Characterizing Machine Guidance in Geospatial Analysis

Yue Hao[a] and Guoray Cai

College of Information Sciences and Tech te University, University Park, PA, U.S.A.

{yqh5470, gxc26}@psu.edu

Keywords: Geographic Information Systems, Geospatial Analysis, Machine Guidance.

Abstract: Geospatial analysis poses challenges for individuals with limited expertise in Geographic Information Science (GIScience) methods and tools, requiring complex decision-making and spatial reasoning, often leading to difficulties or even failures. This research explores *machine guidance* as a novel approach to support domain analysts throughout the geo-analytical process. This approach can be implemented as an intelligent interface agent that is capable of recognizing user's analytical difficulties and providing proactive assistance. We propose a conceptual framework that characterizes the cooperative role of machine guidance in geospatial analysis. We focus on answering two key research questions: (1) *when to guide?* and (2) *how to guide?*. The framework provides a foundation for future research on machine-guided geospatial analysis, informing the development of other computer-aided systems that enhance usability and analytical effectiveness in GIScience.

1 INTRODUCTION

Geospatial analysis is crucial to scientific investigation and decision-making in various domains (Goodchild and Longley, 1999), ranging from human-environment interactions (De Smith et al., 2007), understanding the health impact of COVID-19 and vaccines (Sun et al., 2020; Wang et al., 2021; Mollalo et al., 2021), healthcare resources (Kang et al., 2020), to public health policies (Ramírez and Lee, 2020; Ahasan and Hossain, 2021). These demands for geospatial analysis stimulated the rapid growth of analytical tools and methods (Goodchild et al., 2000). As Geographic Information Systems (GISystems) grow into a type of high-functionality system, it becomes increasingly harder to learn and use (Lieberman et al., 2015).

Despite its significance, geospatial analysis presents challenges due to its complexity. It involves processing and analyzing geographic data by representing spatial phenomena, utilizing tools and statistical methods, and interpreting spatial relationships (Bailey et al., 1995; Goodchild, 2006). Analysts must recognize patterns in spatial data and understand their underlying significance (Haining, 1994). At the technical level, geospatial analysis makes use of a variety of analytical tools and techniques to understand geographic patterns and events (Goodchild, 1992). However, these tasks are often cognitively demanding and require specialized knowledge and skills in geography and GISystems, which are not universally accessible.

The complexity of geospatial analysis tools, combined with the need for GIS expertise, creates barriers for analysts, particularly those outside the GIS field. Existing solutions primarily focus on two approaches. The first approach involves empowering analysts by offering education and training programs in geography and GIScience (Council et al., 2005). While these programs are valuable, they are not scalable due to their high costs in terms of time and money. Second, GISystem user interfaces have been enhanced to better reflect how humans perceive, interact with, and conceptualize the world to improve usability and analytical capabilities (Goodchild, 2009). However, even with improved interfaces, analysts still face significant burdens, such as forming effective analytical strategies, preparing data, and executing the required spatial functions. These limitations highlight the need for innovative solutions to make geospatial analysis more accessible and efficient. To make geospatial analysis practical to a diverse range of applications and analysts, solutions are needed to bridge the cognitive and skill gap.

Motivated by addressing the human cognition and expertise barriers during spatial analysis, we propose **machine guidance** (Ceneda et al., 2018) as a novel approach to make geospatial analysis more accessible. The key idea of our approach is to introduce an intelligent interface agent that offers timely help and

[a] https://orcid.org/0000-0002-8368-4924

Hao, Y. and Cai, G.
Characterizing Machine Guidance in Geospatial Analysis.
DOI: 10.5220/0013240300003935

In *Proceedings of the 11th International Conference on Geographical Information Systems Theory, Applications and Management (GISTAM 2025)*, pages 39-50
ISBN: 978-989-758-741-2; ISSN: 2184-500X

guidance when analysts encounter difficulties in advancing their analytical goals. A machine guidance agent is able to recognize when users are facing difficulties and take the initiative to guide them with appropriate actions (Liu et al., 2018; Ceneda et al., 2019). By leveraging the guidance agent's expertise, human analysts' efforts and cognitive load in identifying clues or suitable solutions when facing challenges can be reduced. Thus, the machine guidance agent is particularly valuable for *domain experts* who are proficient in their specific problem domain but with limited expertise in GISystems or GIScience (Nyerges, 1995; Traynor, 1998).

