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Human-centered GeoAI foundation models: where GeoAI meets human dynamics

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Abstract

This study examines the role of human dynamics within Geospatial Artificial Intelligence (GeoAI), highlighting its potential to reshape the geospatial research field. GeoAI, emerging from the confluence of geospatial technologies and artificial intelligence, is revolutionizing our comprehension of human-environmental interactions. This revolution is powered by large-scale models trained on extensive geospatial datasets, employing deep learning to analyze complex geospatial phenomena. Our findings highlight the synergy between human intelligence and AI. Particularly, the humans-as-sensors approach enhances the accuracy of geospatial data analysis by leveraging human-centric AI, while the evolving GeoAI landscape underscores the significance of human–robot interaction and the customization of GeoAI services to meet individual needs. The concept of mixed-experts GeoAI, integrating human expertise with AI, plays a crucial role in conducting sophisticated data analyses, ensuring that human insights remain at the forefront of this field. This paper also tackles ethical issues such as privacy and bias, which are pivotal for the ethical application of GeoAI. By exploring these human-centric considerations, we discuss how the collaborations between humans and AI transform the future of work at the human-technology frontier and redefine the role of AI in geospatial contexts.

Keywords GeoAI, Human-Centric AI, Human dynamics

1 Introduction

The convergence of geospatial technologies and artificial intelligence (AI) has led to the emergence of Geospatial Artificial Intelligence (GeoAI), a dynamic subfield at the forefront of transforming human interactions with the world (Biljecki & Ito, 2021; Janowicz et al., 2020). Central to GeoAI are foundation models, large-scale frameworks trained on diverse geospatial datasets designed to encapsulate a comprehensive understanding of geospatial phenomena (Biljecki & Ito, 2021; Van Dao et al., 2020; Li & Hsu, 2018; Reichstein et al., 2019). These models excel in analyzing and interpreting complex geospatial data, including satellite images, street view datasets, GIS datasets, and spatial–temporal big data, at both individual and collective levels. The role of human dynamics, which refers to all forms of human activities and interactions, is pivotal in GeoAI. GeoAI gains a nuanced layer of understanding by embedding the concepts of human activities and interactions in space and time. Integrating human

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dynamics with AI and geospatial technologies enables researchers and practitioners to uncover more profound insights into environmental changes, urban development, and natural resource management, among other geospatial phenomena (Shaw et al., 2016; Shaw & Sui, 2018; Ye et al., 2023). For example, urban planners can utilize GeoAI to discern patterns of urban growth, forecast infrastructure needs, and refine city layouts for enhanced efficiency and sustainability, while incorporating the human dynamics into these geospatial configurations (Alastal & Shaqfa, 2022; Mortaheb & Jankowski, 2023; Tao, 2013). As another example, decision-makers in governments can harness GeoAI technologies to comprehend and predict trends in disasters like tornadoes, floods, and wildfires, thereby bolstering emergency response efforts with a focus on human-centric strategies and solutions (Al Qundus et al., 2020; Alizadeh et al., 2022; Fan et al., 2021; Imran et al., 2020; Sun et al., 2020).

The advent of GeoAI has introduced several innovative concepts that are transforming urban studies, including the integration of 'humans-as-sensors' and the development of embedded artificial intelligence systems. Embedded AI refers to AI technologies that are integrated directly into physical devices and systems, allowing for real-time processing and decision-making within geospatial contexts (Charalampous et al., 2017; Lee et al., 2023). This concept is particularly relevant in applications like autonomous vehicles and smart cities, where the ability to process spatial data on-the-fly is critical for functionality and safety. By embedding AI into these systems, GeoAI enhances their ability to interact with and adapt to dynamic environments, making them more responsive and efficient. This approach is pivotal in human-centric AI, which emphasizes the super alignment of between AI-generated decisions (e.g., planning, actions, recommendations) and human values and human factors. Essentially, GeoAI foundation models are developed to perceive the environments through a human lens instead of solely from the perspective of machines (Chen et al., 2023; Janowicz et al., 2020; Proulx et al., 2016). For instance, by integrating human safety risk ratings for streets, GeoAI models can conduct more precise safety assessments for extensive urban areas. For example, GeoAI has been combined with citizen science and computer vision algorithms to map flood depth at the street level (Alizadeh et al., 2022). Reinforcement learning has recently been used to perform intelligent routing in emergency management (Li et al., 2024).

When we combine GeoAI with social media, health, and census data, GeoAI can assess health risks in specific urban locales, aiding in reducing the health hazards faced by local communities (Li et al., 2022). In this way, GeoAI serves as a critical bridge between humans and machines, offering a richer, more human-focused understanding of our constantly evolving world.

In the dynamic realm of GeoAI, the interplay between humans and AI is increasingly influential, reshaping how individuals engage with geospatial technologies. Personalized GeoAI elevates such interactions, customizing insights and recommendations by incorporating more individual preferences and needs (Li et al., 2024; Li and Zhang, 2021). This personalized approach improves user experiences and strengthens the connection between the public and geospatial analysis. Such personalization becomes particularly impactful in diverse applications, like urban mobility and smart city initiatives, where individuals can receive tailored recommendations for efficient trips that reflect their specific preferences, thereby enhancing user satisfaction and promoting sustainable travel behaviors. Furthermore, incorporating human perceptions and mobility patterns into GeoAI enhances predictive precisions. This leads to a more intricate and accurate understanding of the environment, underlining the importance of human factors in advancing GeoAI applications.

