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The generative revolution: a brief introduction

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Abstract

Generative AI is rapidly establishing itself as a key member of the GeoAI battery of methods, models and tools in use today in various health applications. This paper is the first in an Int J Health Geogr two-article series (2025) on the 'Generative Revolution'. It is meant to serve as a brief introduction to the second article entitled 'The Generative Revolution: AI Foundation Models in Geospatial Health—Applications, Challenges and Future Research'.

Keywords Generative AI, Large Language models, AI agents, Geospatial health, Health surveillance, AI-powered public health, Geospatial foundation models, Multimodal data and analysis

Introduction

During the 1970s, Harold Cohen (1928–2016), a British-born painter and professor at the University of California San Diego, was already creating and exhibiting generative AI (GenAI) works produced by AARON, a computer program he helped develop to generate paintings [1]. GenAI leverages vast datasets to generate new, synthetic data reflecting real-world patterns, potentially enabling researchers to perform more comprehensive analyses and make accurate predictions. The past two years (2023 and 2024) were considered the breakout years for GenAI [2]. Organizations regularly using GenAI surged from 33% in 2023 to 66% in 2024 [3]. GenAI is also rapidly establishing itself as a key member of the GeoAI [4] battery of methods, models and tools in use today. This short paper is the first in an *Int J Health Geogr* two-article series (2025) on the 'Generative Revolution' and is meant to serve as a brief introduction to the second article entitled 'The Generative Revolution: AI Foundation Models in Geospatial Health—Applications, Challenges and Future Research'.

Generative AI in health geomatics

GenAI has the potential of expanding the horizons of health geography and public health research by generating new and synthetic multimodal data (textual/numeric, including computer code, and audio-visual data) for various analysis, prediction, visualization and geomatics application development tasks. This ability is particularly valuable in health geomatics, where integrating geospatial and health data is essential for understanding the spatio-temporal dimensions of health and disease [5].

One of GenAI's promising applications in health geomatics is the generation of synthetic health data. Various factors, including privacy concerns, incomplete datasets, and geographical constraints, can limit access to, and utility of, traditional health data. GenAI can address these limitations by creating realistic synthetic data, preserving the statistical properties of the original data while mitigating privacy risks. These synthetic data can augment existing datasets, enabling researchers to conduct more robust analyses and develop more accurate models [6, 7]. GenAI can also enhance health data visualization, which is effective for understanding complex health phenomena and communicating findings to diverse audiences. GenAI

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can create dynamic, interactive visualizations and maps that allow researchers and policymakers to explore data in new and intuitive ways. For example, AI-generated heatmaps and spatial models can reveal patterns and trends that might be otherwise overlooked in traditional static maps.

Chat Generative Pre-trained Transformer (ChatGPT) is an advanced and popular series of GenAI models (large language models or LLMs). First launched by OpenAI in November 2022, ChatGPT was the first conversational GenAI model to capture the attention and imagination of the broader research community and the general public. Various versions of ChatGPT have since been examined and deployed by many researchers, including, for example, as a tool for environmental health research translation and summarization [8]. That latter use, however, is not without limitations related to hallucinations [9] and inaccuracies that require human oversight of the summarization process and all GenAI outputs (human-in-the-loop). OpenAI is not the only developer of LLMs. Many competing LLM series are available today from other providers, such as Anthropic, DeepSeek, Google, Meta, Microsoft, Mistral AI, xAI, etc.

Application scenarios in health and emergency management

LLMs are increasingly used to analyze and generate geospatial narratives, such as extracting insights from research papers, demographic surveys and historical health outcomes [10], and news and social media; identifying possible trends in urbanization [11], disease patterns [12] and crime distribution [13] from relevant textual data; and suggesting equitable health resource allocation strategies, again after ingesting relevant input data.

LLMs can potentially play a significant role in public health by gathering OSINT (Open-Source INTelligence) data to monitor disease outbreaks, health trends, vaccination rates, illegal or unethical health-related practices, and even public sentiment regarding particular health initiatives. Gathering OSINT information about environmental health involves collecting and analyzing public data related to air quality, water quality, climate change, pollution, and other environmental factors and phenomena affecting human health and ecosystem. The convergence of LLMs and geospatial foundation models (GFMs, models with a more specialist "understanding" of all things geospatial—in much the same way that medical/clinical LLMs and foundation models [9] are better optimised for their respective fields compared with general purpose LLMs) can further augment such applications by integrating real-time OSINT data with GFM-derived geospatial information about the natural and built environment.

By processing OSINT data, LLMs can automatically flag unnoticed health and environmental risks for further checking by human researchers and professionals. Such risk detection and monitoring applications can also benefit from integrating and triangulating various sensor data, satellite imagery and policy documents with LLM-derived OSINT data about affected populations, particular symptoms of interest (e.g., respiratory) reported on social networks, etc.; for example, to provide real-time pollution maps to inform and target appropriate municipal responses, such the implementation of traffic restrictions and industrial emission controls in affected places. Moreover, LLMs can be used to synthesize large datasets and regulatory guidelines to help with the correct formulation and implementation of actionable strategies, plans and responses, such as emission control measures or community-specific advisories to mitigate particular health risks. Sufi [14] examined how LLMs can be used to provide localized COVID-19 risk assessments and tailored public health guidance, such as targeted lockdowns and vaccination drives, demonstrating GenAI's potential in proactive pandemic response.

