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RESEARCH ARTICLE



Envisioning generative artificial intelligence in cartography: mapmaking, map use, and ethics

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ABSTRACT

Generative artificial intelligence (GenAI), including large language models, diffusion-based image generation models and GenAI agents, has opened up new possibilities for advancing cartography, spanning both mapmaking and map use. With its exceptional ability to encode extensive knowledge, adapt across contexts, create diverse artistic styles and integrate multimodal information, GenAI holds great potential to enhance cartographic design decisions. It enables efficient, personalized, and creative mapmaking (e.g., conceptualization, data preparation, map design, and map evaluation), and map use (e.g., map reading, interpretation, and analysis). In this paper, we explore why and how GenAI can contribute to cartography through four case studies, including stylesheet design, icon design, map reading, and map evaluation. Despite its unprecedented potential, we also identify its current limitations, particularly in tasks that require high precision, reliability, and a deep understanding of cartographic principles. Moreover, we emphasize the need to consider ethical and social implications, such as issues related to confabulation and hallucination, reproducibility, biases, copyrights, explainability, and sustainability. Overall, this work lays the foundation and provides a roadmap for future studies at the promising yet challenging intersection of GenAI and cartography.

RÉSUMÉ

L'intelligence artificielle générative (IA générative), qui comprend les grands modèles linguistiques, les modèles de génération d'images basés sur la diffusion et les agents IA Générative, a ouvert de nouvelles possibilités pour faire progresser la cartographie, tant au niveau de la création que de l'utilisation des cartes. Grâce à sa capacité exceptionnelle à encoder des connaissances approfondies, à s'adapter à différents contextes, à créer des styles artistiques diversifiés et à intégrer des informations multimodales, l'IA générative offre un grand potentiel pour améliorer les décisions en matière de conception cartographique. Elle permet une cartographie efficace, personnalisée et créative (par exemple la modélisation, la préparation des données, la conception et l'évaluation de cartes) et une utilisation efficace de cartes (par exemple, la lecture,

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l'interprétation et l'analyse de cartes). Dans cet article, nous explorons pourquoi et comment l'IA Générative peut contribuer à la cartographie à travers quatre études de cas, notamment la conception de feuilles de style, la conception de symboles, la lecture de cartes et l'évaluation de cartes. Malgré un potentiel sans précédent, nous identifions également des limites, en particulier dans les tâches qui exigent une grande précision, une fiabilité élevée et une compréhension approfondie des principes cartographiques. De plus, nous soulignons la nécessité de prendre en compte les implications éthiques et sociales, telles que les questions liées à la confabulation et à l'hallucination, à la reproductibilité, aux biais, aux droits d'auteur, à l'explicabilité et à la durabilité. Ce travail donne des bases et fournit une feuille de route pour de futures études à l'intersection prometteuse et encore ambitieuse entre l'IA générative et la cartographie.

1. Introduction

Maps have long shaped human understanding of space and place, and are recognized as one of the most important geographic ideas that have changed the world (Hanson, 1997). Cartography, the art and science of mapmaking, has a rich and profound history (Krygier, 1995). From aiding navigation to creating visually appealing and interactive maps, its evolution has always been intertwined with societal needs and technological progress (Bagrow, 2017). Today, the demand for efficient, personalized, and creative mapmaking is growing, and the emergence of generative artificial intelligence (GenAI) offers unprecedented opportunities to meet these evolving needs (Ai, 2022; A.L. Griffin & Robinson, 2025; Kang et al., 2024, 2025; Li et al., 2025; Y. Liu, 2025; Robinson et al., 2017; S. Wu et al., 2024).

GenAI, exemplified by models such as ChatGPT,¹ Gemini,² LLaMA,³ and DeepSeek,⁴ has attracted significant public attention in recent years. It represents a new class of advanced artificial intelligence (AI) methods capable of generating new content, including text, images, and audio, by learning patterns and representations from existing data (Sengar et al., 2024; Zhuang et al., 2024). As the field rapidly evolves, three main types of GenAI methods have emerged: large language models (LLMs) (W.X. Zhao et al., 2023), diffusion-based image generation models (Croitoru et al., 2023), and GenAI agents (Durante et al., 2024). These models demonstrate remarkable abilities to encode extensive knowledge, generalize across contexts, understand aesthetics, foster creativity, and integrate multimodal information. Collectively, these characteristics open up new possibilities across diverse domains, including cartography, GIScience, and geography.

As illustrated in [Figure 1](#), based on these technological breakthroughs and increasing societal demands, this paper explores several promising directions of GenAI for the next-generation cartography. Focusing on both mapmaking and map use, we examine the feasibility and potential of GenAI through four case studies: stylesheet design, map icon design, map reading, and map evaluation. These examples showcase the unprecedented potential of GenAI to enhance cartographic practice and expand the boundaries of traditional workflows. However, these algorithms are not without limitations and may fail under certain conditions. Recognizing this, we further reflect on key ethical

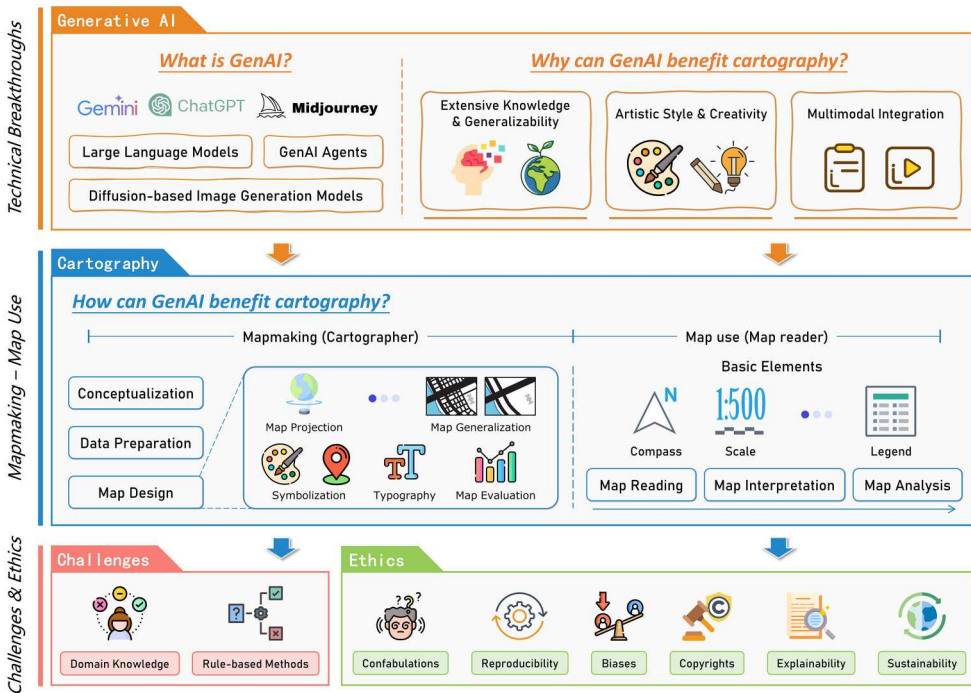


Figure 1. A conceptual framework of GenAI for cartography. This framework provides technical background of GenAI, highlights the potential roles of GenAI in both mapmaking and map use, and discusses challenges and ethical issues.

considerations and societal implications that are essential for fostering responsible and ethical practices in future cartographic production, as well as call for broader attention to this promising yet challenging area.

2. A historical view of cartography and technology

Cartography, the art and science of making maps, has a history spanning over a thousand years (Krygier, 1995). From prehistoric cave drawings such as those in the Abautz Cave, Spain (Utrilla et al., 2009), to modern printed and digital maps, people have long relied on visual representations to convey complex geographic information and facilitate spatial thinking (Maceachren, 1995). The evolution of cartography has always been intertwined with societal needs and technological advancements (Bagrow, 2017).