A concept closely related to personalized GeoAI is the idea of mixed-experts GeoAI, which involves the collaboration of human experts and AI systems in geospatial analysis to support decision-making. The idea of mixed-experts GeoAI represents a significant advancement in the way geospatial analysis is conducted, by integrating the strengths of both human expertise and AI systems to support complex decision-making processes. This approach leverages the strengths of both human expertise and AI's data processing capabilities, creating a powerful synergy that is particularly useful in complex geospatial tasks (von Krogh, 2018; Zhang et al., 2022). For instance, in disaster response scenarios, human experts can provide critical insights based on experience and contextual understanding, while AI systems can rapidly process vast amounts of data to identify patterns and predict outcomes (Fan et al., 2021). The integration of mixed-expert systems in GeoAI has shown promise in various fields, including urban planning, environmental monitoring, and resource management, where the combination of human intuition and machine precision can lead to more effective and informed decisions. Recent studies have also highlighted the importance of iterative feedback loops between humans and AI in these systems, where AI models are continually refined based on expert input, leading to increasingly accurate and reliable outcomes (Jarrahi, 2018). For instance, human experts can provide expert knowledge in disaster response, while GeoAI processes provide data-driven approach to enhance decision-making. The integration of mixed of experts with GeoAI not only leverages the capabilities of AI but also ensures that human remains a central component in addressing the multifaceted nature of geospatial phenomena. As these dynamics continue to evolve, the interplay between humans and GeoAI holds the potential to unlock new possibilities for understanding and navigating the changing world.

While data privacy, security, and ethical challenges are common across AI technologies, GeoAI presents unique issues due to its integration of geospatial data. The reliance on human location trajectories and geographically tagged social media data introduces specific privacy concerns distinct from other AI applications. (Dilmaghani et al., 2019; Murdoch, 2021; Saura et al., 2022; Subramanian, 2017). Geospatial datasets are inherently tied to spatial contexts, leading to challenges such as risks of unauthorized tracking of individual movements and potentials for misuse of location-based information. Furthermore, the combination of geospatial big data with human-centric attributes like facial and gait features amplifies public concerns, as these data sets can be used to create detailed personal profiles, thus intensifying the privacy risks associated with GeoAI (Dilmaghani et al., 2019; Harris et al., 2022; Liu et al., 2019; Lorestani et al., 2024; Murdoch, 2021; Rao et al., 2023). Issues related to privacy, data security, and bias in algorithms must be addressed to ensure responsible and equitable use of these technologies (Janowicz et al., 2020; Kang et al., 2024). Striking a balance between innovation and ethical considerations is crucial to harness the full potential of GeoAI while minimizing potential risks.

The following sections will discuss the pros and cons of GeoAI from human dynamics perspectives, teaming with GeoAI, the future direction of robotics embedding with human-centered GeoAI technology, and potential job opportunities with GeoAI technology.

2 The human perspective: pros and cons

In recent years, some applications and commercial products driven by GeoAI models are starting to affect the life experiences of people. Meanwhile, the academic community is actively exploring and discovering the potential and capability boundaries of GeoAI technologies in enhancing societal productivity and efficiency of individuals' lives (Choi, 2023; Janowicz et al., 2020). However, as an emerging technology, the impacts of GeoAI on human society still need additional in-depth observations and investigations (Del Giudice et al., 2023). Currently, most academic studies consider that GeoAI technologies improve the efficiency and accuracy of human-related tasks and enhances intelligence in people's daily lives and works (Kamel Boulos et al., 2019; Purbahapsari & Batoarung, 2022; Yin et al., 2017). Meanwhile, some scholars and practitioners also express concerns about the excessive reliance on GeoAI technologies, issues related to privacy, and potential impacts on job opportunities in geospatial-related fields (Del Giudice et al., 2023; Kang et al., 2023; Shaw & Sui, 2021; Zhao et al., 2021). Therefore, we discuss the implications of GeoAI technology on human lives below.

2.1 Pros

As one highlight of GeoAI technologies, GeoAI-driven models can process vast amounts of geospatial data, capture the geospatial features in the data, and offer insights that facilitate human decision-making in urban management and planning, environmental assessment, and emergency response (Choi, 2023; Janowicz et al., 2020; Song et al., 2023). The capability of analyzing and interpreting geospatial data enables GeoAI models to contribute significantly to optimizing public resource allocation, predicting environmental changes, and enhancing the overall efficiency of emergency response systems. For example, leveraging GeoAI technologies allows for a rapid and accurate classification of objects or land use in remote sensing images. In the application of wildfire monitoring, classification models powered by GeoAI can detect open fire points and potential ignition locations with sufficient combustibles (e.g., dry trees or shrubs) (Cilli et al., 2022; Jaafari et al., 2019; James et al., 2023; Radke et al., 2019). This facilitates people to take appropriate measures within a relatively short period and reduces the impacts of large-scale wildfires.

Compared to traditional geospatial data analysis approaches, the methodologies driven by GeoAI models can improve efficiency and help to reduce the corresponding costs of data processing and decision-making. This is because GeoAI leverages advanced algorithms and computing power to automate the processing and analysis of large datasets, which would otherwise require extensive manual effort and time. By streamlining these processes, related stakeholders can allocate their resources more effectively, focusing on strategic decision-making rather than labor-intensive data analysis tasks. Meanwhile, the cost spent on repetitive manual data analysis can be further reduced. Taking land use monitoring as an example, GeoAI offers a low-cost and accurate solution to identify the attributes and categories of urban areas, which assists governments in monitoring and assessing differences between planned and actual land use types (Alem & Kumar, 2020; Chaturvedi & de Vries, 2021; Chen et al., 2014). Moreover, based on crowdsourced geospatial data, GeoAI models can predict crowd volume and transportation flows in the short or long term, which supports transportation authorities in better allocating public resources and further reducing the probability of traffic congestion (Ai et al., 2019; Akhtar & Moridpour, 2021; Boukerche et al., 2020; Li et al., 2021; Li et al., 2023; Lin et al., 2018; Miglani & Kumar, 2019). Specifically, based on the crowd and transportation prediction outcomes, the authorities can temporarily increase the capacity of public transportation during the peak hours between high-traffic areas (e.g., between residential and CBD areas), introduce reversible lanes to handle traffic volume on busy roads, and plan new roadways to divert traffic.