Effective machine guidance agent requires two key capabilities. First, the guidance agent must be able to recognize when analysts are facing challenges and whether guidance is needed. Second, it must be able to determine what types of guidance will be provided based on the nature of user challenges. The overall goal is to make an analytic process productive and effective even in cases where users' expertise is inadequate. Towards *defining the conceptual framework for machine guidance in geospatial analysis*, we explore two key questions to inform its design and implementation:

1. *When is guidance needed during the geospatial analytical process*? This involves understanding the nature of geospatial analysis process and identifying the points when users might face challenges.
2. *How should guidance be provided*? Answering this question involves understanding alternative messages and media for communicating guidance and how to choose them to ensure effectiveness and keep them minimally intrusive.

By addressing these two research questions, we aim to characterize a conceptual framework for machine guidance in geospatial analysis. We begin by conceptualizing the geoanalytical process to identify when guidance is most needed. Using a hypothetical scenario, we illustrate how machine guidance can be integrated into the analytical process in various forms. A better understanding of when and how guidance should be designed contributes to the development of a science of design for machine guidance. It can fill the gap that there is a lack of understanding of the machine guidance behaviors in facilitating geospatial analysis. It also can be reused or further developed regarding the mixed-initiative guidance design in the GIS domain. Potentially, it can advance the GIScience agenda on the design and use of effective machine guidance to amplify human capacity for spatial problem-solving.

2 LITERATURE REVIEW

2.1 Conceptualize Geospatial Analysis

Geospatial analysis is a complex problem-solving process that integrates spatial thinking to address scientific questions and support decision-making (Goodchild and Longley, 1999; Fischer et al., 2011). Unlike other analytical domains, geospatial analysis requires viewing problems with a "geographical eye", emphasizing spatial relationships, patterns, and interconnections (Downs, 1997). This process involves systematically handling spatial data and extracting meaningful insights, ensuring that spatial objects and their relationships are accurately represented and understood (Haining, 1994). As an iterative analytical method, it involves multiple stages, including problem identification, strategy formation, analysis, and evaluation (De Smith et al., 2007; Bednarz et al., 2013). We categorize this process into Figure 1. Each step demands cognitive and computational efforts to effectively interpret spatial phenomena, manage uncertainties, and optimize solutions (Goodchild and Janelle, 2010).

The problem-solving aspect of geospatial analysis requires structuring ill-defined spatial problems into well-represented phenomena using spatial concepts such as distance, orientation, connectivity, and scale (Huisman et al., 2009; Miller and Wentz, 2003). Analysts must carefully choose external representations and operations based on the inherent uncertainties in geographic data, as spatial representations and scales influence analytical outcomes (Couclelis, 2003; Grekousis, 2020). Effective geospatial analysis also depends on the strategic integration of data, logical task sequencing, and cognitive reasoning to synthesize and evaluate spatial information dynamically (Dörner and Kreuzig, 1983; Thomas, 2005). Since spatial problems lack predefined solutions, iterative refinement, and expert judgment are necessary to improve decision-making and ensure analytical accuracy (Pretz et al., 2003; Bednarz, 2004).

Figure 1 illustrates the workflow and components involved in geospatial analysis conducted by a human analyst. Analysts, as domain experts, typically start by defining a problem within their specific field. The problem should then be translated into a spatial representation based on the analytical phenomena and their interactions. Next, the spatial problem can be broken down into a series of questions that GIS tools can address. Addressing these questions often requires executions and operations in a coherent workflow within GISystems. Based on the GIS outputs, the analyst compares and selects strategies. The analyst also needs to synthesize and evaluate the outputs

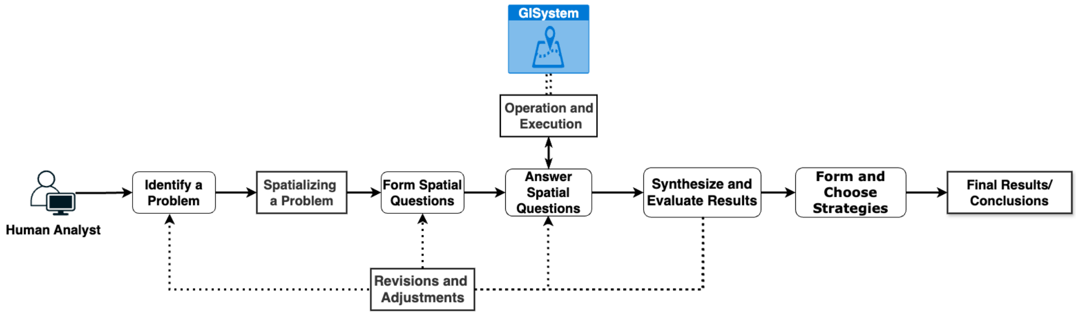


Figure 1: The geoanalytical process that requires a series of tasks and decisions.

and intermediate results to actively evaluate and adjust their analytical workflow as well as the problem-solving strategies.