During the Age of Discovery, societal demands for exploration and trade led to a focus on creating accurate paper maps based on surveying and geodesy. These maps guided adventurers and merchants as they explored unfamiliar territories, while improved geodesy methods greatly enhanced the accuracy of these early maps.

With the advent of the printing press, societal demands shifted toward a wider dissemination of geographic knowledge. Cartographers emphasized map design and focused on both aesthetics and usability in printed maps to reach broader audiences (Perkins et al., 2011). Printing technology made large-scale map production possible and allowed geographic information to spread across social classes.

In the digital era, growing demands for efficient mapmaking and spatial analysis, such as land-use studies, drove significant advancements in cartography, particularly through the emergence of technologies like Geographic Information Systems (GIS). GIS revolutionized mapmaking by introducing computer-aided cartography (Jones, 2014), which significantly reduced the time and effort once required by manual techniques. It also enabled more effective analysis and visualization of spatial data and supported better decision-making in areas such as flood management (Brivio et al., 2002), crime analysis (Chainey & Ratcliffe, 2013), and environmental planning (Goodchild, 2003).

The development of interactive maps later emerged in response to growing societal needs for real-time, user-centered exploration of geographic data (Andrienko & Andrienko, 1999; Roth, 2013). Interactive and story maps allowed users to explore geovisualizations in real time, which improved engagement and understanding of geographic information (Maceachren, 1995). Advances in internet technologies, web development, and UI/UX design have facilitated these interactive experiences and provided a new level of accessibility and interactivity for end users.

Today, new societal demands for GenAI in cartography are driven by the need for more efficient, personalized, and creative mapmaking (Ai, 2022; A.L. Griffin & Robinson, 2025; Kang et al., 2024, 2025; Y. Liu, 2025; Robinson et al., 2017; Sun et al., 2025; S. Wu et al., 2024). From an efficiency perspective, GenAI could automate and accelerate the mapmaking workflow, reducing the time and technical expertise required to translate raw geospatial data into visual representations. Also, GenAI may assist cartographers in managing increasingly large and heterogeneous datasets while ensuring data quality across diverse data sources. In terms of personalization, users increasingly expect maps that can adapt to their specific purposes, whether for different geographic phenomena, education, or storytelling. GenAI can integrate diverse data sources, produce unique visual styles, and help automate or even personalize map creation to meet these demands (Robinson & Griffin, 2024). Creativity represents one of the most transformative dimensions of GenAI. Traditionally, creativity in mapmaking has been considered a uniquely human talent that combines artistic intuition, experiential learning, and design expertise cultivated through practice. GenAI may spark new ideas, inspire mapmaking paradigms, and foster novel aesthetic directions in cartographic design, which could extend and augment human creativity. Furthermore, there is a growing demand for greater interactivity and user-centered design in cartography, where users can generate their own maps or modify existing ones to express their ideas. By augmenting human imagination with generative capacities, GenAI fosters a collaborative creative process between humans and machines, which may redefine how cartographic ideas are conceived and shared (Kang, 2025). Given these new opportunities, the following sections discuss several potential directions for cartography in the era of GenAI.

3. What is GenAI?

GenAI refers to an advanced set of AI models and techniques designed to learn the underlying patterns and structures of data to generate new content, such as text, images, audio, video, or other modalities (Epstein et al., 2023; Sengar et al., 2024; Zhuang et al., 2024). Unlike traditional discriminative models that primarily focus on classifying or labeling

existing data, GenAI emphasizes the creation of (entirely) new outputs based on learned representations of the input data.

The field of GenAI has witnessed significant breakthroughs over the years. In 2014, innovations such as variational autoencoders (VAEs) (Kingma, 2013) and generative adversarial networks (GANs) (Goodfellow et al., 2014) revolutionized image generation and motivated cartographers to experiment with map style transfer (Christophe et al., 2022; Kang et al., 2019). By the early 2020s, further advancements, including diffusion models and transformer-based deep neural networks, made it possible to produce high-quality paintings and textual content (Croitoru et al., 2023; Vaswani, 2017). Cartographers also began adopting these approaches for map generalization (Feng, Qian, et al., 2023; Y. Wang & Feng, 2024; Zhou et al., 2024). More recently, the advent of GenAI agents and the emergence of applications such as MapGPT (Y. Zhang et al., 2024), CartoAgent (C. Wang, Kang, et al., 2025), and GIS copilot (Akinboyewa et al., 2025), have offered new opportunities and potential to empower cartographic automation and creativity. Today, GenAI is attracting increasing attention and continues to evolve rapidly. Here, we provide a technical overview and identify and categorize three types of GenAI models that hold particular promise for advancing cartographic theory and practices.

3.1. LLMs and their variants

These models, exemplified by OpenAI's GPT series, Google's Gemini, Meta's LLaMA, and DeepSeek, are designed to capture complex language patterns from large corpora and can handle a wide range of language understanding and generation tasks, such as translation, summarization, question answering, and code completion (W.X. Zhao et al., 2023). While they were initially developed for text-based applications, their capabilities have now expanded beyond a single modality. Variants such as Large Multimodal Models (LMMs) further extend these abilities to integrate and process multiple modalities (Yin et al., 2024). For example, OpenAI's GPT-5 can process both textual and visual inputs, which allows it to generate image captions and answer visual questions. This multimodal capacity broadens their real-world applications. Cartographers have also begun to explore how LLMs and their variants can be used to create maps (Akinboyewa et al., 2025; Li et al., 2025; Ning et al., 2025; Tao & Xu, 2023; C. Wang, Kang, et al., 2025; Xing et al., 2025; Yang et al., 2025) and extract textual information from image-based maps (Feng, Ding, et al., 2023; Xu & Tao, 2024; Y. Zhang et al., 2025).

3.2. Diffusion-based image generation models

These models are designed to generate high-quality images from various inputs (e.g. text descriptions or sketches). They are based on the physical concept of diffusion and achieve their goal by progressively adding noise to an image over time and then learning to reverse this noising process (Croitoru et al., 2023). Representative models such as DALL-E,⁵ Stable Diffusion,⁶ Imagen,⁷ and Midjourney⁸ have demonstrated state-of-the-art performance in text-to-image generation. These models allow us to turn vivid imagination into reality and open up new possibilities in creative design, visualization, and content creation (Kang, 2025). Cartographers, in particular, have begun exploring diffusion-based generative AI techniques to produce diverse map styles (Y. Chen et al.,

2025; Kang et al., 2023) and generate raster-based map imagery (Affolter et al., 2025; Burghardt, 2025; Courtial et al., 2023; Dunkel et al., 2024).

3.3. GenAI agents

An agent is an autonomous entity that can perceive its environment, reason based on available information, make decisions, and take actions to achieve specific goals (Durante et al., 2024). Agent-based modeling has long been applied to support cartographic design decisions. For example, cartographers have developed agent-based mapping systems to automate tasks such as map generalization (e.g. the European AGENT project) (Barrault et al., 2001; Duchêne, 2003; Duchêne et al., 2018) and label placement (Kim & Xiao, 2012). More recently, researchers have explored the potential of treating deep learning-based algorithms as agents for map generalization (Touya et al., 2019). In the GenAI era, a new generation of agents powered by LLMs and their variants has emerged and has opened new opportunities. Cartographers have begun to build agents that can assist in the mapmaking process and support design decisions (Li & Ning, 2023; Li et al., 2025; Muehlenhaus, 2025; C. Wang, Kang, et al., 2025; Y. Zhang et al., 2024). These agents interact and communicate through unified, language-based exchanges, with solutions emerging from their multi-turn dialogues. A notable example is CartoAgent, which follows the principle of ‘Data-Style Separation’ to generate maps that are both visually appealing and geographically accurate (C. Wang, Kang, et al., 2025).