Furthermore, GeoAI facilitates personalized location-based services, which can provide tailored solutions for individuals based on their unique geospatial needs and preferences (Gao et al., 2023; Sojahrood & Taleai, 2021; Yao et al., 2023). For some location-based recommender services, GeoAI is able to recommend travel destinations and travel modes to meet the different requirements of different users. Taking tourists as an example, a recommendation system driven by GeoAI models can arrange travel itineraries that include the destinations or scenes where the tourists are interested with appropriate transportation modes. The recommended itineraries allow the tourists to achieve their travel desires at acceptable costs. Another location-based service driven by GeoAI leverages the knowledge or features captured from street view data to recommend appropriate routes that meet the users' need for personal safety or comfort when they walk in cities (Gong et al., 2018; Kang et al., 2020; F. Zhang et al., 2018a, 2018b). A CNN-based deep learning model can identify streets with different safety levels in cities, which uses massive street view data and corresponding manually labeled safety level indicators (Zhang et al., 2021). According to the classification results, users can arrange their preferred routes to avoid incidents that threaten their safety. Like the safety level classification, GeoAI models can predict outdoor comfort in cities. Liu et al., (2023) developed a graph-based deep learning model leverages crowdsourced data and computer vision to predict individuals' comfort on sidewalks, which can provide users with a reference on the comfort level of their outdoor trips.

GeoAI models open new possibilities for innovative applications, such as autonomous vehicle navigation, environment-aware autonomous robots, and smart city development (Janowicz et al., 2020; Van Brummelen et al., 2018). These applications leverage GeoAI for spatial reasoning, optimization, and prediction to create more intelligent and responsive systems. For instance, in autonomous vehicle navigation, GeoAI can process and interpret complex spatial environments in real-time, enabling vehicles to make safe and efficient decisions on the move (Badrloo et al., 2022). Similarly, environment-aware autonomous robots can utilize GeoAI to navigate and perform tasks in dynamic and unpredictable settings, such as disaster response scenarios or agricultural monitoring (Shakeri et al., 2019). In general, the emergence of GeoAI has provided the opportunity to enhance the convenience and efficiency of human lives. Applications driven by GeoAI exhibit significant potential for expansion and innovation, offering extensive opportunities for advancement in the future.

2.2 Cons

Despite the promising advancements in GeoAI, concerns arise regarding the potential consequences of over-reliance on these technologies (Lepri et al., 2021; Zhao et al., 2021). Excessive dependence on GeoAI can diminish the importance of human expertise in the geospatial domain. As automated systems take over tasks traditionally performed by human professionals, there is a risk of eroding the deep understanding and intuition that human experts bring to the interpretation of complex geospatial data. It is crucial to strike a balance between the capabilities of GeoAI and the irreplaceable insights provided by geo-domain experts, ensuring that human knowledge and intuition continue to play a vital role in decision-making processes.

Another significant challenge associated with integrating GeoAI is the potential for job displacement (Moradi & Levy, 2020). The automation of manual geospatial tasks through AI algorithms could lead to a reduced demand for specific roles in the geospatial industry (Huang & Rust, 2018; Jaiswal et al., 2023; Ramachandran et al., 2024; Tschang & Almirall, 2021; TU et al., 2023; Vrontis et al., 2023). Jobs involving routine data collection, analysis, and mapping may be particularly susceptible to automation, raising concerns about job displacement and the need to reskill the workforce. Efforts should be directed towards proactive measures, such as providing training programs and fostering the development of new skills, to mitigate the impacts of job displacement and ensure a smooth transition for professionals in the geospatial field (Ramachandran et al., 2024; TU et al., 2023; Vrontis et al., 2023).

GeoAI applications present distinct privacy and ethical challenges that are particularly acute due to their reliance on geospatial data, which is inherently tied to individuals' physical locations and movements. Unlike general AI systems, which may process abstract or anonymized data, GeoAI often involves the collection, storage, and usage of highly sensitive and personal location-based information (Janowicz et al., 2020; Kang et al., 2024; Shi et al., 2023; Walker & Winders, 2021). This raises unique risks, such as potentials for unauthorized surveillance or unintended exposures of individuals' whereabouts and daily routines. The integration of geographically tagged social media data further complicates these issues, as it can lead to the creation of detailed personal profiles that combine both spatial and social information (Jaiswal et al., 2023; Liu et al., 2019; Lorestani et al., 2024; Rao et al., 2023). Such profiles can be misused, leading to privacy breaches that are more invasive than those typically associated with non-geospatial data. Addressing these concerns requires a concerted effort to develop ethical frameworks and technological safeguards specifically tailored to the complexities of geospatial data. This includes implementing strict access controls, enhancing data anonymization techniques, and ensuring that data usage complies with privacy regulations and user consent. For instance, the tracking and analysis of the location data of individuals can lead to invasive surveillance and privacy breaches if not handled with the utmost care and responsibility. Such practices can expose individuals' habits, routines, and even confidential activities, raising significant concerns about data security, and the potential for misuse by various actors (i.e., corporations and governments). In addition, bias in GeoAI algorithms, resulting from unrepresentative or skewed data sets, can lead to unfair or discriminatory outcomes (Jarrahi, 2018; Ntoutsi et al., 2020; Roselli et al., 2019). For example, location-based services might offer biased recommendations or exclude certain demographics, reinforcing existing inequalities.

To address these challenges, it becomes imperative to approach the development of GeoAI with a thoughtful and ethical framework (Liu et al., 2019; Lorestani et al., 2024). Striking a balance that preserves human expertise while embracing the efficiency and capabilities of GeoAI is essential for sustainable and responsible integration of these technologies in geospatial data usage and analysis.

