Search strategy. (b) Annual publication trends from 2014 to 2024.

a new paradigm in geographic information science (Goodchild and Li 2021; Janowicz et al. 2020). Compared with traditional statistical analysis or physical modelling methods, GeoAI can effectively captures spatial heterogeneity, neighbourhood effects, distance decay and scale effects in spatial partitioning (Y. Liu et al. 2023). It also supports the credible transfer of existing knowledge, facilitating simulations across different geographic regions, thus providing technical support for prediction and forecasting in complex systems (Mai et al. 2024). Furthermore, GeoAI possesses the ability to uncover new spatiotemporal patterns and evolutionary laws, despite the frequent questioning of their generalizability (Hu et al. 2024). These advantages enable GeoAI to deeply integrate spatial analysis into urban computing, significantly enhancing the understanding and analysis of social systems (De Sabbata et al. 2023; Li et al. 2024). As shown in Figure 1, based on the search results from the Web of Science core collection, the number of research papers on the application of GeoAI in urban computing shows a continuous growth trend, with a total of 2,386 papers published during 2014–2024. In particular, the rate of growth in paper publication has increased significantly since 2021, reflecting the rising interest and commitment to EL in the academic community. Regarding the research content, the word frequency analysis of the titles and abstracts of the 2,386 retrieved papers is shown in Figure 2. GeoAI tackles 'interpolation', 'prediction' and other tasks in various application areas such as 'traffic' and 'environment' by modelling the effects of 'correlation' and 'heterogeneity' of urban spatio-temporal data through key technologies like 'neural networks' and 'knowledge graphs'. The results of the paper search indicate that GeoAI holds great potential in the field of urban computing.

In this work, we provided a comprehensive summary of the core technologies underpinning GeoAI in urban computing, encompassing geospatial data representation, spatiotemporal interpolation and prediction, geo-related knowledge graphs and pretrained spatiotemporal foundation models. Then, we examined the typical application scenarios of GeoAI in urban computing, covering intelligent transportation systems, environmental surveillance, public safety enhancement, and sustainable urban

Figure 2. Word cloud visualization of keywords.

development. Finally, we identified key challenges in GeoAI-enabled urban computing, including the integration of deep learning and knowledge graph, interdisciplinary collaboration for intelligent solutions, risk mitigation of deceptive spatiotemporal data, and the incorporation of human-centric principles in GeoAI technologies.

2. The connotation of GeoAI

GeoAI represents a novel developmental paradigm that emerges from the profound integration of GIS and AI. By synthesizing advancements in AI and data science, it aims to establish more intelligent geographic information systems and provide a robust technological framework to support a wide range of downstream applications, including image classification, object detection, scene segmentation, simulation and interpolation, relationship inference, geographic information extraction and querying, online data integration, and geographic scene enhancement (Chen et al. 2024; S. Gao 2020; Janowicz et al. 2020).

As illustrated in Figure 3, GeoAI's development spans five interconnected phases shaped by computational and spatial innovations. 'Theoretical Beginnings' (1950s-1970s) established theoretical underpinnings through seminal works like Tobler's First Law of Geography and early spatial modelling paradigms. 'Tool-Driven GIS' (1980s-2000s) industrialized workflows through commercial GIS platforms (Arc/Info, ERDAS), GPS integration, and SQL databases. 'ML-GIS Fusion' (2010–2015) integrated big data and machine learning (SVMs, random forests) with cloud computing, revolutionizing real-time analytics using IoT streams and LiDAR point clouds. 'Deep GeoAI' (2015–2020) harnessed deep learning (CNNs, graph neural networks) for automated satellite imagery interpretation, UAV photogrammetry, and explainable AI (XAI). Since 2020, 'Foundation Model' integrated generative AI-driven large-scale architectures with federated multi-agent ecosystems (digital twins, autonomous drones), embedding ethical frameworks to orchestrate adaptive terrain simulations and self-evolving planetary intelligence through transformer-based neural networks. Overall, the development of GeoAI is driven by the synergistic interaction of two major forces: on one hand, the rapid advancement of AI technologies has significantly enhanced the capabilities in geo-spatial data analysis, thus effectively addressing the demands of complex system applications (Mai, Janowicz, et al. 2022). On the other hand, the continuous generation of geo-spatial data provides abundant resources for training AI models and developing algorithms. Particularly, with the support of large-scale datasets, AI is capable of automatically uncovering patterns and regularities within the data. Moreover, GIS technologies

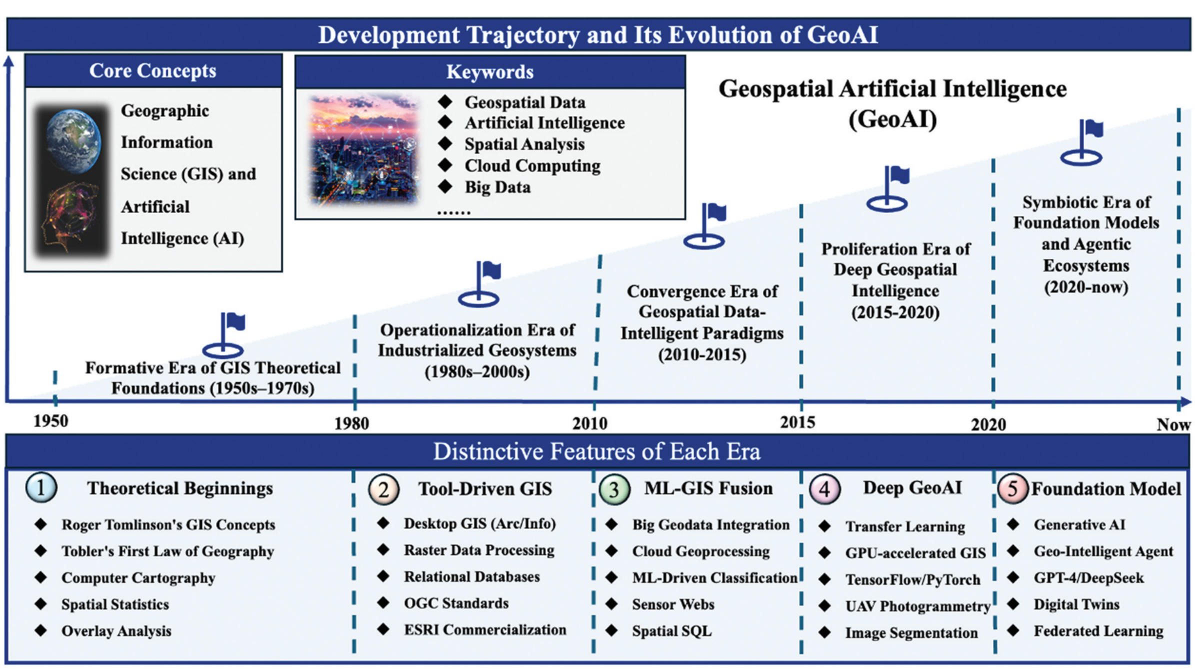

Figure 3. The development trajectory of GeoAI.