As GenAI continues to advance, new subtypes beyond these three primary categories are likely to emerge. Each category of GenAI methods has distinct characteristics and may be suited to different cartographic tasks. In the future, the convergence of these models may give rise to hybrid GenAI frameworks that integrate multiple modalities and methodological approaches, which will further advance both the theoretical foundations and practical applications of cartography.

4. Why can GenAI benefit cartography?

There is no doubt that GenAI brings new possibilities to cartography. Before we explore specific cases, this section outlines several characteristics of GenAI that distinguish it from traditional statistical or earlier AI models, to clarify its advantages and to show how it may support different cartographic design decisions (Figure 2).

4.1. Extensive knowledge & generalizability

GenAI, through pre-training, encodes large bodies of knowledge about real-world facts, concepts, events, and the relationships among entities. It can link map elements to their real-world semantics which allows cartographic design choices that are both contextually appropriate and logically coherent. Moreover, unlike earlier task-specific methods (Feng et al., 2019; C. Wang et al., 2024), GenAI can handle multiple tasks and support several design decisions simultaneously. Traditionally, reading geographic data, designing visual variables, and critiquing map design have been treated as separate stages, each with its own tools and workflows; GenAI has the potential to integrate them into

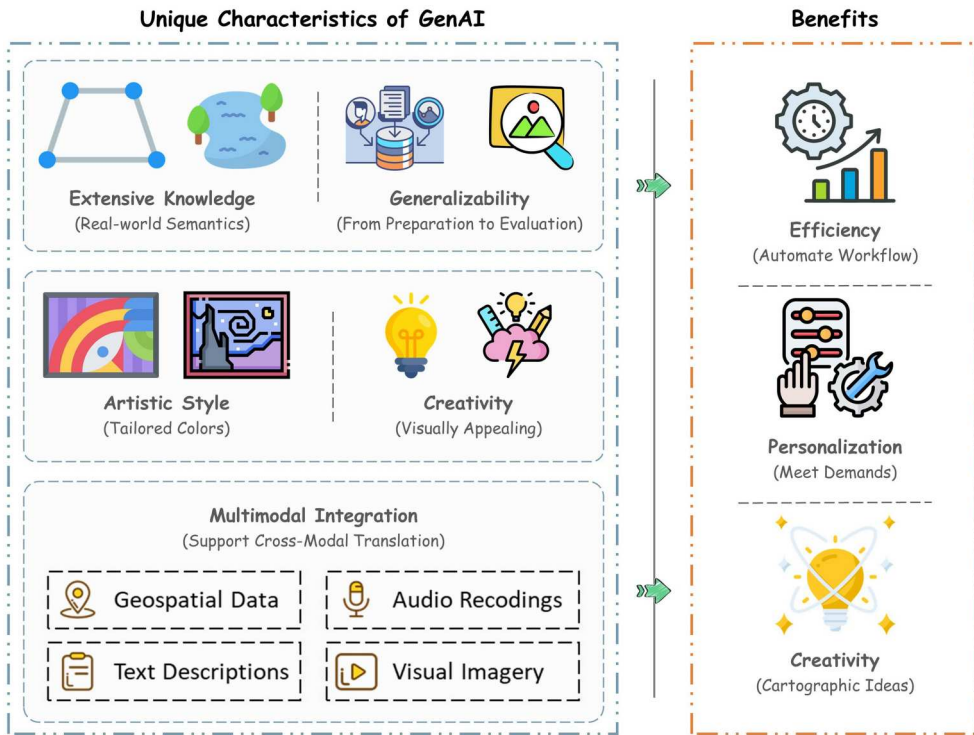


Figure 2. Unique characteristics of GenAI and its benefits for cartography. GenAI can encode extensive knowledge, adapt across contexts, create diverse artistic styles, and integrate multimodal information. These abilities make mapmaking and map use more efficient, personalized, and creative.

a single pipeline and improve efficiency (C. Wang, Kang, et al., 2025). Despite this promise, cartography-specific knowledge remains underrepresented in current GenAI models. This limitation arises from two primary challenges. On the one hand, experiential and design-based expertise in cartography is hard to encode in AI systems; on the other hand, domain-specific training datasets that capture cartographic principles, aesthetics, and professional practice are scarce.

4.2. Artistic style & creativity

Traditional cartographic methods often follow pre-defined styles and established conventions, which limit their ability to adapt to diverse user needs. By contrast, GenAI provides the flexibility to tailor map styles and colors to specific purposes and audiences, such as scientific visualization, public engagement, and storytelling, and thereby supports personalized designs (Kang et al., 2025; Yang et al., 2025). For example, a GenAI system can evoke the aesthetic of a specific historical period by reproducing the visual styles of that era. Additionally, it may empower the general public to produce visually appealing maps, even if the users have limited cartographic design expertise. Thus, GenAI could democratize access to high-quality mapmaking tools. This focus on creativity enhances interactivity, fosters user-centered design, and promotes greater user engagement.

4.3. Multimodal integration

Unlike traditional methods that often handle a single input or output modality, GenAI can seamlessly integrate and process multiple data forms, such as satellite imagery (Q. Wang et al., 2025), geospatial data (Hou et al., 2025), textual descriptions (Mai et al., 2024), and even audio (J. Wang et al., 2025). This multimodal capability is especially valuable in cartography, where representing or interpreting geographic phenomena is challenging and often requires frequent cross-modal translation. For example, LLMs and diffusion models can convert textual prompts into cartographic images to support automated map generation and stylesheet design (Affolter et al., 2025; Burghardt, 2025; Courtial et al., 2023; Dunkel et al., 2024). In addition, LMMs can interpret visual map content and produce textual explanations that aid in map reading, interpretation, analysis, and critique (Feng, Ding, et al., 2023; Xu & Tao, 2024; Y. Zhang et al., 2025). Although different GenAI architectures excel at different tasks, integrating multiple agents with complementary strengths further expands this potential (C. Wang, Kang, et al., 2025). Moreover, the multimodal nature of GenAI can enhance accessibility and inclusivity, as it can help blind or visually impaired individuals access and understand maps by converting visual geographic information into auditory descriptions (Manu et al., 2025; Robinson & Griffin, 2024).

Together, these three characteristics of GenAI, including extensive knowledge and generalizability, artistic style and creativity, and multimodal integration, help advance the goals of efficient, personalized, and creative mapmaking. A new form of human-AI collaborative practice is emerging and may reshape the cartographic design practice.

5. How can GenAI benefit cartography?

In this section, we first review several key components of cartography to provide a theoretical framework (Section 5.1). Then, recognizing that GenAI holds the potential to automate mapmaking processes, meet personalized user needs, and enhance user engagement, we introduce a series of applications and emerging subfields in Section 5.2 to illustrate how cartography can benefit from the integration of GenAI.

5.1. Theoretical components of cartography

Cartographic practice, through the use of cartographic language such as symbols and labels, aims to effectively and accurately communicate geographic information between cartographers and map readers (A. Griffin, 2021; MacEachren, 2004). Based on the *Cartography and Visualization* section of the GIS&T Body of Knowledge (UCGIS, 2024), we divide this process into two components: **mapmaking** and **map use** (Figure 1).

Mapmaking refers to the steps by cartographers to design and produce maps, involving a series of interconnected cartographic design decisions. It typically begins with *conceptualization*, during which cartographers define the map's purpose, identify the target audience, and determine the geographic phenomena to be represented. Traditionally, this relies on the cartographer's knowledge, experience, and creativity to translate cartographic ideas into a design concept. GenAI may enhance this process by facilitating brainstorming, style exploration, and task reasoning, which help generate initial map concepts or suggest alternative design ideas.