3 Teaming with GeoAI

Considering the impact of GeoAI on human life, we need to further discuss the conveniences and challenges brought by GeoAI from both individual and collective perspectives. From the perspectives of individuals, GeoAI-related applications can provide accurate, personalized recommendations, navigations, and comprehensive views by integrating data from various sources to help people better plan and organize their daily routines and activities. GeoAI, performed as a virtual advisor, offers personalized and feasible suggestions to users, allowing users to make decisions based on their actual circumstances (Maria et al., 2022). For groups and teams' cooperation, GeoAI-related applications provide an efficient platform linked to human-based (empirical) and AI-based (data-driven) insights to achieve more comprehensive solutions for real-world issues. Hybrid teams composed of GeoAI and human experts adopt a workflow of training-feedback-retraining, gradually deepening the model's understanding of the real-world problem, while achieving reasonable, feasible, and robust results. Additionally, GeoAI can offer consultancy to human groups, assisting them in understanding the situation of problems from multiple perspectives and making reasonable solutions. While offering advantages, the potential issues of personal GPS or other spatial data privacy breaches, societal inequality, and the development costs of GeoAI models are also significant challenges that need to be discussed and further addressed.

3.1 Individual perspective

The RLHF (Real-time, Local, Holistic, Feedback-driven) approaches ensure that GeoAI systems can provide timely, localized, comprehensive, and adaptive insights into individuals' daily lives. The development of GeoAI-driven applications in personalized location services (e.g., trip recommendations, health care, emergency responses), geoprivacy protection, user-friendly interface design, and affordability have attracted significant attentions in recent years (Ye et al., 2023). Although GeoAI models open up opportunities to provide better individual services, these models face some critical challenges that require more discussions and further study.

GeoAI-driven tools and services have ushered in an era of unprecedented personalization, where technology seamlessly adapts to individual needs. This level of personalization is particularly evident in location-based services, which have seen significant advancements through the integration of GeoAI technologies (Chen et al., 2023). One of the most notable aspects of GeoAI for individuals is its capacity to provide tailored recommendations, such as personalized travel itineraries and navigation routes, which are designed to align with user preferences and real-time environmental conditions (Gao et al., 2023; Kang et al., 2024). These services are increasingly relying on sophisticated GeoAI algorithms that can process vast amounts of geospatial data to offer insights that are both timely and contextually relevant. Whether suggesting the best local dining options, nearby entertainment events, or customized travel itineraries, GeoAI applications enhance daily lives by aligning with personal preferences and routines. Navigation is another facet where individual perspectives shine through. GeoAI systems assist in optimizing travel routes based on real-time data, taking into account user-defined preferences. Furthermore, these applications offer a comprehensive worldview, delivering information about local phenomena, events, and services, allowing individuals to plan better and organize their daily routines and activities. In essence, GeoAI caters to the unique needs of each individual, offering not only efficiency and convenience but also a sense of empowerment over their surroundings (Bingley et al., 2023).

Compared to traditional recommendation services, GeoAI-driven recommendation systems can learn and remember historical user selections for specific services and then offer helpful recommendations when users visit new places. GeoAI systems consider locations as a critical factor, recognizing that user preferences may vary significantly depending on where they are. The GeoAI-driven recommendation systems can leverage the historical contexts of users' interactions across different geographical areas and learn users' preferences for traveling and visiting destinations. Based on the learned knowledge, the recommendation systems can provide thoughtful suggestions that best meet the users' needs when they travel to new places. Moreover, the GeoAI-driven recommendation systems can provide adaptive and personalized explorations for users. The recommendation systems can record the destinations chosen by users and adaptively learn the preferences and patterns for individuals' destination selections. Based on the adaptive recommendations, the systems focus on personalization and aim to make each user's experience unique by offering recommendations that resonate with their specific tastes and interests. For example, based on historical and real-time traffic data, GeoAI-based navigation systems can forecast future road traffic conditions and suggest the best route, which facilitates people's daily lives in arranging their trips and activities (Li et al., 2024).

GeoAI introduces unique privacy challenges that go beyond the scope of traditional AI applications, particularly in the context of user-friendly interfaces and privacy data applications (Dilmaghani et al., 2019; Murdoch, 2021). While general AI systems often deal with non-spatial data, GeoAI's reliance on human location trajectories and geographically tagged social media data necessitates a more nuanced approach to privacy (Rao et al., 2023). For instance, user interfaces that display real-time location data or offer personalized location-based recommendations must balance providing valuable insights with protecting sensitive information (Jaiswal et al., 2023). The integration of such data within GeoAI systems increases the risk of unauthorized tracking and profiling, which can lead to significant ethical and privacy concerns (Liu et al., 2019; Lorestani et al., 2024). Additionally, the use of geospatial data in health and emergency response applications, while beneficial, must be carefully managed to prevent inadvertent disclosure of personal information, especially when these datasets are combined with other sensitive attributes like health records or biometric data (Alizadeh et al., 2022). As a result, GeoAI-driven user interfaces must incorporate advanced anonymization techniques, geospatial data encryption, and user-consent mechanisms to safeguard individual privacy while still enabling meaningful spatial analysis (Murdoch, 2021; Saura et al., 2022). Moreover, GeoAI can assist in compliance with geoprivacy regulations by automatically identifying and masking sensitive information in geospatial datasets. However, it is important to note that a fine line exists between leveraging geospatial data for beneficial insights and infringing on individuals' privacy. Ensuring that GeoAI applications do not unintentionally reveal sensitive geoprivacy information or contribute to surveillance without consent is a critical challenge.