serve as a platform for generating annotated data required for machine learning, thereby improving the efficiency of data annotation and feature extraction (P. Liu and Biljecki 2022).

GeoAI models can generally be classified into implicit and explicit spatial models. Implicit spatial models treat geographic location as a regular dimension within the feature vector, without placing special emphasis on the role of spatial position or spatial relationships in the model. For instance, incorporating geographic coordinates into a K-means clustering model is an example of implicit spatial modelling (Long et al. 2023). In contrast, explicit spatial models explicitly integrate spatial locations and spatial constraints into the model, constructing spatially constrained clustering models, such as those based on Delaunay triangulation, to effectively capture spatial dependencies between geographic entities (S. Gao 2020).

While GeoAI is frequently conflated with spatial intelligence, it should be distinguished from the concept of 'spatial intelligence' introduced by Professor Fei-Fei Li. The latter concept, rooted in visual intelligence research, focuses on enabling machines to perceive, comprehend, reason about, and generate three-dimensional environments, ultimately aiming to construct a comprehensivelarge world model. For instance, Durante et al. (2024) proposed a concept of visual-spatial intelligence that emphasizes building a real-time perception model of a small local area, enabling machines to understand their surrounding environment through computer vision. Similar to large language models, this approach aims to enhance machines' ability to comprehend their environment. In contrast, GeoAI focuses on 'geospatial intelligence', to achieve the perception, cognition, learning, prediction, adaptation, and autonomous adjustment of geospatial systems through multimodal large geospatial models. Geospatial intelligence not only involves geographic locations but also encompasses the spatial distribution patterns of geographic phenomena and human activities. It aims to understand and predict the evolution of geographic phenomena within multidimensional spaces, providing scientific support for decision-making in areas such as smart cities, environmental protection, and resource management.

The goal of GeoAI is to develop intelligent geospatial analysis models driven by both data and knowledge. These models iteratively optimizes themself through learning techniques, facilitating the establishment of large geospatial models and fundamentally enhancing capabilities in spatial localization, spatial reasoning, behavioural regulation, and spatial decision-making. Through this process, GeoAI not only addresses the limitations of traditional GIS analysis methods but also provides the theoretical foundation and practical support for dealing with complex systems.

3. Generic GeoAI technologies

The rapid development of GeoAI has led to a variety of methodological branches, yet four foundational pillars including data representation models, spatiotemporal imputation and prediction, geo-related knowledge graphs, and spatiotemporal foundation models which stand out as the core enablers of generic GeoAI frameworks. This selective emphasis stems from their interdependent roles in tackling the fundamental challenges of geospatial data: heterogeneity (multi-source and multi-scale data fusion), incompleteness (sparse sensing and missing records), and semantic complexity (context-aware reasoning).

3.1. Data representation model

In the era of AI and foundation models, feature vectors have become the cornerstone for building high-precision models (Bhatia and Aka 2022; Huesmann and Linsen 2025). As is shown in Figure 4, the data representation models restructure spatial and temporal information into feature vectors, enabling a comprehensive depiction of data distributions, structures, and potential relationships (L. Wang, Cheng, and Lu 2025). Advancing data representation methods is one of the core tasks in machine learning to provide robust support for downstream tasks such as geographic process prediction and spatial clustering (Lee and Lauw 2024; T. Liu et al. 2018; Mai et al. 2023; X. Wang et al. 2024). Feature engineering and representation learning are the two primary approaches to data representation. Feature engineering relies on expert knowledge and predefined rules to process data. While it provides good interpretability, it often struggles to capture complex patterns. In contrast, representation learning employs automated methods (e.g. embedding techniques) to learn features directly from data. This makes it more flexible and adaptable to different tasks (Bengio, Courville, and Vincent 2013), and positions it as a more advanced form of feature engineering.