Following conceptualization, *data preparation* involves collecting and processing geographic features and their associated attributes. Recent advancements in geo-foundation models and specialized AI agents have enabled the automation of data cleaning and feature extraction, supporting cartographers in efficiently preparing and managing geographic data (Li et al., 2025; Y. Zhang et al., 2024).

The next stage refers to map design where cartographers design maps through a set of cartographic design decisions to represent and convey geographic information effectively. Key dimensions involve map projection, generalization, symbolization, typography, and evaluation, etc. Specifically, *map projection* involves selecting an appropriate projection that preserves certain properties (e.g. shape, area, distance, or direction) based on the map's purpose and audience (Battersby, 2017). *Map generalization* simplifies geographic information to ensure that essential elements remain clear and legible at the given scale (Feng, 2023; Raposo, 2017). Recent studies have also begun exploring how GenAI can understand map projections (Xing et al., 2025), and support map generalization (Wei et al., n.d.; S. Wu et al., 2024).

Symbolization translates real-world features into abstract graphic forms using visual variables such as shape, size, color, orientation, and texture (White, 2017). It plays a key role in the artistic aspect of maps, as effective symbolization determines how users perceive spatial patterns of geographic phenomena. Traditional symbol design relies on cartographers' experience and aesthetic judgment to ensure informativeness, balance, and consistency. With GenAI, this process might be augmented through automated style generation and context-aware recommendations (C. Wang, Kang, et al., 2025).

Typography focuses on the design, placement, and styling of textual elements on the map (Guidero, 2017), while *map evaluation* is an iterative process that assesses the clarity, accuracy, usability, and visual quality of the final product (Buttenfield, 1993; T. Chen et al., 2021; Kronenfeld et al., 2023; C. Wang et al., 2024). GenAI may assist in this process by learning optimal label placement strategies and produce more contextually-aware map typography.

Map evaluation, and often map critique, represents the final and often iterative stage of mapmaking. It aims to assess a map's clarity, accuracy, usability, and visual quality (Buttenfield, 1993; T. Chen et al., 2021; Kronenfeld et al., 2023; C. Wang et al., 2024). Traditional evaluation methods include expert review and user studies that examine perceptual accuracy and cognitive load when seeing maps. GenAI may offer new opportunities for automated map assessment, such as using vision-language models to compare generated maps with design standards, detect visual inconsistencies, or simulate user interpretations (C. Wang, Kang, et al., 2025).

Map use, on the other hand, centers on the perceptual and cognitive activities of map readers, which typically include map reading, interpretation, and analysis. Through *map reading*, users recognize symbols and labels and understand the geographic information they represent (Buckley & Kimerling, 2021). *Map interpretation* involves examining not only individual map elements but also their relationships and emergent spatial patterns (Kimerling et al., 2016). Finally, *map analysis* requires reasoning and critical thinking about these observed patterns to derive meaningful insights, based on a high level of cognitive ability and prior knowledge (Kang et al., 2024; Roth, 2024). With its ability to encode extensive world knowledge, understand visual semantics, and reason across multimodal inputs, GenAI introduces new opportunities for map use. Cartographers have tested

whether GenAI can now ‘read’ maps by interpreting symbology, extracting textual or geographic information, and explaining map content in natural language (A.L. Griffin & Robinson, 2025; Tao & Xu, 2023; Xu & Tao, 2024). Such capabilities may assist users in understanding complex geographic representations, identifying geographic patterns through visual analytics (Roth, 2024), and translating visual information into audio descriptions to enhance accessibility for visually impaired users (Robinson & Griffin, 2024).

Collectively, GenAI offers new possibilities to complement and support both mapmaking and map use. In the following subsections, we provide four examples to showcase how GenAI could support a variety of cartographic design decisions.

5.2. Symbolization – stylesheet design

A map style is a collection of distinct yet cohesive features in cartographic design, shaped by aesthetic, symbolic, and compositional choices (Christophe, 2009, 2012; Kent, 2017; Ory et al., 2015). Cartographers have long defined map styles through the use of symbols, colors, patterns, and other graphic elements in a stylesheet to guide how geographic information is visually represented, communicated, and emotionally perceived (Ory et al., 2013). Map style is thus a central component of artistic design in cartography, i.e. determining whether a map is visually appealing. Historically, the creation of map styles has depended heavily on the creativity, expertise, and aesthetic sensibilities of cartographers. In recent years, researchers have explored the use of GANs for map style transfer, enabling the automatic translation of stylistic characteristics from one map to another (Christophe et al., 2022; Kang et al., 2019; M. Wu et al., 2022). GenAI introduces new possibilities to design novel stylesheets that symbolize map elements in ways that are not only semantically aligned with the real world but also visually appealing.

To illustrate this potential, we present an example following the CartoAgent (C. Wang, Kang, et al., 2025). As illustrated in Figure 3, GPT-4o was first prompted to appreciate a painting to analyze its aesthetic features such as color palette, composition, and texture. Based on the extracted color schemes and stylistic attributes, GPT-4o was then instructed to act as a stylesheet designer, refining the style of an existing map according to the identified artistic characteristics. The resulting map is presented in Figure 3. Here, we list two takeaways. First, GenAI, in this case GPT-4o, was able to accurately identify the content, color palette, theme, and design of the painting. Second, its map symbolization was reasonable and contextually appropriate: on the one hand, it maintained consistency with the color scheme of the original artwork; on the other hand, it accounted for the real-world connotations of map elements. For example, GPT-4o used different colors for roads of different hierarchies to provide visual differentiation. These findings suggest that GenAI has the potential to produce maps that are not only aesthetically appealing but also effective in communicating geographic information, ultimately enhancing the artistic aspects of cartography.

5.3. Symbolization – map icon design

Map icons are clear, easily recognizable markers that represent geographic places and make them easier to locate (Tyner, 2014; Wood & Fels, 1986). Traditionally, creating