GeoAI also improves healthcare and disease surveillance for individuals' lives. Taking the Covid-19 pandemic as an example, GeoAI models can analyze various data sources, including travel patterns, social media posts, and satellite imagery, to predict Covid-19 outbreak locations and spread. This information not only helps public health officials and governments prepare and respond more effectively but also prompts and warns the public to avoid or reduce travel to high-risk areas. GeoAI is instrumental in developing dashboards and maps that track the spread of COVID-19 in real time. During the pandemic, the Johns Hopkins University COVID-19 dashboard provided the public with up-to-date information on case numbers, hospitalizations, and deaths, which became a vital resource worldwide (Dong et al., 2022). This information helps the governments and researchers control the pandemic spread and facilitates the public to understand the big picture of this pandemic status and trends. Beyond COVID-19, GeoAI enables more efficient delivery of telehealth services by optimizing scheduling and routing for home healthcare providers. This ensures that patients receive timely care, especially in remote or underserved areas.

The integration of GeoAI with user-friendly interface designs can significantly improve the accessibility of geospatial data analysis. By simplifying the interaction with complex GeoAI tools, non-expert users can benefit from advanced spatial insights without needing specialized training. This democratization of GeoAI applications has the potential to empower a broader range of users to leverage geospatial data or geospatial analysis results in their works and lives. Meanwhile, developing a user-friendly interface that is both powerful enough to handle the complexities of GeoAI analytics and intuitive enough for general users is a significant design and technical challenge. The risk is creating interfaces that are either too simplistic to be useful for advanced analysis or too complicated for non-specialist users to navigate effectively. A possible solution is to integrate users' feedback into the interface design process, which requires the GeoAI models to understand the feedback and make responsive updates in the interface.

GeoAI can make geospatial analysis more affordable by automating processes that previously required significant human labor and expertise. This automation can reduce costs for businesses and governments, making spatial insights more accessible to smaller entities or resource-constrained organizations. Additionally, as GeoAI technologies become more widespread, the costs associated with them are likely to decrease, further enhancing their affordability. However, the initial development and implementation costs of GeoAI systems can be high, especially for cutting-edge applications. This includes the costs of acquiring high-quality geospatial data, investing in computing infrastructure, and developing or purchasing GeoAI algorithms and software.

3.2 Team perspective

GeoAI-based systems extend their transformative influence beyond individual experiences and seamlessly integrate into the realm of team collaboration (Mortaheb & Jankowski, 2023; Scheider & Richter, 2023). These applications serve as a unifying platform where the synergy of human-based empirical knowledge and AI-driven insights converges, fostering more comprehensive solutions for real-world challenges. Teams and groups benefit from GeoAI approaches by leveraging their ability to analyze and process vast amounts of geospatial data, providing valuable insights and recommendations that aid in decision-making. GeoAI facilitates the exchange of real-time, data-driven information among team members, allowing for quicker and more informed responses to complex issues. This fusion of human expertise and AI capabilities in GeoAI applications transcends traditional boundaries, creating an efficient and cooperative platform that elevates the collective problem-solving potential of groups and teams, leading to more effective, sustainable, and innovative outcomes.

GeoAI-based approaches can uncover some hidden patterns that might be neglected or missed by humans in real-world phenomena or issues. As a virtual member in team collaboration, GeoAI-driven approaches can support urban design/planning and management using their powerful learning capabilities. Moreover, the urban digital twin driven by GeoAI approaches is an important platform that can accurately generate urban simulation and prediction results based on processing different types of spatial–temporal data (Li and Zhang, 2021; Ye et al., 2023).

In summary, GeoAI applications offer both individual and collaborative advantages, enhancing efficiency and convenience in daily life while fostering teamwork and a symbiotic relationship between humans and AI. For individuals, GeoAI provides personalized recommendations, navigational support, and comprehensive information by amalgamating data from diverse sources, enabling better daily planning in low-cost and efficient ways. In the context of group and team cooperation, GeoAI is an efficient platform combining human expertise with AI-driven insights, facilitating more comprehensive problem-solving for real-world challenges.

3.3 GeoAI in spatial decision support systems

Spatial Decision Support Systems (SDSSs) are computing systems that combine Geographic Information System (GIS) capabilities with decision support tools to facilitate informed and effective decision making in spatial contexts (Zhang et al., 2021b). Traditional spatial decision support tools heavily rely on Multi-Criteria Decision Making (MCDM) techniques, which enable decision-makers to consider multiple objectives and criteria when evaluating alternative spatial scenarios (Song et al., 2024; Zhang et al., 2014; Z. Zhang et al., 2018a, 2018b). With the rapid development of GeoAI, AI models have been used to process real-time data to provide prediction in various application areas. While AI can contribute to decision-making process by providing data-driven insights, MCDM provides an expert-based approach to decision making by incorporating diverse criteria, values, and preferences. Pham et al. (2021) combines deep learning algorithm with MCDM to assess flood risks using hazard, exposure, and vulnerability measures.

The increasing quality and quantity of geoscience data can pose challenges in terms of memory and processing requirements when performing GeoAI analysis, where advanced Cyberinfrastructure and high-performance computing play an important role in designing a GeoAI-based spatial decision support system to support timely decisions. CyberGIS fulfills an essential role in enabling computation- and data-intensive research and education across a broad swath of academic disciplines leading to widespread scientific advances and broad societal impact (Wang et al., 2013; Z. Zhang et al., 2018a, 2018b).

4 Shaping the future of robotics with GeoAI

The intersection of Artificial Intelligence (AI) and geospatial technology has paved the way for a new age of innovation and exploration, catalyzing the development of embodied AI in geospatial scenarios. Embodied AI, a paradigm where AI systems are integrated into physical entities or robots that can interact with, navigate, and sense the real-world environment, offers a transformative approach to addressing complex challenges in geospatial contexts. This fusion of AI and physical embodiment not only enhances robot self-control and autonomous navigation but also improves human–robot interactions by enabling robots to better understand and respond to human cues and commands. Moreover, the importance of evaluating the trustworthiness of GeoAI technologies in these interactions has been underscored, ensuring that robots operate reliably and align with human expectations for safety and efficiency. As GeoAI-powered robots become more prevalent, ethical and privacy concerns surrounding data collection and processing must be addressed to maintain public trust. Additionally, increasing the interpretability of AI models is crucial for enhancing the efficiency of interactions and enabling robots to understand human needs more effectively.