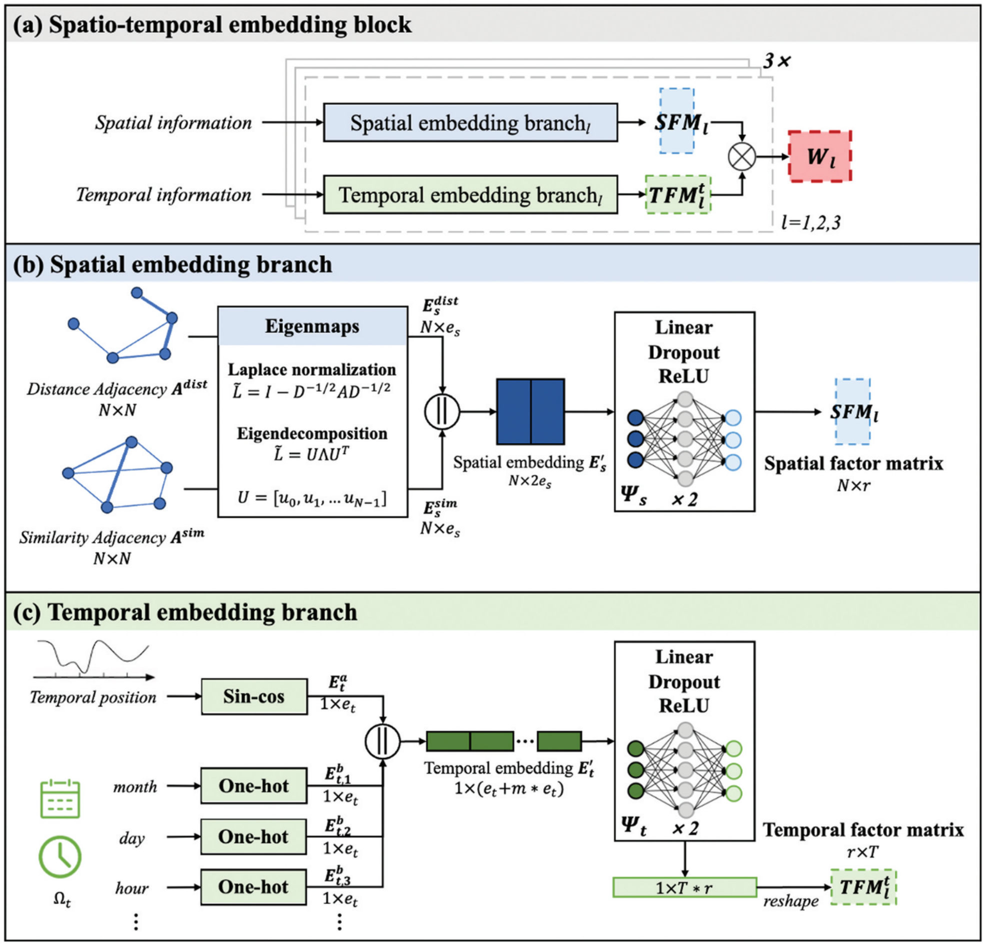

Figure 4. A data representation model proposed by L. Wang, Cheng, and Lu (2025). (a) Overall architecture. (b) Structure of spatial embedding branch. (c) Structure of temporal embedding branch.

In geospatial analysis, spatiotemporal data often exhibit complex patterns and intrinsic relationships that traditional feature engineering struggles to capture accurately (Hamdi et al. 2022). Geospatial representation learning (GRL) leverages deep learning models to automatically extract and model latent features from geospatial data. This approach significantly improves accuracy and supports tasks such as geographic information retrieval, recommendation, and inference (Donghi and Morvan 2023; P. Wang et al. 2024; L. Xu et al. 2020; Yuan 2024). The key task of GRL is to enhance the understanding and predictive capability of geographic phenomena by learning the multidimensional characteristics of geospatial data (Donghi and Morvan 2023). Representative geospatial representation methods include: (a) Learning semantic features of Points of Interest (POI), built environments, and surrounding areas to improve place information retrieval and intelligent recommendation capabilities, such as the Place2Vec (B. Yan et al. 2017) and POI2Vec (S. Feng et al. 2017) models. (b) Quantifying interaction features of roads through large-scale floating car trajectories data, such as the Road2Vec model (K. Liu et al. 2017). (c) Characterizing place associations and similarity features through human mobility data, such as the Mot2Vec model (Crivellari and Beinat 2019). (d) Constructing location representations by abstracting geospatial position and relationship features, such as the Space2Vec model (Mai et al. 2019). While current GRL methods show strong capabilities in capturing hierarchical spatial patterns and modelling complex spatiotemporal relationships, they still face several key limitations. These include reliance on labelled training data, sensitivity to uneven geographic sampling, and limited ability to preserve spatial structures in the learned representations. These challenges highlight the need for future research in areas such as self-supervised geospatial pretraining, physics-informed representation learning, and multi-agent simulation frameworks to support more reliable spatial intelligence.

3.2. Spatiotemporal interpolation and prediction

Spatiotemporal interpolation and prediction are core tasks in spatiotemporal data mining, aiming to identify spatiotemporal differentiation patterns of natural and human elements and explore the implicit deep interactions among these elements (P. Liu and Biljecki 2022). As is shown in Figures 5 and 6, spatiotemporal interpolation focuses on addressing the sparsity of geographic observation samples (S. Cheng, Peng, and Lu 2020; P. Wang et al. 2024), while spatiotemporal prediction emphasizes inferring the evolutionary trends of geographic object attributes over time and space (Chang et al. 2022; Shu and Ye 2023; A. Zhu et al. 2018).

With the continuous growth of spatiotemporal big data and advancements in computational capabilities, GeoAI-based methods for spatiotemporal interpolation and prediction have proven effective in modelling complex spatiotemporal dependencies, including spatiotemporal correlations, heterogeneity, and nonlinear relationships, which helps improve prediction accuracy (S. Cheng, Lu, and Peng 2021; X. Luo et al. 2025; P. Wang et al. 2024). For example, multi-view learning integrates information from different temporal and spatial perspectives, enabling a more comprehensive understanding of spatiotemporal dynamics (W. Cheng

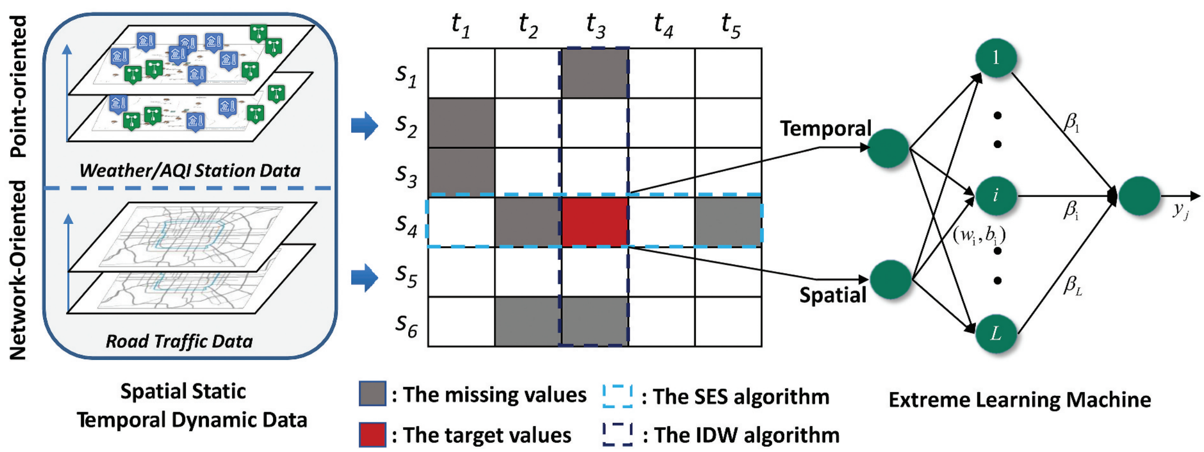

Figure 5. A spatiotemporal interpolation model proposed by (S. Cheng, Peng, and Lu 2020).