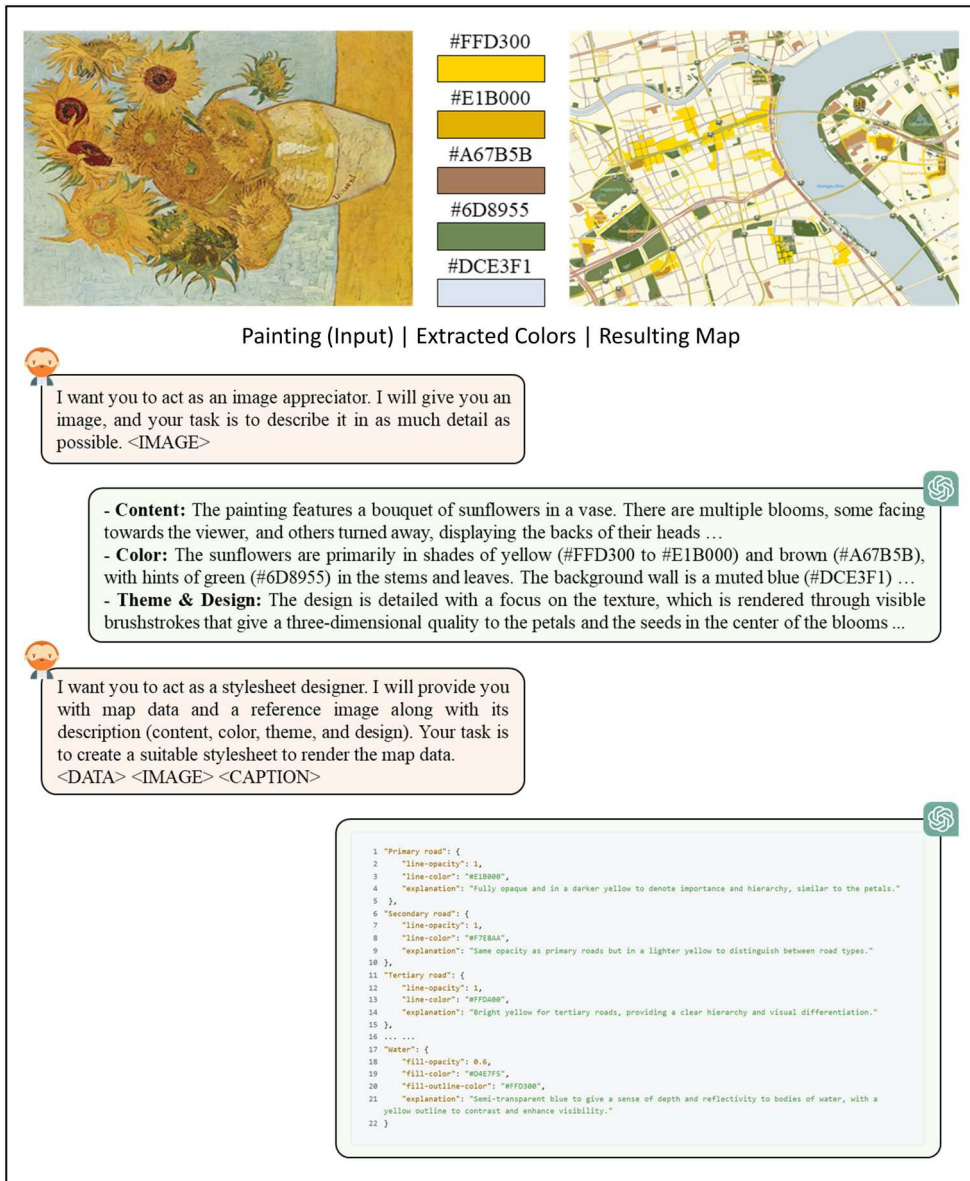


Figure 3. A potential application of GenAI in stylesheet design: GPT-4o was first prompted to appreciate a painting and then refined the style of an existing map accordingly.

well-designed icons that closely resemble their referents has been time-consuming. GenAI, however, can help customize and efficiently generate icons tailored to specific needs. As shown in Figure 4, tools like DALL-E quickly produce sets of pictorial symbols for subway stations, bus stops, mountain-biking trails, and traffic lights. These icons not only convey the semantics of their referents and enhance interpretability, but also maintain a minimalist aesthetic suitable for cartographic display.

Help me generate a pictorial sign for ____.



A subway station



A bus stop



A mountain biking trail



A traffic light

Figure 4. A potential application of GenAI in map icon design: DALL-E was used to quickly produce sets of pictorial symbols for subway stations, bus stops, mountain-biking trails, and traffic lights.

5.4. Map reading

GenAI has already demonstrated its ability to interpret natural, remote sensing, and medical images (Gong et al., 2025; Jang et al., 2024; F. Liu et al., 2025), but can it also understand maps (in a human-like way) (A.L. Griffin & Robinson, 2025; Xing et al., 2025; Xu & Tao, 2024)? Some researchers prompted GPT-4o to write a description discussing the patterns shown in a population density map and found that the model produced insightful results (A.L. Griffin & Robinson, 2025). To further explore this potential, we examined two additional types of thematic maps: choropleth maps and flow maps. These maps are frequently seen online and are widely used to visualize natural and social phenomena, such as the results of the U.S. presidential election.⁹

As illustrated in Figures 5 and 6, GPT-4o correctly identified the type of each map, described the spatial patterns based on their legends and annotations, and drew meaningful conclusions. For example, in Figure 5, it accurately recognized that Trump had secured more than the required 270 electoral votes and would win the 2024 presidential election. It also noted that several key states had shifted their support compared with the 2020 election and regarded this shift as a decisive factor behind the victory.

Integrating GenAI into map reading can bring multiple benefits. For cartographers, map design is often unconsciously shaped by prior knowledge, personal experience, and cultural background, which may lead to cartographic decisions that unintentionally bias readers. GenAI-based map reading can help identify such biases in advance and ensure that spatial and thematic information is communicated more clearly and objectively. For the general public, GenAI not only enhances user engagement through interactive question-answering and multimodal integration but also contributes to more effective cartographic education (A.L. Griffin & Robinson, 2025; Xing et al., 2025). Geological maps, for example, often use many colors and patterns to represent rock types, ages, and geological structures and are often information-dense and difficult to interpret. GenAI, based on its visual perception and associated geological knowledge, can generate natural-language explanations that clarify complex concepts and help learners better understand these maps (Huang et al., 2025). Finally, for blind or visually impaired individuals who have long faced challenges in map reading, GenAI can translate visually represented geographic information into alternative modalities such as audio descriptions,