4.1 GeoAI in robot self-control

With the miniaturization of high-performance computing hardware and the development of Internet of Things (IoT) technologies, more and more robots or physical entities are being used in people's daily lives and work. In particular, the capabilities of robots equipped with GeoAI applications in geospatial awareness and adapting learning under different environments have dramatically increased (Charalampous et al., 2017; Lee et al., 2023; Sanneman & Shah, 2020; Zender et al., 2007). GeoAI facilitates robots in accurately determining their position and creating maps of their surroundings, making them more capable of autonomous navigation in complex and dynamic environments. The robots can adjust their control algorithms to adapt to obstacles and changes in surface conditions autonomously by assessing the terrains they navigate using GeoAI-driven programs. These GeoAI-enabled robots can adapt to different scenarios, such as land surveying, environment monitoring, and industrial automation,

For land surveying tasks, robots equipped with GeoAI applications can adopt the most appropriate autonomous control strategy based on their perception of the surrounding environment (Roh et al., 2019; Su et al., 2023; Tung & Yaseen, 2020). Taking the example of quadruped robots, according to their perception of surroundings using a series of sensors (e.g., GPS, IMU, cameras, and lidar), they can control eight drive motors on their four legs with appropriate angular velocities to move across different terrains. The central processing unit in quadruped robots can understand the characteristics of the surrounding environment and the types of obstacles in the path using the data collected by the sensors and AI-based algorithms. The central processing unit then sends appropriate messages to motion control modules to guarantee that the robots can move smoothly and safely.

In addition, GeoAI-enabled equipment for land surveying and environmental monitoring can perform smartly with less human intervention. Taking a drone as an example, the flight control system can manipulate the attitude of a drone to avoid collisions with tall buildings or other types of obstacles (Lahsen-Cherif et al., 2022). In wildfire monitoring, drones can leverage the data collected by onboard infrared temperature sensors and GeoAI-driven models to detect burning areas and smoking spots (where there is no open flame, but the temperature has reached the ignition point) in forests. Based on the detected wildfire spots, drones can plan the optimal flight path and report the positions and plant species near the wildfire to facilitate fire suppression strategies and emergency responses (Boroujeni et al., 2024; Ramadan et al., 2024). During a wildfire monitoring process, drones are able to detect the targets and plan the flight path autonomously with less human intervention, which vastly reduces the impact of human factors (e.g., errors in operations and judgment) on environment monitoring tasks.

Evaluating trustworthy human-centered GeoAI technology in robot self-control is crucial because trust serves as a foundational element for successful human–robot interaction, particularly in dynamic and service-oriented environments. Trustworthiness in GeoAI-enabled robots is shaped by users' propensity to trust the system, the reliability of the robot's geospatial functions and design, and the contextual appropriateness of its tasks (Weitz et al., 2019). As highlighted in the development of the Social Service Robot Interaction Trust (SSRIT) framework, factors such as familiarity, self-efficacy, anthropomorphism, and perceived service risk play pivotal roles in fostering or undermining trust (Chi et al., 2021). In robot self-control, trustworthy GeoAI ensures that robots make accurate, context-aware decisions while aligning with human expectations for safety, efficiency, and social norms. Further studies should also aim to develop standardized methods for assessing trustworthiness in various real-world scenarios, including land surveying, environmental monitoring, and industrial automation. By advancing our understanding of trust in GeoAI-driven robot self-control, researchers can help mitigate user uncertainty, increase adoption rates, and promote seamless human–robot collaboration, ultimately enhancing the effectiveness and safety of autonomous systems in geospatial tasks.

4.2 GeoAI in human–robot interaction

Besides the contributions to robot self-control, GeoAI technology also facilitates human–robot interaction. As machines work alongside humans, one of the most significant tasks for robots is understanding people's cues and commands under various scenarios. Accurately understanding the cues and commands helps decrease the possibility of causing damage or even loss of lives during a robot's work. One of the prerequisites for an accurate understanding of human commands is that robots are aware of their surroundings at all times, as well as the potential dangers in their surroundings. GeoAI-related technology improves the geospatial awareness of robots and helps robots understand the implications of human cues and commands precisely.

The best example to illustrate the contributions of GeoAI in human–robot interaction is the autonomous driving technology that has rapidly developed in recent years (Gonzalez et al., 2016; Khayyam et al., 2020; Li et al., 2018; Xing et al., 2019). Based on the environmental sensors (i.e., Lidar, Cameras, GPS, IMU) deployed at various positions in a vehicle, the autonomous driving systems can evaluate the risk level of collisions and accidents with other objects on the road. When the driver gives an incorrect instruction that could lead to a traffic accident, the autonomous driving system refuses to execute the instruction to avoid a collision. Moreover, the independent driving system can execute the driver's commands with a safety strategy based on the road conditions. For instance, autonomous driving systems will control the vehicle to perform overtaking or acceleration commands given by the driver only when it is safe. In general, autonomous driving systems with GeoAI technology can better safeguard the driver and other road users and provide better user experiences.

Another example of GeoAI technology in human–robot interaction is the personalized service robots in hospitals and large shopping malls (Ludwig et al., 2023; Scheider & Richter, 2023). Robots with GeoAI technology can assist patients and visitors in finding their way around. These robots can provide real-time navigation instructions, locate specific hospital departments, and provide information on appointments and wait times. They can provide assistance to disabled people by finding wheelchair-friendly routes, providing auditory instructions, allowing users to control elevators, access automatic doors, and providing turn-by-turn guidance through complex buildings and outdoor spaces. In addition, robots in shopping malls or large buildings can offer personalized services to individuals in various settings. Notably, a robot in shopping malls can incorporate indoor geospatial and business information to guide shoppers to the nearest store with the best prices, discounts, or promotions. These robots leverage detailed indoor 3D models, indoor navigation technology, sensors, and GeoAI technology to understand their surroundings precisely. Based on the collected spatial information, these robots can offer helpful recommendations to users.