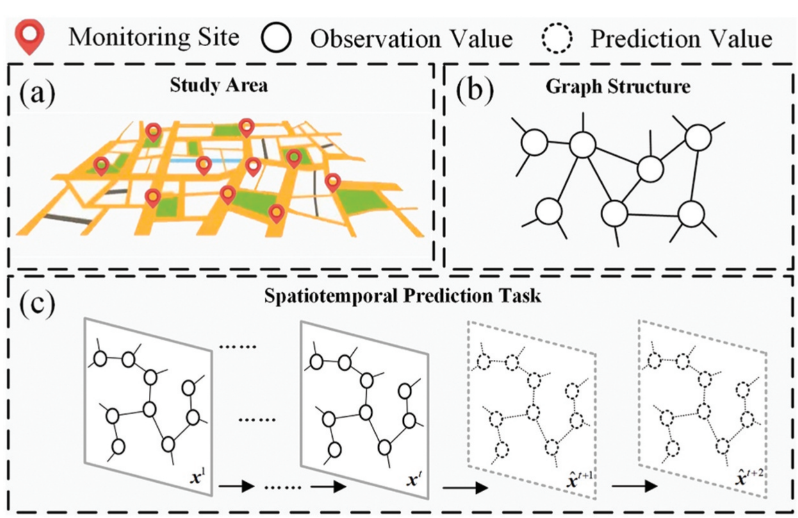

Figure 6. The diagram of spatiotemporal prediction (P. Wang et al. 2024). (a) Study area. (b) Graph structure. (c) spatiotemporal prediction task.

et al. 2018; Wei, Feng, and Yang 2024; Yao et al. 2023). Multi-task learning enhances the modelling of spatiotemporal relationships by jointly optimizing multiple related tasks within a unified framework (H. Luo et al. 2021; Y. Zhu et al. 2022; Zou et al. 2024). Deep learning methods leverage deep neural networks to automatically extract complex patterns from large-scale spatiotemporal data.

Unlike traditional spatial statistical methods, GeoAI-based spatiotemporal interpolation and prediction approaches are less dependent on strict statistical assumptions. This gives greater flexibility in addressing challenges such as data sparsity, nonlinearity, and dynamic changes (Jin et al. 2024; L. Xu et al. 2021). Driven by data, GeoAI can autonomously learn spatiotemporal patterns, which improve the accuracy and reliability of interpolation and prediction. However, despite these advantages, current GeoAI methods still face important limitations. They are often sensitive to data quality, lack transparency in how features are learned, and may not generalize well in rapidly changing geographic environments. These challenges highlight the need for next-generation solutions that combine physics-informed neural architectures, self-supervised pretraining for spatiotemporal reasoning, and adaptive uncertainty quantification. Such advances are essential for improving the reliability and applicability of GeoAI in real-world, high-risk geospatial scenarios.

3.3. Geo-related knowledge graphs

Geo-related knowledge graphs play a pivotal role in the research and applications of GeoAI, particularly in intelligent analysis and reasoning tasks. Current knowledge representation methods are primarily designed to meet human needs for management and retrieval, often emphasizing digital storage while overlooking the requirements for machine comprehension (Ji et al. 2020; Zhao et al. 2024). For instance, as shown in Figure 7, J. Gao et al. (2024) proposed a geo-related knowledge graph for mining tourist preferences and decision support. Geo-related knowledge graphs are important tools for achieving machine comprehension (Janowicz et al. 2020; P. Liu and Biljecki 2022; Papadakis et al. 2022; Potnis et al. 2023). Reason for this, Geo-related knowledge graphs offer a promising framework for modelling spatially linked entities and relationships in urban computing. Their strengths lie in enabling structured, location-aware knowledge representation, supporting applications such as spatial search (Chadzynski et al. 2021), service recommendation (J. Gao et al. 2023), and urban behaviour analysis (H. Wang et al. 2021). By bridging symbolic reasoning with machine learning, they help uncover complex spatial patterns that are difficult to capture with traditional approaches (Y. Liu et al. 2023).

However, current Geo-related knowledge graphs implementations face several limitations. These include difficulties in aligning heterogeneous spatial references (e.g. informal place names vs. coordinates) (He, Li, and Zhang 2024), inconsistencies in entity semantics across domains (Mai, Huang, et al. 2022), and challenges in integrating multimodal data (e.g. text, images, spatial graphs) (Sun et al. 2021). In addition, most models rely heavily on implicit embeddings, making it difficult to interpret or validate spatial reasoning outcomes. Future research should focus on three key directions: (1) developing lightweight and scalable spatial alignment techniques across data sources, (2) designing hybrid symbolic-neural models to enhance interpretability and reasoning capabilities, and (3) enabling dynamic, self-evolving KGs that adapt to real-time urban changes and diverse user needs. These efforts are essential to fully realize the potential of Geo-related KGs in practical and adaptive GeoAI systems.

3.4. Spatiotemporal foundation models

Deep learning and machine learning methods have demonstrated their effectiveness in capturing complex patterns and long-term dependencies in spatiotemporal data (Tan, Liu, and Liu 2021; S. Wang, Cao, and Yu 2022), driving the evolution from large language models (e.g. the GPT series (OpenAI et al. 2024; Ye et al. 2023)) to multimodal foundation models (e.g. models integrating vision and language). As shown in Figure 8, spatiotemporal foundation models, built on deep learning techniques and advanced computational architectures, are designed to process and analyse large-scale data that involve geospatial complexities and spatiotemporal dynamics (S. Wang et al. 2024). These models enhance analytical capabilities and can infer unknown geographic patterns and latent rules, enabling more accurate predictions and decision support in areas such as smart cities, environmental monitoring, and traffic management.