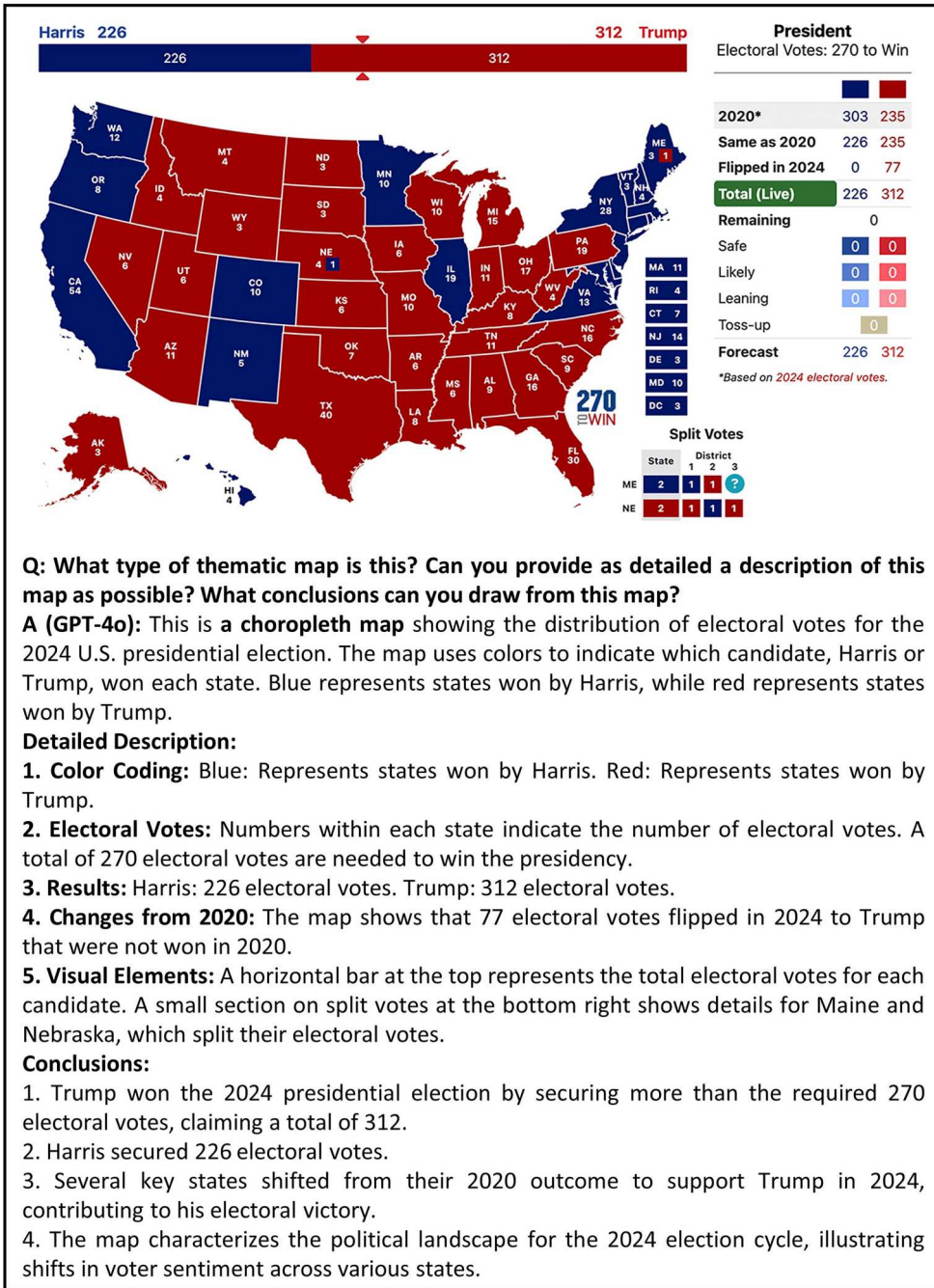


Figure 5. A potential application of GenAI in reading choropleth maps: GPT-4o was prompted to identify the type of a thematic map about the U.S. election, provide a detailed description, and draw meaningful conclusions.

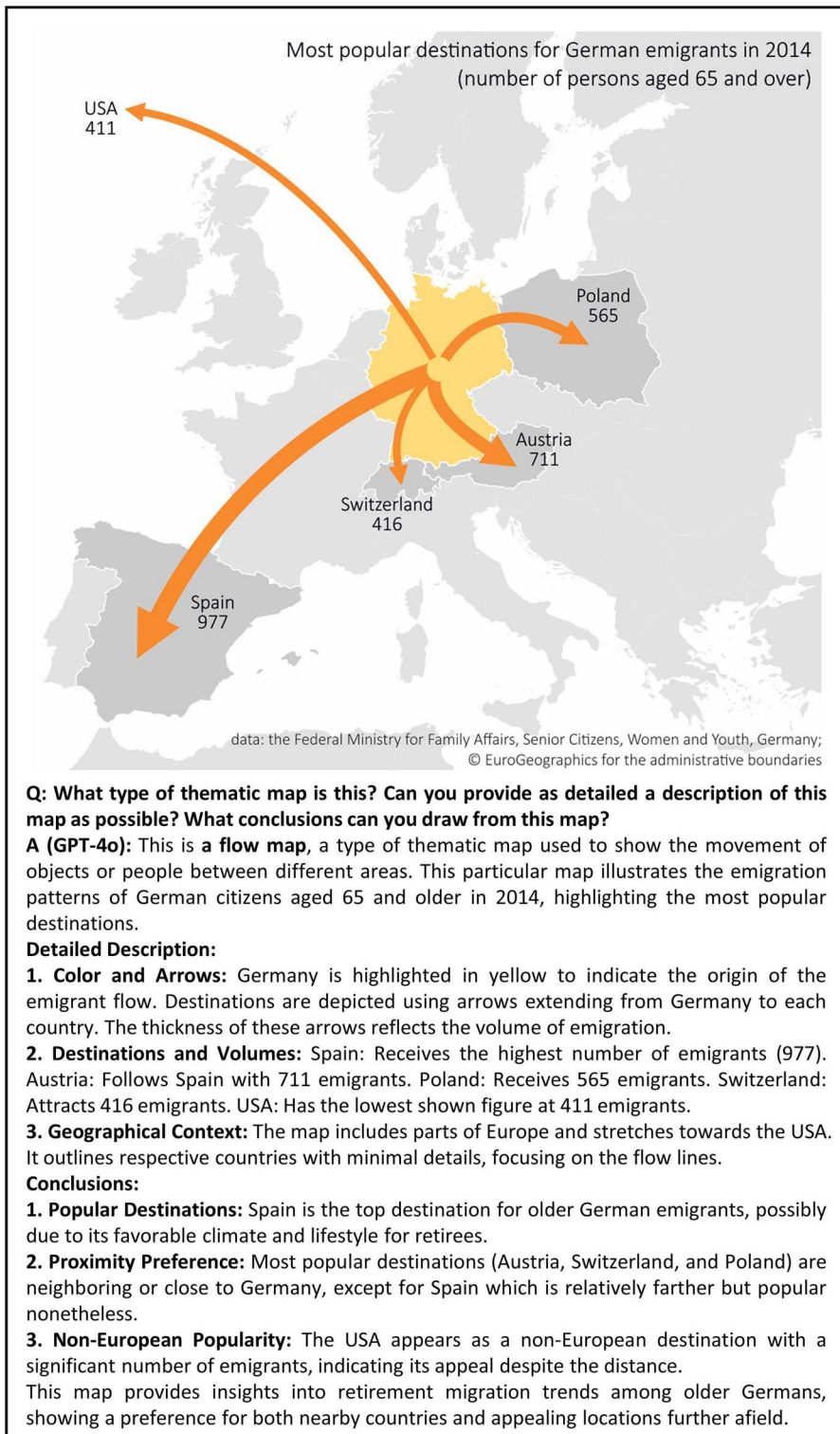


Figure 6. A potential application of GenAI in reading flow maps: GPT-4o was prompted to identify the type of a thematic map depicting the emigration patterns of German citizens, provide a detailed description, and draw meaningful conclusions.

which allows them to access and comprehend maps more effectively (Manu et al., 2025; Robinson & Griffin, 2024).

5.5. Map evaluation

Map evaluation, often map critiques, refers to the systematic assessment of map quality before it is finalized or published (Dodge et al., 2009). Through critiques of aesthetic design and suggestions to improve the clarity and accuracy of maps, this process ensures that maps are not only visually appealing but also effectively communicate their intended messages. With its ability to encode extensive knowledge, handle artistic styles, and integrate multimodal information, GenAI has the potential to support and partially automate the review of large numbers of maps, and to assist users, particularly non-experts, in producing high-quality cartographic outputs (C. Wang, Kang, et al., 2025).

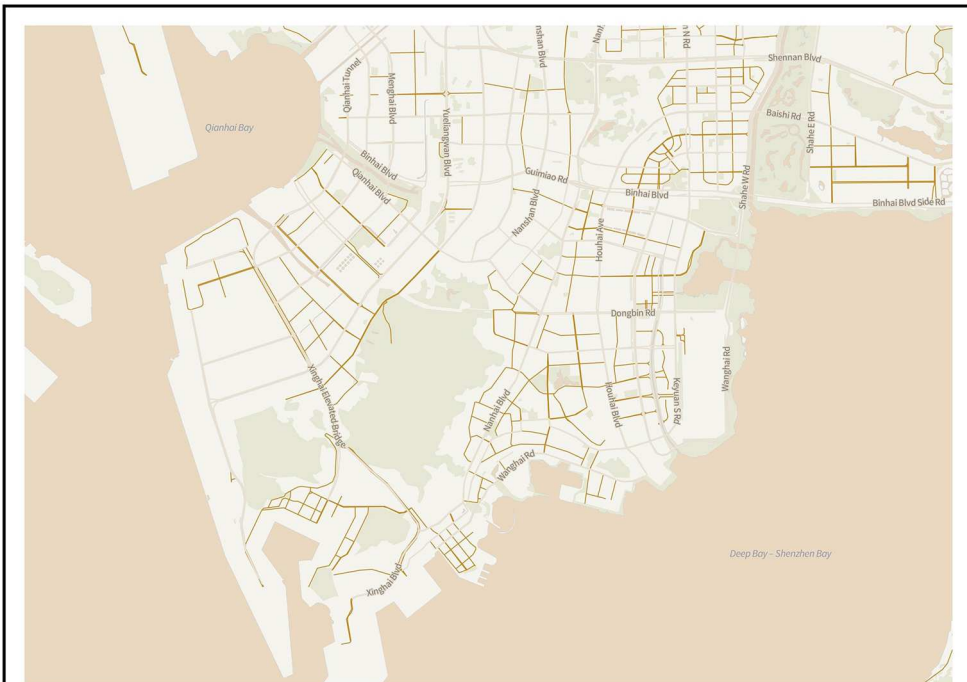
As illustrated in Figure 7, we asked GPT-4o to judge whether a given map omitted essential elements, contained design flaws, and effectively conveyed spatial information. The results demonstrated that GPT-4o was able to accurately identify missing map elements (e.g. scale, legend, compass) and detect design flaws. For example, it recognized that the color scheme was counterintuitive and noted that this violated established cartographic conventions, where cool colors are generally preferred for representing water. Similarly, it observed problems in visual hierarchy and pointed out that minor roads appeared more prominent than major ones, which could compromise navigability. In addition, GPT-4o provided constructive feedback on map typography (e.g. through strategic label placement and size adjustments to enhance readability).