2.2 Cognitive Challenges of Geospatial Analysis and the Need for Support

Geospatial analysis includes an essential goal of making critical decisions based on locations. It improves one's understanding of the geographic phenomenon presented by the data by discovering and revealing the previously unknown patterns (Huisman et al., 2009). Cognitively, it is challenging to see things and situations spatially for structuring problems, finding answers, and expressing solutions (Council et al., 2005). Generating new knowledge from the result requires human reasoning and understanding (Ward et al., 1999). It requires thinking and operational skills from three different dimensions: spatial concepts, spatial representation, and spatial reasoning (Council et al., 2005).

However, constraints of human perception and cognition, such as limited field of view in perception and working memory in cognition, have been documented in psychological studies (Baars, 1997; Baddeley, 1992; Creem-Regehr et al., 2005). These limitations impact how we perceive and comprehend complex data and situations. Choosing the suitable representation, for instance, is a demanding task that requires one's cognitive efforts in deciding the explicit relation and structures of the space as well as the unknown parts (e.g. data scale and aggregation level) that one is going to explore (Freksa et al., 2017; De Smith et al., 2007). Spatial representation should match the spatial phenomenon as well (Dungan et al., 2002). At an operational level, proper choice and use of analytical tools are critical (De Smith et al., 2007). Generated outputs entail spatial patterns that vary greatly depending on particular methods that are applied (De Smith et al., 2007). Making these critical decisions is inherently a demanding process that requires adequate training to gain spatial thinking skills (Dramowicz et al., 1993). External assistance is often required in facilitating the analysts to go through these procedures.

2.3 Inadequate Support to Geospatial Analysis

Efforts to support an effective spatial analytical process exist in two tracks. One track is to train analysts to think spatially about geographic phenomena and their representations through education and training (Council et al., 2005). The second track is to improve analytical tools and their interfaces in supporting geospatial analytical tasks.

GIScience education and geographical education are interconnected and complement each other in providing students with a comprehensive understanding of geography and the tools needed to address geographic challenges in various domains (Roche, 2014; Shin et al., 2016). Based on the geographic foundations, the concept of spatial thinking serves as a framework for structuring problems, finding solutions, and expressing answers. GIScience education and geographical education share common goals of enhancing spatial thinking, using geospatial data, and preparing students to address real-world challenges. Efforts and research findings suggest that GISciences and geospatial education are more than learning technical skills but the cognitive ability to solve practical questions at different stages (Downs et al., 1988; Verma and Estaville, 2018). However, researchers are afraid that the use of GISystems as a means will become the end so that the users are not able to think and solve problems spatially without the help of physical tools (Downs, 1997). The process is also hard to scale up considering the relevant cost of money and time (Johnson and Sullivan, 2010).

On the other hand, the design and usability of GISystems are improved by making them more closely resemble the way humans reason about the world (Goodchild, 2009). User handbook and supporting documentation can be one important facilitation. It shows its power and usefulness when users are new to a certain field when timely instructions can significantly improve their analytical process (Ceneda et al., 2016). The emergence of tutorials and guidelines (Perry et al., 2002; Kurland and Gorr, 2007) offer a means of doing spatial analysis by learning. Help resources offered by the software vendors (e.g. ArcGIS Online services) make the GISystems easier to learn and use (Goodchild, 2000). Implementation of question-based GISystem (Scheider et al., 2021; Scheider et al., 2019; Schulze, 2021; Gao and Goodchild, 2013), workflow-based GISystem used for analyzing general or domain-specified problems (Lim et al., 2005; Yeo and Yee, 2016; Badea and Badea, 2013; Kruiger et al., 2021), and sketch-based GISystem (Curtis, 2012) offered new ways for users in interacting with the GISystems in order to ease analyst's difficulties when doing geospatial analysis. For instance, users can express spatial relations more efficiently by applying the electronic pen to the map display (Cohen et al., 1997).