However, as GeoAI-powered robots become more integrated into human environments, ethical and privacy concerns are becoming increasingly significant. Robots equipped with GeoAI can process large amounts of geospatial and personal data, such as location, movement patterns, and human biological information (fingerprints or facial features). This raises concerns about the potential misuse of sensitive data, unauthorized surveillance, and breaches of personal privacy. As mentioned in Sect. 2.2, ensuring that data collection and processing comply with ethical standards and privacy regulations is essential for maintaining public trust. Future research should focus on developing privacy-preserving techniques, such as data anonymization and secure data storage, to protect individuals' information. Additionally, establishing transparent policies and ethical guidelines for human–robot interaction will help mitigate these concerns and promote responsible deployment of GeoAI technologies.

Another interesting direction for improving human–robot interaction is increasing the interpretability of AI models used in GeoAI systems. Many AI models function as "black boxes," making it difficult for users to understand how decisions are made. By enhancing interpretability, robots can provide more details for their actions, making interactions with humans more efficient and fostering greater trust from users. For example, if a robot can clarify why it chose a particular path or action based on geospatial data, users can better understand its reasoning and adapt their commands accordingly. Interpretability also allows robots to better grasp human needs by incorporating feedback more effectively. Future research should develop explainable AI frameworks that can break down complex geospatial decisions into human-understandable explanations, ultimately leading to smoother and more intuitive human–robot collaborations.

5 Future jobs with GeoAI foundation models

Incorporating GeoAI foundational models into social production and life could generate job opportunities related to the development and deployment of GeoAI, as well as work in areas such as ethical and privacy protection. These emerging job roles will form a GeoAI industrial ecosystem, adding more employment opportunities to society and promoting diversification of the social division of labor (Tschang & Almirall, 2021; Vrontis et al., 2023). Geographic Information Systems (GIS) specialists, GeoAI model developers, and GeoAI analysts are the most important components in the GeoAI industrial system. GIS specialists have extensive experience in spatial–temporal data processing and data mining. They can provide specialized knowledge of geospatial information to GeoAI model developers to ensure the effectiveness of GeoAI foundation models. For example, as GeoAI becomes more embedded in fields like urban planning and environmental monitoring, the demand for professionals skilled in geospatial data analysis, AI model development, and data ethics is expected to rise significantly (Kaplan & Haenlein, 2020; Ramachandran et al., 2024). Additionally, the interdisciplinary nature of GeoAI will likely create demands that require expertise in both geospatial sciences and AI, offering a new dimension to the job market (Vrontis et al., 2023). On the other hand, AI model developers who have computer science (CS) backgrounds can leverage the knowledge provided by GIS specialists to design effective architectures of GeoAI models for addressing specific geospatial tasks. GeoAI analysts who interpret the results generated by GeoAI models can provide actionable feedback to the model developers to improve the model performance further. In addition, GeoAI analysts can provide operational recommendations to policymakers or urban planners based on the simulation or prediction results generated by GeoAI models. GeoAI analysts can help prevent policymakers without AI experience from misunderstanding the model results, preventing inappropriate policies or plans from being enacted (Del Giudice et al., 2023).

Moreover, the rise of GeoAI will necessitate the creation of new educational programs and reskilling initiatives aimed at preparing the workforce for these emerging roles (Bughin et al., 2018). Universities and vocational institutions may need to develop specialized curricula that integrate geospatial technology with AI and data science, ensuring that graduates are equipped with the necessary skills to thrive in this evolving field (Bughin et al., 2018). This shift in educational focus could lead to the establishment of new academic disciplines and professional certifications that align with the specific needs of the GeoAI industry ecosystem. The quality of GeoAI-related data can affect the performance of GeoAI foundation models, and the quantity of the data is massive, which facilitates the generalization and accuracy of the models. Thus, GeoAI data specialists need to have strong experience in geospatial-related data preprocessing to minimize the outliers or errors in the data. GeoAI data specialists also require the ability to process and manage big geospatial data in the TB (Terabyte), even at the PB (Petabyte) level. Experienced data specialists who can provide data assurance for training or validating GeoAI foundation models have significant roles in the GeoAI industrial ecosystem.

Furthermore, the automation of certain geospatial tasks through GeoAI may displace some traditional roles, but it will also create opportunities for higher-skilled positions that involve overseeing AI systems, interpreting complex data, and ensuring ethical compliance (Brynjolfsson & McAfee, 2014; Kaplan & Haenlein, 2020). For instance, GeoAI analysts and data specialists will play a crucial role in interpreting AI-generated insights, making informed decisions, and providing feedback to improve the performance of AI models (Li et al., 2024). The integration of AI into geospatial workflows will likely transform job roles, emphasizing the need for continuous learning and adaptation in the workforce (Vrontis et al., 2023).

In terms of user experience, the GeoAI industry needs interface designers and art designers to develop intuitive interfaces for human-AI interaction in geospatial applications. The interface designers are essential for the market of GeoAI-related applications. GeoAI interface designers are instrumental in creating user-friendly interfaces that make geospatial applications accessible to many users. They design intuitive interfaces that reduce the learning curve and make it easy for people to interact with complex AI-powered systems. Intuitive interfaces enable users to extract insights and make informed decisions rapidly, saving time and resources, such as emergency responses in GeoAI applications. GeoAI often deals with intricate and large datasets. Interface designers create visualizations and data presentations that simplify complex information, making it more digestible and actionable for users. The interface designers facilitate seamless interactions between users and AI models. They create interfaces that allow users to input their data and preferences, enabling AI systems to provide personalized insights and recommendations. In addition, with the help of art designers, GeoAI applications can give simple, aesthetic, and harmonized interfaces that facilitate the interactions between human and complex GeoAI systems.