Map Doctor provides another early exploration.¹⁰ Based on prompts and retrievable resources containing cartography-specific knowledge and expertise from world-renowned practitioners, Map Doctor may offer feedback on cartographic products to assist in improving and critiquing map designs. However, this remains an early exploration. It is highly challenging to comprehensively encode cartographic knowledge GenAI systems.

Because of its extensive world knowledge and multimodal reasoning capabilities, GenAI holds great promise for assisting in the evaluation of maps. However, two major challenges remain before GenAI can serve as a reliable evaluator to support map critique process. First, cartographic knowledge and principles have not been sufficiently encoded or represented in GenAI models. These cartographic principles are necessary to guide GenAI to produce valuable evaluations that align with cartographic practices. Second, cartographic design inherently involves subjectivity, as different individuals may perceive and interpret maps in diverse ways. This makes it challenging to formalize and encode cartographic experiences and principles within computational systems. Thus, despite early explorations, GenAI is still far from being trusted to support map critiques.

6. When does GenAI fall short in benefiting cartography?

While GenAI brings substantial benefits to cartography, several limitations remain. First, GenAI models are prone to confabulation and hallucination, which makes it difficult to accurately represent and communicate geographic information (See Section 7.1). Therefore, cartographic tasks that require precise geographic presentation are not suitable for



Q: Does this map lack essential elements? Are there any design flaws in this map? Can it effectively convey spatial information?

A (GPT-4o): This map has a few elements that could be improved to effectively convey spatial information:

1. Missing Elements:

- **Scale:** There's no scale bar, making it hard to understand distances.
- **Legend:** Without a legend, it's unclear what different colors or line types represent.
- **Compass:** No compass rose is present, which would help in orienting the map.

2. Design Flaws:

- **Color Choices:** The color for water bodies is warm, which might be counterintuitive as cool colors are typically used for water.
- **Visual Hierarchy:** Major roads should be more prominent than minor roads for better navigation.
- **Labels:** Labels are present for some roads, but they can be more strategically placed or sized for easier reading.

3. Effectiveness:

- **Spatial Information:** The map shows roads and geographical features, but without a scale, legend, and compass, it might not effectively convey spatial relationships or assist in navigation.

Improving these design elements and including missing components would significantly enhance the map's utility.

Figure 7. A potential application of GenAI in map evaluation: GPT-4o was prompted to judge whether a given map omitted any essential elements, contained design flaws, or effectively conveyed spatial information.

GenAI. When the goal is to produce consistent and reproducible cartographic outputs, GenAI might not be applied or should be applied with great caution. On the contrary, cartographic design decisions that prioritize creativity or diverse visual outcomes are more appropriate for GenAI.

Second, the current GenAI models often lack the cartographic domain-specific knowledge and intuitive expertise that professional cartographers possess (Fu, Zhou, Xin, et al., 2024). This limitation may stem from the inherent subjectivity of cartographic creativity and the difficulty of systematically capturing and encoding cartographic knowledge into training datasets. For example, GenAI may struggle to understand fundamental cartographic theories, such as those related to geospatial information visualization, including the cartographic cube (MacEachren, 1994), or information-theoretic models of map communication (Li, 2020). Similarly, while some GenAI agents can already produce thematic maps through dozens of tool calls, the resulting maps do not yet reach the quality achieved by experienced cartographers, particularly in terms of the aesthetic dimension of maps (Akinboyewa et al., 2025; Tao & Xu, 2023; Y. Zhang et al., 2024). These limitations highlight that integrating GenAI into cartography and using it to support cartographic design decisions is a non-trivial challenge. Unfortunately, much of the existing literature in the broader AI and Geospatial AI (GeoAI) communities continues to focus on automating the mapmaking process. Other important cartographic dimensions, such as the construction of cartographic knowledge, artistic expression, and social implications of cartography, remain comparatively underexplored, and deserve broader attention (Mai et al., 2025; Robinson et al., 2023).

At the same time, traditional cartographic approaches, such as rule-based methods, remain valuable. These approaches adhere to well-established principles rooted in cartographic theory. They can generate maps that meet strict legal, technical, and aesthetic requirements without unintended variations, while offering transparency and traceability that enable users and stakeholders to clearly understand the rationale behind each design decision. By adhering to these existing frameworks, traditional cartographic approaches excel at producing maps that precisely and accurately represent geographic information while maintaining consistency and reliability. Therefore, a hybrid approach that combines traditional cartographic practice with GenAI is highly valuable. For example, CartoAgent innovatively integrates the long-standing cartographic principle of 'Data-Style Separation' with LMMs and demonstrates a promising approach to generating maps that are both accurate and visually appealing. It enhances the artistic aspects of map design by leveraging the strengths of GenAI while preserving spatial accuracy (C. Wang, Kang, et al., 2025).

7. Ethics in GenAI for cartography

While GenAI offers unprecedented potential for cartography, its ethical and societal implications must be carefully accounted for to ensure responsible practices throughout both mapmaking and map use. In the following discussion, we highlight several key issues that require particular attention as GenAI becomes more widely integrated into cartographic workflows, including inaccuracies due to confabulation and hallucination, challenges in reproducibility, potential biases, copyright concerns, the need for explainability, and

questions of sustainability (Buckley, 2023; Buckley & Case, 2025; Kang et al., 2023; Lin & Zhao, 2024; B. Zhao et al., 2021).

7.1. Inaccuracies due to confabulation and hallucination

GenAI models sometimes produce outputs that appear fluent and plausible yet are fabricated, unsupported, or factually inaccurate, a phenomenon commonly referred to as *confabulation* (Farquhar et al., 2024). Closely related to confabulation is *hallucination*, which refers to the generation of content that does not exist in the model's input data or contradicts known facts (Ji et al., 2023). For example, when prompted to create a cartographic product, GenAI may invent non-existent rivers or mountains, generate fictitious place names or labels, or produce maps that distort scale, distance, or the relative positioning of geographic features. Such confabulations and hallucinations pose significant challenges to maintaining trust in the accuracy and reliability of geographic representations, and may lead to real-world harm (Gartner, 2025; Karsznia, 2025). For instance, navigators might plan unsafe or impractical routes through inaccessible areas based on fabricated features. To address this issue, two approaches may be considered. First, researchers can incorporate tool-calling functions from traditional cartographic systems to enforce spatial constraints and ensure data accuracy and reliability (Fu, Zhou, Feng, et al., 2024). Second, it is necessary to develop human-in-the-loop GenAI workflows. Involving more human experts in model development, validation, and continuous monitoring can enhance the accuracy and trustworthiness of AI-generated maps (Kang et al., 2024).