When treating geospatial analysis as an activity, however, it is an incremental process that involves a continuous loop of observing and evaluating the outcomes so that the analytical goal can be refined (Figure 1). Help is needed from the system's side as a mediation tool in reducing the cognitive difficulties (Rogers, 2004). Forming the question itself also involves the efforts in simplifying and dividing the problem into sub-goals and the analytical approach should actively manage and link a series of tasks logically (De Smith et al., 2007). Therefore, the question-based systems and workflow-based systems fail to solve complex spatial analytical problems. Advancement of the design should go beyond the simple automation process without the involvement of interactions and feedback on new information. However, there is still a lack of design in current systems that support or guide interactive spatial analytical behaviors. Human ability and skills like communication and coordination contribute to collaborations with other people and can be extended to the computational systems in forming human-computer collaborations that are the joint efforts of the computer system(s) and human user(s) towards a shared analysis goal (Terveen, 1995). One promising research avenue is to investigate a mixed-initiative approach that combines system-initiated guidance with user-initiated guidance to enhance human-machine intelligence (Pérez-Messina et al., 2022).

3 TOWARDS MACHINE GUIDANCE TO GEOSPATIAL ANALYSIS

We define Machine Guidance in geospatial analysis as a mixed-initiative approach designed to help analysts navigate complex spatial tasks when they meet difficulties. The concept of machine guidance originates from early automation and industrial control systems, particularly in manufacturing and robotics (Kendoul, 2012; Li et al., 2009). Over time, fields such as Visual Analytics (VA), enabling user-interactive guidance developed to enhance data visualization and analysis through computer assistance (Ceneda et al., 2016; Collins et al., 2018). Unlike autonomous agents or other systems that provide assistance only upon request, guidance proactively identifies when help is needed and delivers timely, context-aware support throughout the analytical workflow, enabling analysts to make well-informed decisions.

Research on conceptualizing the machine guidance design as well as their physical implementations thrived in VA and data science domains which have plentiful discussions and years of accumulation (Ceneda et al., 2016; Ceneda et al., 2018; Ceneda et al., 2020; Pérez-Messina et al., 2022; Sperrle et al., 2022). However, the GIS domain has yet to fully formalize its integration. There is no formal discussion on how the guidance approach in guiding geospatial analysis can be achieved and thus calls for an attribution. Users of the GIS applications are no longer restricted to the GIS experts but a wider range of users with expertise in specific domains (Slocum et al., 2001). We define the target users of the machine guidance as those who have occasional needs to conduct geospatial analytical tasks based on their domain interests and expertise. This group of users are experts in a particular problem domain but are novices in the tool domain related to GISystems (Nyerges, 1995). They are without or with only a little knowledge of geography or GISceince (Traynor, 1998). More importantly, they have a goal of doing geospatial analysis for critical decision-making.

When supporting geospatial analysis to solve domain problems, guidance should assist human analysts across various analytical stages (Pérez-Messina et al., 2022). Its essential capability is recognizing when the user needs help and what kind of help should be offered at the moment (Ceneda et al., 2016). Followed Figure 1, Figure 2 highlighted the moments when guidance can be introduced. Since geospatial analysis consists of interconnected sub-tasks and continuous decision-making, guidance must dynamically adapt to changes throughout the process. It should