Last but not least, establishing an ethics review mechanism (e.g., an independent council) will have far-reaching implications for the development of GeoAI. GeoAI applications often involve sensitive and location-based data, raising ethical concerns. The council helps identify and address these dilemmas, ensuring that technology is used in ways that respect privacy, security, and human rights. The council safeguards the rights of individuals, particularly in contexts where location data can be misused. This council ensures that the design and implementation of GeoAI technologies prioritize user consent, data protection, and transparency. Moreover, this council can assess the potential risks associated with GeoAI applications, including security breaches, data breaches, and unintended consequences. Meanwhile, based on the abovementioned tasks, they can ensure that the adoption of GeoAI technologies aligns with long-term sustainability goals. They can advocate for continuous education and awareness regarding ethical issues related to AI and provide guidance and resources for AI developers, users, and policymakers to make informed decisions.

6 Mixed experts GeoAI

A robust and powerful GeoAI system needs expertise from various domains, such as climatology, urban planning, and ecology, into the GeoAI model. It ensures that the AI system has a holistic understanding of geospatial phenomena, benefiting from the collective knowledge of multiple experts. By incorporating expertise from diverse domains, the GeoAI model becomes enriched with a comprehensive understanding of spatial phenomena. Climatologists contribute insights into the intricate patterns of weather and climate, and urban planners provide nuanced perspectives on city development and infrastructure needs. In contrast, ecologists contribute valuable information about ecosystems and biodiversity.

One of the most significant advantages of hybrid expert GeoAI systems is their ability to combine the strengths of human intuition and contextual understanding with the computational power and data-driven insights of AI. For instance, in urban planning, human experts can provide nuanced perspectives on city development and infrastructure needs, while AI systems can analyze large datasets to identify trends and predict future scenarios (Moradi & Levy, 2020). This collaboration leads to more sustainable and resilient urban designs that are both data-driven and context-sensitive (Jarrahi, 2018).

Moreover, the application of hybrid expert systems is not limited to urban planning. In disaster management, these systems play a critical role in enhancing the accuracy and effectiveness of emergency responses. Human experts can interpret AI-generated predictions of disaster impacts, adjusting strategies based on real-time data and situational awareness. For example, during flood management, human experts might rely on AI to simulate various flooding scenarios, but their expertise is essential in deciding which scenarios are most relevant and how to implement appropriate responses (Alizadeh et al., 2022).

However, the integration of human and AI expertise also presents challenges. One of the primary challenges is ensuring that the AI models are transparent and interpretable, allowing human experts to understand and trust the AI's recommendations (Kaplan & Haenlein, 2020). This is particularly important in fields like environmental monitoring, where the consequences of decisions can be significant and far-reaching. Additionally, there is a challenge of maintaining a continuous feedback loop between human experts and AI systems. This iterative process is crucial for refining the AI models and ensuring they remain relevant and accurate over time (Gonzalez et al., 2016; von Krogh, 2018).

Furthermore, there is a growing interest in exploring how hybrid expert GeoAI systems can be scaled to handle increasingly complex and large-scale geospatial problems. Recent research suggests that as these systems evolve, they will need to incorporate more sophisticated models of human decision-making and collaboration, ensuring that the insights generated by AI are both actionable and ethically sound (Bughin et al., 2018; Tschang & Almirall, 2021). This underscores the importance of ongoing research and development in this area, as well as the need for cross-disciplinary collaboration to address the challenges and maximize the potential of hybrid expert GeoAI systems.

7 Conclusion

This study highlights the transformative potential of human-centered GeoAI foundation models, where GeoAI intersects with human dynamics to revolutionize geospatial analysis and applications. By integrating human intelligence, needs, preferences, and interactions, GeoAI foundation models offer more nuanced and context-aware insights, enhancing domains such as urban planning, environmental monitoring, and disaster response. The humans-as-sensors approach exemplifies the power of leveraging human inputs to refine geospatial data analysis, while mixed-experts GeoAI underscores the value of combining human expertise with AI-driven insights for sophisticated decision-making. These models not only improve the accuracy and applicability of geospatial technologies but also ensure that AI-driven decisions are aligned with human needs and values.

However, the deployment of human-centered GeoAI brings forth critical challenges related to trust, ethics, and privacy. Trustworthiness in GeoAI systems, particularly in applications like robot self-control and human–robot interactions, have to be rigorously evaluated to ensure reliability, safety, and user confidence. Privacy concerns stemming from the use of sensitive location-based data necessitate the development of robust data anonymization techniques, ethical guidelines, and privacy-preserving frameworks. Furthermore, the interpretability of AI models remains a key area for future research, as enhancing model transparency will foster better human-AI collaboration and enable more effective human-centered interactions.

Looking forward, future research directions in human-centered GeoAI should focus on the following priorities:

1. Developing standardized frameworks for evaluating trust in GeoAI-enabled systems to improve user adoption and safety in real-world applications.
2. Enhancing ethical safeguards to address privacy risks, data security, and algorithmic bias, ensuring responsible and equitable GeoAI deployment.
3. Advancing interpretability in GeoAI models to allow clearer insights into AI-driven decisions, improving human–robot collaboration and user trust.
4. Exploring mixed-experts GeoAI to refine the synergy between human expertise and AI processing capabilities, particularly in dynamic and high-stakes environments.

5. Personalizing GeoAI services to align with individual and community needs, enhancing user experience and the applicability of geospatial technologies.

By addressing these challenges and future directions, human-centered GeoAI has the potential to unlock new avenues for innovation, create safer and more reliable technologies, and redefine the role of AI in geospatial contexts. This interdisciplinary approach, balancing technological advancement with human values, will be pivotal in shaping the next generation of GeoAI applications and ensuring their positive impact on society.

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