7.2. Reproducibility

Reproducibility, in disciplines such as GIS and computer science, refers to the ability to obtain consistent results when identical methods are applied to the same data under the same conditions (Wilson et al., 2021). This raises an important question: should reproducibility be emphasized when integrating GenAI into cartography?

On the one hand, reproducibility is essential. For example, when a GenAI-based disaster risk map is used for urban planning or emergency decision-making, it must be verifiable and replicable; otherwise, it cannot be trusted or referenced. On the other hand, GenAI is inherently generative rather than deterministic. Even with identical inputs, it may produce slightly different outputs due to factors such as sampling temperature. However, this non-determinism can foster greater creativity and innovation in cartography and allow practitioners to explore more unconventional designs. Therefore, more interdisciplinary discussions involving cartographers, AI researchers, and researchers in ethics are needed to assess how reproducibility should be defined, balanced, and pursued in the context of GenAI for cartography.

7.3. Biases

Unlike confabulation and hallucination, which produce fabricated content without any basis in real data, bias in GenAI refers to the systematic deviation of outputs caused by skewed training data, model design, or human influence during training or prompting

(Gallegos et al., 2024; C. Wang, Tang, et al., 2025). Most GenAI models are trained and optimized to capture dominant patterns within datasets; as a result, they tend to overrepresent majority trends while underrepresenting rare or minority patterns. Such imbalances can have significant negative consequences. They may not only disadvantage certain regions or social groups but also suppress creativity and diversity in cartographic design (Lin & Zhao, 2024).

For example, a GenAI model trained primarily on Western map styles may consistently center Europe and North America, label places only in English, and produce incomplete or inaccurate representations of data-scarce regions such as those in Africa. Moreover, maps are not neutral representations of geographic space; rather, they often reflect and reinforce the values, priorities, and intentions of their creators. GenAI systems, which heavily rely on data provided by major technology companies or government entities, and developed countries, frequently reflect and even amplify these dominant perspectives (Lin & Zhao, 2024). Consequently, their outputs often align with particular worldviews, which makes it crucial to democratize GenAI so that it represents the perspectives of local and marginalized communities.

Potential solutions include incorporating data from diverse and underrepresented regions or groups, adopting fairness-aware algorithms that reweight underrepresented data or penalize biased outcomes, and implementing human-in-the-loop AI for cartography. Additionally, fostering community involvement and collaboration with experts in ethics, sociology, and related disciplines to develop participatory cartography with GenAI could enhance the development of more inclusive and equitable GenAI systems for cartography.

7.4. Copyrights

In GenAI, copyright refers to the legal protection of both the materials used to train models and the outputs those models generate (D. Zhang et al., 2025). In cartography, this may include copyrighted map data, geographic datasets, and visual designs incorporated into training, as well as GenAI-produced maps and visualizations derived from that training. Current copyright and trademark laws struggle to address cartography-specific issues. For example, model developers may unintentionally use proprietary map data from official or commercial providers and thereby expose themselves to infringement claims. Another dilemma arises when a map originally designed by a cartographer is ingested by a GenAI model and the output is subsequently modified in response to user prompts. Who, in this case, owns the copyright to the resulting work? Does it belong to the cartographer who created the original design, the user who crafted the prompt, or both?

Addressing these challenges requires both technical and legal responses. Technically, methods such as machine unlearning could enable models to ‘forget’ copyrighted inputs and reduce infringement risks (Nguyen et al., 2022). Providers and cartographers can also implement technologies like watermarking to protect generated content or develop tools to quantify the contributions of human users in AI-generated works (Hosny et al., 2024). Legally, clearer rules are needed to define ownership and establish frameworks that balance the rights and interests of all stakeholders.

7.5. Explainability

GenAI models are often referred to as ‘black boxes’ because users may not, or in many cases cannot, fully understand the mechanisms behind their outputs. Explainability, therefore, aims to clarify and interpret the decisions and results generated by these models to enhance human trust in GenAI-driven maps (Prestby, 2023, 2025).

The significance of explainability varies depending on the role of the user, but for cartographers and GIS professionals, it is particularly essential. These professionals rely on the accuracy and validity of outputs for decision-making in domains such as urban planning, environmental management, and resource allocation. Explainability not only helps them understand how a GenAI model generates specific maps or arrives at particular conclusions, but more importantly, provides insights when maps are found to be misleading or unethical. By understanding the reasoning behind GenAI-generated content, cartographers can identify errors or biases and make targeted adjustments to improve model performance.

7.6. Sustainability

Sustainable AI refers to the development and deployment of AI systems that promote ecological integrity and social justice (Van Wynsberghe, 2021). As GenAI becomes increasingly integrated into cartography, its environmental implications are twofold. On the one hand, GenAI can significantly contribute to environmental monitoring and climate action. For example, it can generate near-real-time global land-cover maps or simulate future scenarios under different environmental conditions to support the Sustainable Development Goals (SDGs). Furthermore, GenAI has the potential to help create maps that enhance public awareness and promote environmental education (Fish & Kreitzberg, 2023). However, on the other hand, the development and operation of GenAI models involve substantial carbon emissions, energy consumption, and resource usage due to the growing complexity and computational demands of these models (Shi et al., 2025; Strubell et al., 2020). Therefore, it is essential to balance the social and environmental benefits of GenAI with its ecological and ethical costs.

To achieve this balance, a comprehensive analysis (from data collection and model training to deployment) is needed to assess the environmental footprint of GenAI-driven cartographic applications. Researchers have also explored potential solutions to develop ‘Green Cartography’ (M. Wu et al., 2024). By optimizing color schemes and symbolization, it is possible to reduce energy consumption on digital displays and achieve eco-friendly and energy-efficient map designs (Han et al., 2021; M. Wu et al., 2024). Furthermore, transparency, accountability, and interdisciplinary collaboration should be promoted to ensure that GenAI is developed and applied for mapmaking in a sustainable way (Shi et al., 2025).

8. Conclusion

To conclude, in this paper, we first discuss several unique capabilities of GenAI that may benefit cartography, including its ability to encode extensive knowledge, adapt across contexts, handle artistic styles, foster creativity, and integrate multimodal information.

We then explore the opportunities that GenAI offers for both mapmaking and map use through four example applications: map style design, map icon design, map evaluation, and map reading. We further discuss the challenges associated with integrating GenAI into cartographic practice and emphasize the importance of ensuring its ethical use. Key concerns such as confabulation and hallucination, reproducibility, biases, copyrights, explainability, and sustainability must be carefully acknowledged and addressed.

Despite these contributions, our paper may not cover all possible use cases. Moreover, given the rapid development of GenAI, the examples provided may quickly become outdated. Nevertheless, we believe that this study offers valuable insights for researchers, professionals, policymakers, and the general public to navigate the landscape of potential applications of GenAI in cartography. We advocate for sustained dialogue, inclusive perspectives, and innovative practices to further explore this promising yet challenging area and advance cartography in the era of GenAI.

Notes

1. <https://chatgpt.com/>.
2. <https://gemini.google.com/>.
3. <https://www.llama.com/>.
4. <https://www.deepseek.com>.
5. <https://openai.com/index/dall-e-3/>.
6. <https://stability.ai/>.
7. <https://imagen.research.google/>.
8. <https://www.midjourney.com/home>.
9. www.270towin.com/2024-election-results-live/president/, <https://gistbok-ltb.ucgis.org/page/24/concept/7223>.
10. <https://chatgpt.com/g/g-14WuzVoyJ-map-doctor>.

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