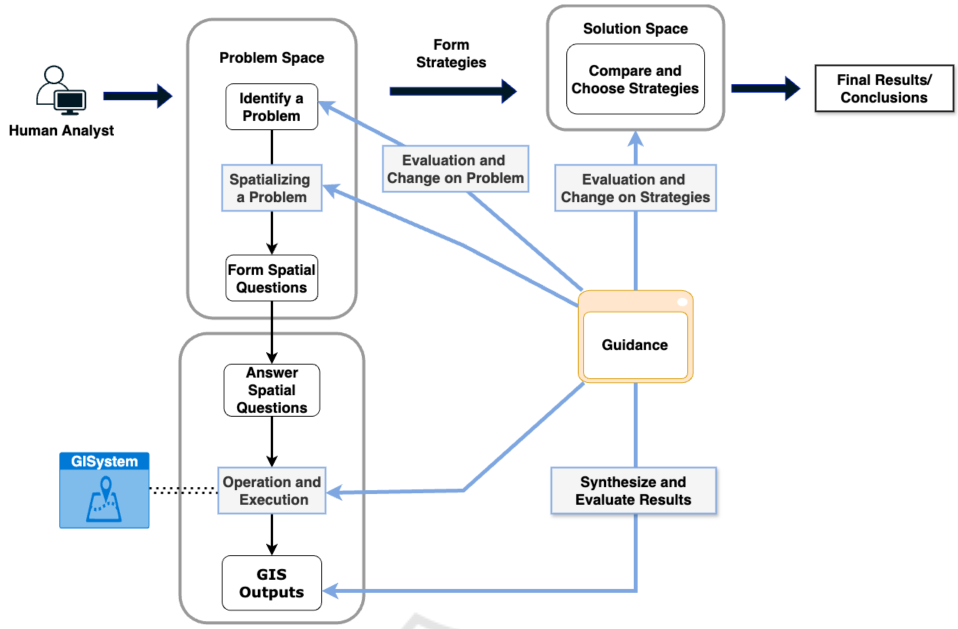


Figure 2: When or where machine guidance can enhance a geospatial analytical workflow (outlined in blue).

provide both high-level analytical strategies and computational support, such as selecting appropriate tools and parameters (Ceneda et al., 2020). Therefore, the core challenge in designing effective guidance lies in accurately identifying analytical difficulties and delivering support with appropriate content.

In the following sections, we first identify when guidance can be needed based on the conceptualized geospatial analytical process. We then frame and explain how guidance can be provided in the process. To demonstrate when and how a human analyst interacts with and benefits from machine guidance, we present a hypothetical scenario:

> *Lucy, a public health promotion analyst, is working to improve the local food environment in Wisconsin. Her objective is to identify counties with limited food access, focusing on those with a high prevalence of food deserts. Additionally, she aims to prioritize densely populated counties, as interventions in these areas would have a greater impact. With limited state funding, she must strategically allocate resources to maximize effectiveness.*

Based on this scenario, Table 1 outlines several moments when guidance can be introduced (MG) alongside the analyst's requests and feedback (User).

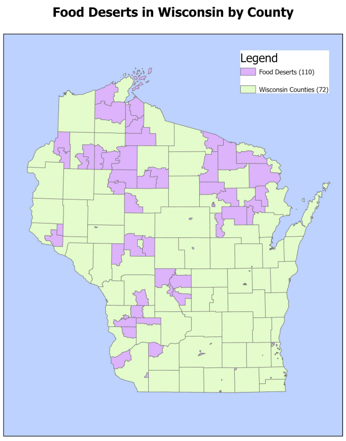
3.1 When to Provide Guidance

Addressing the question of *when guidance is needed*, we propose that timely intervention is essential whenever analysts face challenges that hinder their progress. As noted in Figure 2, guidance can be introduced throughout the process from different aspects. Particularly, we introduce a conceptual framework that informs the design and development of machine guidance that operates on three levels:

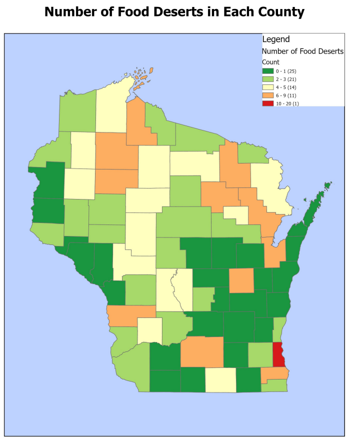
- **Problem-solving Level** Guidance helps analysts spatialize and refine problems. User 1 indicates the analytical goal of understanding the food shortage conditions so MG 1 provided guidance by retrieving a dataset representing counties and food deserts, which offered insights into the current food environment in each county. This enabled the analyst to develop a foundational understanding of the phenomenon and prepared the analyst for subsequent exploratory steps using the available data. Additionally, analytical goals may need refinement based on intermediate findings. For instance, the initial problem may be ill-defined or unrealistic. Guidance can assist analysts in evaluating their goals and making necessary adjustments.
- **Operational Level** Guidance supports analysts in developing GIS workflows and executing specific spatial functions within a GISsystem. When analysts are uncertain about how to tackle a particular question, guidance can help construct workflows by suggesting appropriate methods and operations. Additionally, if analysts are unfamiliar with specific tasks, guidance can automate processes to abstract operational complexities and

Table 1: Interactions between the Lucy (User) and the machine guidance agent (MG) when assisting her in locating targeted counties.