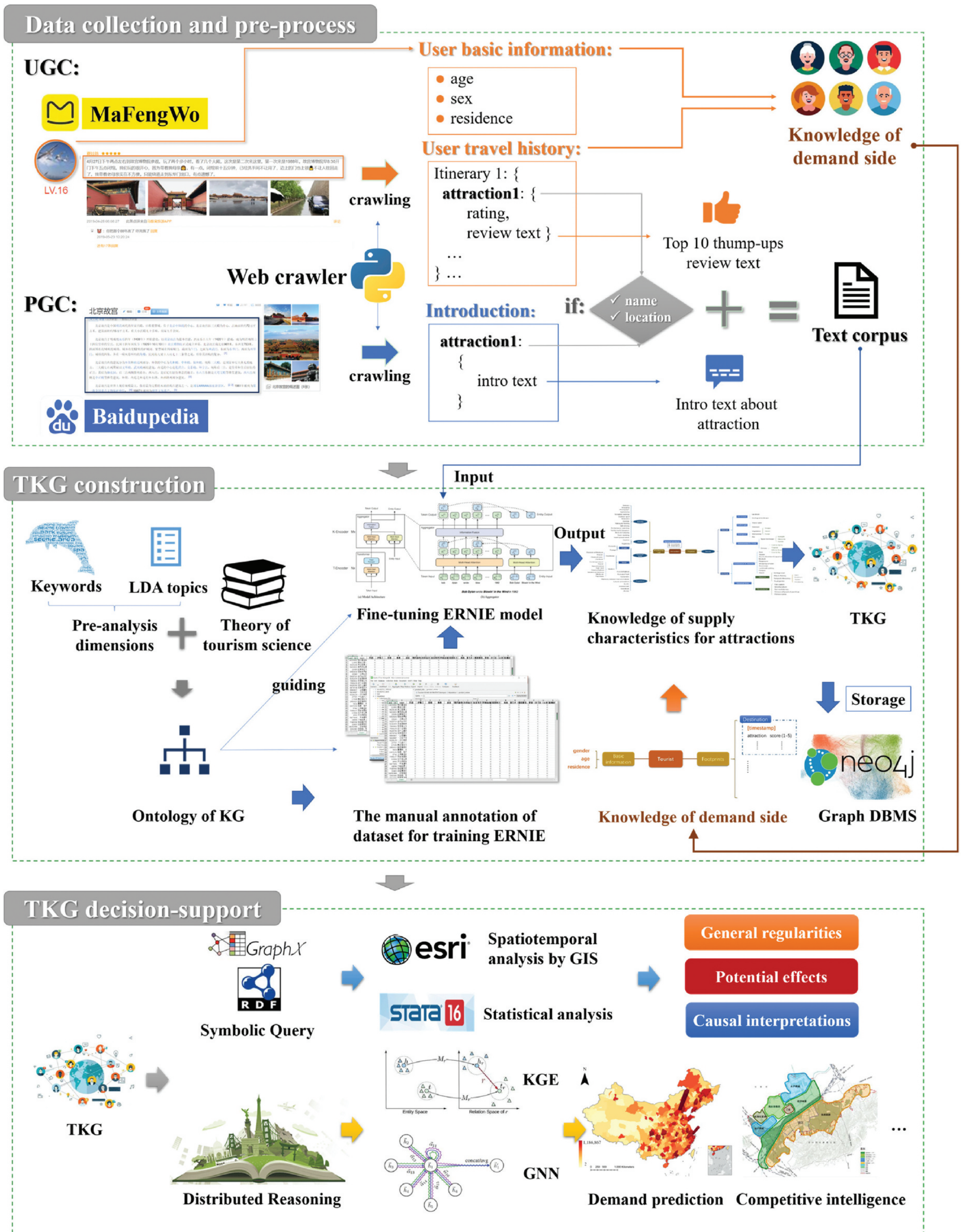

Figure 7. A geo-related knowledge graph proposed by J. Gao et al. (2024) for mining tourist preferences and decision support.

The core components of geographic spatiotemporal foundation models include Geospatial Embedding Models and Masked Geospatial Models. Geospatial embedding models embed the spatial attributes and semantic information of geographic objects into high-dimensional vector spaces. By leveraging neural networks and other advanced methods, these models enable feature learning from geographic data,

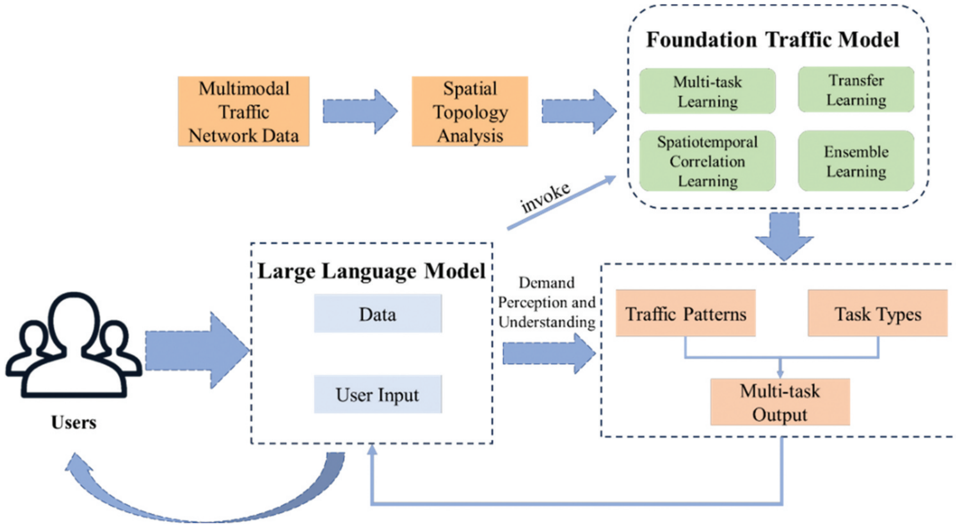

Figure 8. Conceptual framework of a foundation traffic model (S. Wang et al. 2024).

allowing for the identification and classification of geographic objects (Y. Feng, Jin, et al. 2024; Tu et al. 2022; J. Yang et al. 2021). This process enables models to capture complex relationships between geographic features and environmental, social, and economic factors, supporting deeper contextual understanding and more precise representations. As a result, geospatial embedding models can effectively handle multidimensional geographic information and perform accurate prediction and reasoning.