National emergency management services in many parts of the world, such as the US FEMA (Federal Emergency Management Agency) and the EU Copernicus EMS (Emergency Management Service), are already using AI-powered dashboards to provide better geospatial analyses of natural disaster risks, and help in assessing high-risk areas, guiding evacuation plans, and optimizing emergency resource allocation. Such dashboards could well benefit from GenAI tool integration, e.g., by offering their users timely, context-specific LLM-generated summaries of emergency protocols, etc.

Explainable GenAI

Explainable AI (XAI) emphasizes making AI models more interpretable and understandable. This can be useful for the academic and professional communities as well as the general public by making AI more approachable, trustworthy and actionable [15]. XAI has been applied, for example, to study heart disease [16] and to predict acute critical illness from electronic health records [17]. However, when it comes to GenAI, LLMs are essentially 'black boxes' in that even the experts who develop and train them do not know exactly how they work, make predictions, or what will be their next response to a given prompt. But some reasoning LLMs such as DeepSeek R1 output their 'chain of thought' alongside their answers, which may help users better understand how the answers were reached or (some of) the logic behind them [18].

Nevertheless, even though explainability remains a desirable feature, it is not always possible (due to inherent technology limitations) nor essential. McCradden and Stedman [19] examined the role of explainability in health AI tools, emphasizing that effective decisions should align with care objectives and be legally defensible. They argued that clinicians must consider factors beyond AI explainability and accuracy, such as ethical accountability and practical applicability. Through case examples, they demonstrated that ethical and legally sound decisions can still be safely achieved even in the absence of explainability.

Where feasible, the integration of GenAI and XAI (e.g., reasoning LLM 'chain of thought') into health geomatics could represent a significant leap forward, enabling researchers to better harness the power of AI to enhance their analyses and derive new insights.

Challenges and ethical considerations

The adoption of GenAI technologies is not without its challenges. Inequalities and inequities often accompany technological advancements, and GenAI is no exception. Furthermore, GenAI models are only as unbiased and reliable as the data on which they are trained. Biased or incomplete training data will likely generate inaccurate, even erroneous, models.

There are ongoing debates about these and other critical and ethical questions. While embracing the potential benefits, concerns regarding GenAI's transparency, stochasticity and hallucinations, verification, rules for accountability, security and counter-AI attacks, and other critical perspectives are raised [20, 21]. These issues are presented in more details in [5, 9].

Moreover, using synthetic data raises important ethical questions about privacy and consent. While synthetic data can help mitigate privacy risks, it is essential to ensure that the generation and use of these data comply with ethical standards and legal regulations. Researchers must be transparent about their methods to generate and validate synthetic data and ensure they are used responsibly.

Access to GenAI tools and technologies is often unevenly distributed, with resource-rich institutions and regions having greater access to these technologies than their less-resourced counterparts, and personal AI utilization varying by geography, industry, job title and age [3]. Such disparities can lead to a digital divide, where the benefits of AI are not equitably shared, and existing health disparities are widened. However, with the fast pace of technology and consumer hardware developments, it is now increasingly possible to run many large language models, including some with reasoning capabilities, completely offline on lower cost PCs and laptops [22, 23].

Future directions and opportunities

Despite these challenges, the future of GenAI in health geomatics holds immense promise, with numerous opportunities for innovation and impact. A key area of growth is the integration of GenAI with technologies like the Internet of Things (IoT). IoT devices, such as wearable health monitors and environmental sensors, generate vast amounts of real-time data that can be integrated with AI models to offer comprehensive, timely insights into health and disease patterns, as well as matching, actionable recommendations. Another exciting avenue is the use of GenAI in predictive modeling and simulation within sophisticated AI agentic systems designed to assist human researchers in their tasks (e.g., Google's AI co-scientist, a multi-agent AI system built with Gemini 2.0 [24]). For example, future GenAI-generated models could simulate the spread of infectious diseases under different conditions, allowing for more effective planning and intervention strategies.

Author contributions

MNKB conceived the manuscript's scope and direction, and invited PK and LM to contribute. PK, LM, and MNKB all made contributions of equal importance to the paper and participated in its literature review, writing and revision. All authors read and approved the final version of the manuscript. Disclaimer: Views and opinions expressed are those of the author(s) only. Reference in the manuscript to any specific commercial product, process or service by trade name, trademark, manufacturer or otherwise does not necessarily constitute or imply its endorsement, recommendation or favouring by the authors or the entities they are affiliated to, and shall not be used for commercial advertising or product endorsement purposes.

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Declarations

Ethics approval and consent to participate

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