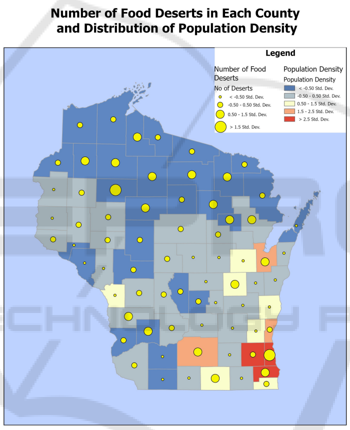
Dialogue	Guidance Response
User 1: I want to find counties in Wisconsin with food shortages. **MG 1**: Counties in Wisconsin and the food deserts in the state are presented. We found 110 food deserts. **User 2**: For each county, I need to know how many food deserts are there. **MG 2**: We counted how many food deserts by county as a measurement. **User 3**: I need to find counties with a large number of food deserts and are densely populated. How can I do that? **MG 3**: We have two strategies. (a) Manual Selection: You can analyze the distribution of food desert counts in relation to population density and manually select counties that meet your criteria. *While a-1 offers more flexibility in analyzing each variable individually, a-2 enhances pattern recognition by integrating both factors into a single visual representation, making it easier to identify areas of concern at a glance. If the goal is to detect broad trends and prioritize interventions efficiently, a-2 is the preferable choice. However, if a more detailed breakdown of each factor is required before drawing conclusions, a-1 may be more useful.* (b) Automated Selection: We have identified 6 counties where both the number of food deserts and the population density exceed the mean which may pinpoint areas of interest. **User 4**: Strategy (b) results are easier to follow but I can not deal with all these counties. How about using more than 5 food deserts for selection? **MG 4**: After adjusting the selection condition, we found 5 counties. **User 5**: I will do more exploration visually. Thank you. **MG 5**: Any other requests? ...	See MG 1 – MG 4 maps below



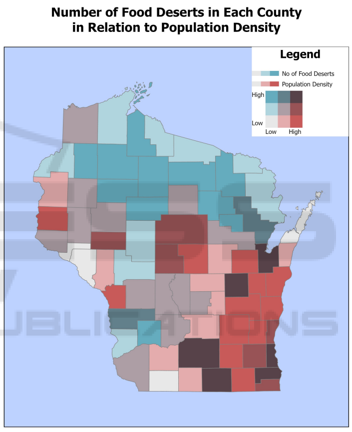
MG 1



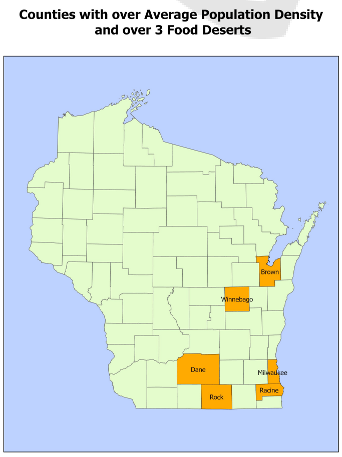
MG 2



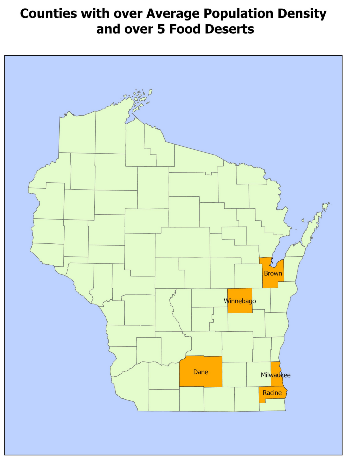
MG 3 (a)-1



MG 3 (a)-2



MG 3 (b)



MG 4

streamline execution. For instance, User 2 explicitly expressed the goal of determining the number of food deserts in each county, prompting the guidance system to assist by performing the necessary operations, such as a Spatial Join, to directly achieve this objective (MG 2). This support alleviated the analyst's burden of figuring out how to obtain the counts and which operations to execute within the GISystem.

- **Strategy Level** Guidance aids analysts in devising and selecting problem-solving strategies. In MG 3, the guidance offers two different strategies with three different methods. Multiple solutions may exist for a given problem, requiring analysts to simulate different processes and explore "what-if" scenarios (MG 4) to determine the most suitable approach. The guidance agent facilitates this process by assisting analysts in exploring, evaluating, and comparing different strategies to identify the optimal solution.

From another perspective, guidance can be initiated either through explicit requests or by inferring implicit hints. In MG 1, the system proactively assists the analyst by interpreting the phenomenon as a starting point, fetching data it deems relevant to the current analytical goal without requiring explicit input. Instead, it infers the specific data needs based on the stated objective. In contrast, MG 2 through MG 4 were triggered by the analyst's direct feedback, where the guidance responded to explicit requests for assistance regarding their current intention. It ensures that guidance can take the initiative to help by adapting to inferred needs as well as meet user-initiated demands, enhancing human-system collaboration.