Masked geospatial models, on the other hand, employ masking mechanisms to obscure portions of the input data, compelling the model to learn how to infer and reconstruct the missing information (S. Cheng, Peng, and Lu 2020; Shao et al. 2022). This approach significantly enhances the model's robustness and accuracy, particularly when dealing with incomplete or missing data. By capturing local spatial patterns and long-term dependencies in spatiotemporal data, masked geospatial models excel in handling large-scale and complex geographic datasets, such as urban mobility (J. Wang et al. 2023), climate change (Y. Yang et al. 2024), and traffic patterns (Avila and Mezić 2020). This capability positions them as powerful tools for analysing and interpreting complex geospatial phenomena.

Despite their transformative potential in decoding complex spatiotemporal interdependencies and improving predictive robustness under data scarcity, spatiotemporal foundation models face several challenges, including high computational costs, limited interpretability in cross-domain generalization, and biases arising from uneven geospatial data coverage. Future advancements may leverage lightweight neuromorphic computing and causality-infused hybrid architectures to enhance efficiency while ensuring ethical transparency. These advances could build adaptive, self-updating geospatial intelligence systems that are more reliable and useful in solving real-world urban problems.

4. Applications of GeoAI in urban computing

Urban computing integrates artificial intelligence and geospatial analysis to support data-driven decision-making in urban management. GeoAI, which combines these two domains, enables the development of decision support systems tailored to complex urban challenges. This integration significantly improves the practicality and adaptability of urban computing. This paper focuses on four representative application areas: intelligent transportation systems, public safety, environmental monitoring, and sustainable urban development. These areas were selected for several reasons. First, they are highly data-driven and strongly reliant on geospatial information, making them well aligned with the strengths of GeoAI. Second, they represent core components of urban systems with strong practical relevance and policy impact. Third, there is a substantial body of existing research on GeoAI in these fields, offering a solid foundation for summarizing key approaches and insights.

4.1. Urban computing and the role of GeoAI

Urban computing is an interdisciplinary field that leverages advanced computational techniques to analyse and optimize urban systems (Y. Liu et al. 2023). By integrating multimodal data from traffic sensors, satellite imagery, social media feeds, and IoT networks, urban computing enables data-driven decision-making for smarter and more efficient city management. It employs methodologies such as knowledge discovery, computer vision, and edge computing to extract valuable spatiotemporal patterns and facilitate real-time analytics. Knowledge discovery uncovers hidden correlations in urban dynamics, supporting applications in traffic optimization, public safety enhancement, environmental surveillance, and sustainable urban development (Shu and Ye 2023). Computer vision enhances urban monitoring by analysing street-view imagery and aerial data for infrastructure risk assessment, pollution tracking, and anomaly detection. Meanwhile, edge computing enables decentralized, low-latency processing for adaptive traffic control, emergency response coordination, and intelligent energy management, improving both efficiency and privacy (Biljecki and Ito 2021). Beyond these traditional approaches, the emergence of multimodal fusion and generative AI further expands the capabilities of urban computing. Multimodal fusion integrates heterogeneous data sources to improve model robustness, while generative AI enables scenario simulation, predictive modelling, and automated decision support for urban planning and disaster management. These advancements collectively drive smarter, more resilient, and more adaptive urban environments (Y. Yan et al. 2025).

Within this context, the integration of GeoAI strengthens urban computing by embedding spatial awareness into intelligent systems. By fusing geospatial analytics with AI-driven methodologies, GeoAI enhances the interpretability and adaptability of urban models, addressing challenges such as fragmented data silos and the dynamic nature of urban environments. This synergy fosters more precise, scalable, and context-aware solutions for urban governance.

4.2. GeoAI for intelligent transportation system

With rapid urbanization, intelligent transportation systems are essential for sustainable urban development and informed decision-making (Zheng et al. 2011). GeoAI enhances real-time traffic data analysis and prediction by fusing multi-source data such as sensors, GPS devices, and social media and improving transportation system efficiency.

Currently, GeoAI-driven models have been widely applied to various urban traffic problems, such as traffic flow prediction (S. Cheng et al. 2019; Du et al. 2020) and traffic state recognition (S. Cheng, Peng, and Lu 2020; X. Liu et al. 2013). To better capture the dynamic and complex spatiotemporal patterns in traffic flow, researchers have proposed advanced techniques, such as spatiotemporal data fusion (Song et al. 2019), graph neural networks (Song et al. 2019), and adaptive learning mechanism (Y. Wang et al. 2023). These methods effectively integrate multi-source data to improve both prediction accuracy and real-time response performance. For example, Zhang et al. (2019) proposed generative adversarial nets with graph CNN to address the limitations of traditional approaches in handling the nonlinearity, stochastic, and time-varying nature of traffic data. Du et al. (2020) developed a deep irregular convolutional residual LSTM network to better capture periodic and long-term trends. Ji et al. (2023) introduced a spatiotemporal self-supervised learning framework that improves the representation of spatiotemporal heterogeneity. Overall, GeoAI not only enhances traffic prediction capabilities but also facilitates real-time and context-aware optimization of transportation systems. Its ability to dynamically adapt to changing urban conditions makes it an essential component of next-generation intelligent transportation systems.

4.3. GeoAI for public safety enhancement

Traffic accidents and criminal activities pose serious threats to urban public safety. In the era of big data, GeoAI enhances public safety by integrating and analysing multi-source spatiotemporal data, such as surveillance videos, social media, and geographic information. By leveraging AI-driven spatial analysis, GeoAI enables accurate crime prediction, violation detection, and disaster monitoring, providing valuable support for proactive risk mitigation and emergency response.

Current research has explored a variety of GeoAI applications in urban public safety, including crime prediction (Shah, Bhagat, and Shah 2021), violation analysis (X. Luo, Wang, and Zhang 2023), and disaster monitoring (Kamilaris and Prenafeta-Boldú 2018). For example, Huang et al. (2018) explored the muti-dimensional interdependence between crime and urban spatial data using deep neural networks, and implicitly simulated the interaction characteristics of region, category and time. Catlett et al. (2019) employed spatial analysis and autoregressive models to identify high-risk crime areas and predict crime trends. Deng, He, and Liu (2023) incorporated the spatiotemporal autocorrelation characteristics of crime by introducing spatiotemporal lag variables and tree models, significantly enhancing the accuracy of crime prediction. GeoAI provides a data-driven foundation for crime prevention, law enforcement optimization, and disaster response planning, making it a valuable tool for improving urban public safety.

4.4. GeoAI for environmental surveillance

Urban environmental surveillance relies on sensor networks, but high deployment and maintenance costs restrict sensor density, making it difficult to achieve comprehensive and high-resolution monitoring. To address these challenge, GeoAI integrates multi-source data, including remote sensing, meteorological records, population mobility, road networks, and points of interest (POIs), to improve environmental monitoring beyond sparse sensor coverage. By leveraging advanced AI techniques such as semi-supervised learning, deep neural networks, and spatiotemporal modelling, GeoAI enables more accurate, scalable, and data-efficient monitoring of environmental conditions.

Numerous studies have demonstrated the effectiveness of GeoAI in environmental monitoring, particularly for air quality assessment. For example, Zheng, Liu, and Hsieh (2013) proposed a semi-supervised learning framework that combines data from monitoring stations with crowdsourced information to mitigate data sparsity. W. Cheng et al. (2018) improved air quality prediction by integrating feedforward and recurrent neural networks with an attention pooling mechanism to optimize feature weights across monitoring stations. Y. Xu et al. (2019) introduced a two-stage artificial neural network that fuses remote sensing and meteorological data for data completion, employing tensor decomposition and spatiotemporal constraints. Y. Feng et al. (2024) developed a spatiotemporal field neural network that integrates spatial field representations with graph structures, preserving high-frequency information through pyramid reasoning to support large-scale environmental inference. GeoAI provides a robust and flexible framework for high-resolution, large-scale environmental surveillance, supporting more effective monitoring, decision-making, and sustainable urban management.

4.5. GeoAI for sustainable urban development

Sustainable urban development requires a comprehensive understanding of key factors, including traffic flow, population mobility, POI distribution, and the structure of urban functional areas. Traditional survey-based methods are often time-consuming, labour-intensive, and limited in both accuracy and scalability. GeoAI has transformed this field by enabling the efficient integration and analysis of large-scale urban data, providing new opportunities for data-driven, adaptive, and intelligent planning strategies.

GeoAI has been increasingly applied to support sustainable urban development in areas such as urban community planning (Zheng et al. 2023) and urban resilience. For instance, Zheng et al. (2023) proposed a reinforcement learning-based model that facilitates collaboration between human planners and AI algorithms, optimizing urban community design to enhance liveability and resource efficiency. Wiedemann et al. (2024) developed a linear programming model for optimizing bicycle network design, offering insights into sustainable mobility solutions that balance non-motorized and motorized transport. Hong et al. (2024) constructed a spatiotemporal disaster knowledge graph to model cascading disaster effects and support urban resilience planning. By identifying spatial vulnerabilities and simulating potential impacts, this framework supports long-term sustainability and risk reduction. GeoAI enhances the efficiency, accuracy, and adaptability of sustainability-oriented initiatives. Its applications in resource-efficient urban design, green mobility planning, and disaster resilience demonstrate its potential to drive sustainable urban development and foster more resilient, livable, and environmentally responsible cities.

5. Challenges in GeoAI enabled urban computing

5.1. Integration of deep learning and knowledge graphs

Real-time learning of multi-source spatiotemporal data and the automated accumulation of field knowledge are at the heart of advancing smart cities. However, the effective integration of deep learning and the knowledge graph still faces significant challenges. Deep learning, as an implicit model, has demonstrated outstanding performance in addressing complex tasks, such as image recognition and speech understanding. However, its limitations in interpretability, reproducibility, and transferability constrain its broader applicability across various fields (Mai et al. 2025). In contrast, the knowledge graph, as an explicit model, possesses stronger interpretability and reasoning capabilities, but its construction process is complex, inefficient, and highly dependent on massive fields of knowledge. Therefore, achieving effective integration between data-driven deep learning paradigm and knowledge-driven symbolic reasoning remains a key challenge in GeoAI.

To address this bottleneck, researchers are exploring two main directions. One approach leverages geographic prior knowledge to guide or constrain deep learning models, improving their interpretability and alignment with geographical principles (Hao et al. 2024). The other utilizes the powerful feature extraction capabilities of deep learning to automatically identify geographic entities, relations, and events from multi-source heterogeneous data, thereby accelerating the construction and updating of geo-related knowledge graphs (Tian et al. 2023). A promising future direction is the development of hybrid representation spaces that integrate data-driven statistical patterns with structured symbolic knowledge, while embedding symbolic logical reasoning processes within end-to-end differentiable neural networks. This integration facilitates the joint evolution of learning and reasoning. Such a fusion not only address their respective limitations but also supports the development of models with strong perceptual capabilities, interpretability and reasoning ability. Ultimately, this synergy has the potential to provide more intelligent, reliable, and transparent decision support for urban computing.

5.2. Interdisciplinary collaboration for intelligent solutions

Urban computing, an interdisciplinary field encompassing natural sciences, social sciences and computing technologies, demands a systematic perspective to foster interdisciplinary collaboration. Currently, studies primarily focus on technological breakthroughs, while the exploration of integrating domain characteristics within urban socio-economic systems and developing comprehensive solutions remains insufficient. Additionally, the role of public management in smart cities must be urgently strengthened, as the complexity of human behaviour patterns and social phenomena presents significant challenges in modelling and analysis on human-centred social systems. This complexity is not only reflected in the diversity of individual and crowd behaviour but also involves the interaction of social, cultural, economic, and environmental factors (Suresh et al. 2021). Therefore, overcoming the barriers imposed by differing theoretical paradigms, terminologies, and research methodologies across disciplines remain a key challenge for establishing a unified analytical framework that can integrate multidisciplinary knowledge.