3.2 How to Provide Guidance

3.2.1 Guidance in Different Formats

Based on how the guidance is delivered and communicated to its user, we can categorize the guidance design based on its output format (Pérez-Messina et al., 2022). Guidance can be offered with:

- **Numeric reports and textual information**, like describing what to do next in words or a list of values. In our scenario, the guidance provides continuous textual explanations, enabling the analyst to clearly understand both the ongoing processes and the specific support being offered by the system.
- **Visual displays**, like showing a map, chart, or diagram on the screen. With the visual clues, the user does not need to rely on their memories or imaginations when scoping their questions. Throughout MG1 to MG4, the guidance system generates maps as outputs, enabling the analyst to visualize spatial patterns and facilitating easier comparisons. This visual evidence improves the analyst's ability to track and advance the analytical process, ensuring it aligns effectively with the intended goals.
- **Physical operations**, like direct operation on the system end to derive the expected output or answer. In MG2, for instance, the Spatial Join operation was done as part of the guidance behavior.
- **Other formats**. Other possible formats like videos, animations, and audio also can be considered.

The listed formats are not exclusive from each other and can be combined to provide more details if needed. For instance, texts and maps are combined to guide the analyst in our scenario. In MG3, textual explanation offers hints on how to compare and decide which strategy can be more suitable. Need to mention that incorporating excessive content into a single guidance—such as using multiple formats, offering overly detailed information, or combining too many elements—can lead to cognitive overload. To ensure clarity and usability, guidance should avoid overwhelming analysts with excessive details that may hinder their ability to make informed judgments. Instead, it should prioritize simplicity and focus on delivering concise, relevant information tailored to the user's immediate needs.

3.2.2 Guidance in Different Degrees

Degree of guidance means how much assistance is provided (Ceneda et al., 2019; Ceneda et al., 2016). The guidance that is **orienting** or **directing** the user has a higher degree of freedom and flexibility compared to **prescribing** guidance that demonstrates a fixed solution.

- **Orienting guidance orients "where to go".** It only suggests high-level hints and suggestions. It is aimed at maintaining users' current thinking process ("mental map") and offering the potential solutions that can be adopted (Ceneda et al., 2016). At the problem-solving level, it guides the user to think about and decide on what is the proper next step.
- **Directing guidance directs "what can be chosen".** It offers concrete recommendations like the possible options and alternatives that can lead to desired results (Ceneda et al., 2016). It is more detailed and concrete than the orienting guidance. In MG3, the guidance provides two strategies in

three methods to identify densely populated counties with a high number of food deserts. By presenting multiple options, it not only offers flexibility but also empowers the analyst to retain control, allowing them to choose and decide the most suitable approach for their next steps.

- **Prescribing guidance prescribes "what to do".** It can offer step-by-step directions to solve a specific problem. Unlike cases where the analyst is unsure of the next steps, here the analyst knows the goal but may not know how to achieve it. This prescriptive process can largely be automated (Ceneda et al., 2016). For instance, the process of calculating counts (MG2), and the task of applying a different selection condition (MG4), are both automated. This approach conceals the operational complexities and presents only the final outputs.

3.3 Design Challenges and Opportunities

Designing a computational system capable of providing effective machine guidance for spatial problem-solving presents several challenges. One of the primary difficulties lies in recognizing when and how to intervene without disrupting the analyst's workflow. The assistance should only be provided when it is genuinely needed and when the analyst is ready to receive it (Maes, 1995). Otherwise, unnecessary interruptions could confuse the analyst and interfere with the analytical process (Ceneda et al., 2020). Detecting the need for assistance can be achieved through explicit user requests or implicit behavioral monitoring, such as tracking user interactions, detecting recurring difficulties, or even analyzing physiological indicators like stress-related facial expressions (Ceneda et al., 2016; Ceneda et al., 2021). A well-designed system must balance responsiveness with non-intrusiveness to ensure a seamless analytical experience (Maes, 1995).