To address to this challenge, researchers are increasingly working to bridge disciplinary boundaries. For example, in urban transportation research, GeoAI is no longer limited to analysing physical spatiotemporal data such as vehicle trajectories. It is now being combined with behavioural and economic factors from the social sciences such as commuters' socioeconomic backgrounds and travel preferences, to better understand the root causes of traffic congestion and residents' mobility needs (Zomer, Moustaid, and Meijer 2015). Therefore, future studies should emphasize the deep coupling of natural and social sciences, adopting systematic approaches to integrate the advantages of different disciplines. This will improve the comprehensiveness and flexibility of urban computing, enabling more effective responses to the complex challenges of smart cities and providing stronger theoretical and technical support for sustainable and inclusive urban governance.

5.3. Risk mitigation of deceptive spatiotemporal data

In Gartner's 2025 Top 10 Strategic Technology Trends, misinformation security is highlighted as a key focus, emphasizing the need for systematic methods to distinguish between truth and falsehood and ensure the security and trustworthiness of AI systems. This concept closely aligns with the AI TRiSM (AI Trust, Risk, and Security Management) framework, which ensures the safe, compliant, and reliable operation of AI systems through transparency, explainability, and data integrity technologies. In urban computing, the accuracy of spatiotemporal data is critical, as false or deceptive data may lead to decision-making errors, affecting system stability and resource scheduling efficiency (Boutayeb, Lahsen-Cherif, and Khadimi 2024). For example, German artist Simon Weckert showed how to fake Google Maps using 99 mobile phones to make a false traffic jam[1]. Furthermore, AI systems remain vulnerable to the quality and integrity of their training data. For example, recent research indicates that replacing just 0.001% of training tokens with fabricated text can increase harmful content output by 7.2% in a 1.3 billion-parameter large model (Alber et al. 2025). As a result, detecting and mitigating increasingly sophisticated and covert data manipulation techniques in large-scale, dynamic, and heterogeneous urban data streams has become a critical challenge.

Current efforts to address this issue focus on two main strategies. The first strategy involves using multi-source data for cross-validation and consistency checks to identify potential anomalies, such as comparing traffic information derived from different navigation platforms, sensors, and social media feeds (J. Gao et al. 2018). The second aims to develop more robust anomaly detection algorithms, particularly those utilizing deep learning techniques to capture subtle variations in spatiotemporal patterns (Giasemis and Sopasakis 2025). However, these approaches often lag behind the rapid evolution of adversarial techniques. A forward-looking solution requires the development of proactive, intelligent, and adaptive systems to ensure data integrity. These systems should possess four key capabilities: proactive perception, precise diagnosis, rapid response, and continuous evolution. To achieve this, they would integrate geographic knowledge and domain-specific rules for semantic plausibility checks, leverage federated learning to protect data privacy, and support cross-domain collaborative validation for sharing and validating threat intelligence. Ultimately, an end-to-end data governance framework aligned with AI TRiSM (Trust, Risk, and Security Management) principles is essential. Such a framework will help ensure ongoing data trustworthiness within GeoAI systems, enhance the detection of fraudulent data, and support the secure, reliable, and resilient operation of smart cities.

5.4. Human-centric notions in GeoAI technologies

In urban computing, excessive attention on algorithmic efficiency can lead to neglecting ethical and human-centric concerns. For instance, while algorithm-driven express or takeout delivery systems improve operational efficiency, they may also impose excessive workloads on deliverymen, highlighting challenges related to social equity and labour rights in the application of technologies. As GeoAI technologies becomes more widely applied in urban management and public services, its social impact and ethical responsibilities are increasingly coming to the forefront (Mai et al. 2025). Consequently, systematically integrating ethical considerations throughout the entire lifecycle of GeoAI models, from design and development to deployment, remains a major challenge.

To address this issue, the research community is actively exploring methods to embed ethical principles into all stages of GeoAI development and application (Richter and Scheider 2023). A key focus of these efforts is the advancement of 'Trustworthy GeoAI', supported by two main technological directions. The first involves the development of algorithmic fairness metrics and bias mitigation techniques tailored to geospatial contexts, aimed at preventing systematic discrimination based on attributes such as location, ethnicity, or income (P. Liu, Zhang, and Biljecki 2024). The second focuses on the design of explainable GeoAI methods that improve the transparency of model decision-making processes and facilitate accountability. A promising pathway involves establishing a comprehensive governance framework that spans research, deployment, and regulatory oversight. This includes incorporating the 'Value Sensitive Design' approach into the early stages of system development, embedding core human values such as fairness, privacy, autonomy, and well-being, into system objectives from the outset, rather than treating them as retrospective considerations. In parallel, there is a pressing need to implement independent third-party mechanisms for algorithmic impact assessment to systematically evaluate potential socio-ethical risks before system deployment. In addition, building inclusive, multi-stakeholder governance structures involving technical experts, social scientists, policymakers, and public representatives is essential. Collectively, these efforts aim to foster a responsible, human-centred GeoAI ecosystem where technological innovation contributes to the broader goal of societal well-being.

6. Summary

GeoAI is leading the transformation of urban computing. It leverages the technologies with various advantages, such as data representation models, interpolation and prediction, geo-related knowledge graphs and spatiotemporal foundation models. These tools had many applications in urban computing for their ability of efficient processing and analysis of massive spatiotemporal data. Thereby enhancing the effectiveness and real-time responsiveness of urban management. GeoAI has significantly improved the precision, adaptability, real-time responsiveness, and efficiency of urban computing. It has enabled accurate traffic prediction in intelligent transportation systems, efficient disaster response, real-time environmental monitoring, and effective strategies for sustainable urban development. However, several key challenges remain. First, the integration of data-driven and knowledge-driven paradigm is essential to combine their respective strengths such as the high accuracy of data-driven models and the interpretability of knowledge-based approaches. Second, fostering interdisciplinary collaboration across social, environmental, and economic domains remains difficult but is critical for building unified platforms for complex urban analysis. Third, the absence of proactive, intelligent, and adaptive systems for identifying and mitigating deceptive spatiotemporal data undermines the robustness and reliability of GeoAI applications. Fourth, insufficient attention to ethical and human-centred concerns may lead to issues related to social equity, labour rights, and data privacy. Future research should integrate diverse GeoAI techniques and cross-domain datasets to maximize their complementary advantages. In addition, more attention should be given to the detection of deceptive data and the incorporation of human-centred values to improve the safety, fairness, and usability of GeoAI in urban computing.

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