Another significant computational challenge involves equipping the system with reasoning and planning capabilities. The system must be able to track the progress of an analysis, recognize what has been completed, identify gaps in the current strategy, and suggest appropriate next steps. This requires integrating structural knowledge, which enables the system to monitor and manage analytical workflows (Armstrong et al., 1990). Furthermore, a control process is needed to oversee and guide execution, ensuring that if an approach fails, alternative solutions can be explored (Hayes-Roth and Hayes-Roth, 1979). The system must also infer the analyst's current stage and anticipate their information needs, adjusting guidance accordingly. Recent advancements in Artificial Intelligence (AI), particularly Large Language Models (LLMs) and GeoAI, offer promising solutions for enhancing the design of machine guidance agents. These technologies can improve the agent's ability to interpret user queries, infer analytical goals, and adaptively learn from user interactions to refine future assistance (Li and Ning, 2023). A learning module could be integrated to analyze user behavior over time, helping the system provide more personalized and context-aware recommendations (Smith et al., 1987). Leveraging AI-driven techniques can significantly enhance the effectiveness of computational guidance systems by making them more intuitive, adaptive, and capable of supporting complex spatial analyses.

How to store and represent the required expertise is another essential challenge. The mentioned expertise should encompass various types of information, including declarative knowledge (basic information about spatial and non-spatial objects), procedural knowledge (strategies for applying spatial operations), and control knowledge (heuristics for evaluating the validity of actions and solutions) (Hofer et al., 2017). The system must be able to intelligently select and compare spatial operations based on their purpose and suitability for different analytical goals. For instance, when selecting datasets for Wisconsin, the representation could vary based on the scale and purpose of analysis, whether as a point on a small-scale map or as a polygon in a larger-scale map. Knowledge of metadata such as geometry type, spatial extent, and scale is crucial for ensuring that the correct datasets are retrieved and applied computationally.

4 DISCUSSION

To ensure the successful implementation of the machine guidance approach, several critical research questions must be addressed. First, the conceptual framework requires further evaluation and refinement. While our characterizations (Sections 3.1, 3.2) provide an initial understanding of the machine guidance approach in geospatial analysis, it remains uncertain whether they accurately reflect real-world analytical workflows, the specific challenges analysts face, and the most effective formats for delivering guidance. One way to bridge this gap is through observational studies to examine how analysts approach geospatial problem-solving in real-world scenarios. Additionally, empirical research is needed to determine the optimal timing and presentation of guidance to maximize its effectiveness. A user-centered approach will offer valuable insights for designing more intuitive and effective machine-guided systems.

Secondly, it is computationally challenging to determine when to provide the guidance. Although we have outlined potential strategies in Section 3.3, their implementation is still limited, particularly in the context of geospatial analysis. Future research should explore methods to intelligently recognize the need for guidance, ensuring that it is provided in a timely and non-disruptive manner. This could involve developing adaptive systems that learn from user behavior and context to offer guidance only when it is most beneficial.

Third, ensuring the scalability of the expertise embedded within the guidance while maintaining its specificity across diverse domains is critical. This raises important questions about what information or knowledge should be captured, how it should be represented, and the level of detail required to balance generality and domain-specific relevance. Addressing these questions is essential for creating guidance systems that are both adaptable to a wide range of applications and sufficiently detailed to provide meaningful support in specialized contexts. Future research should explore methods for capturing and structuring domain knowledge in a way that ensures scalability without sacrificing precision and ultimately ensures machine guidance applications are effective across various analytical domains.

To sum up, our study is to establish proof-of-concept design principles for machine guidance. While we have identified various design opportunities, our work remains at the conceptual stage and lacks computational implementation and practical evaluation. Future efforts are needed to develop concrete computational frameworks for machine guidance and to conduct empirical evaluations. Implementing these systems in real-world applications will provide valuable insights through user feedback, which can help refine and validate the proposed design features. Addressing the mentioned challenges will not only advance the field of machine-guided geoanalytical systems but also pave the way for broader applications in other domains where human-machine collaboration is critical.

5 CONCLUSIONS

We propose using *machine guidance* as a new approach to support analysts' geospatial analytical process. As a complex and mentally demanding endeavor, geospatial analysis poses a significant challenge for individuals with limited GIS knowledge and experience. This challenge highlights the importance of machine guidance, which encapsulates reasoning and processing steps within the system itself, allowing analysts to focus on interpreting analytical outputs rather than navigating complex workflows.

As a starting point, we characterized a conceptual framework focusing on (1) *when* guidance should be introduced and (2) *how* guidance can be delivered to help the analyst. Specifically, our approach suggests that machine guidance should be placed when the user meets difficulties when doing geospatial analysis. At these moments, users may struggle with decision-making due to the need for extensive mental effort, often lacking sufficient knowledge or expertise to solve the issue at hand. Using the hypothetical scenario, we presented various machine guidance that are in different degrees and formats.

To the best of our knowledge, this research marks the first attempt to integrate machine guidance into GISystems, with the potential to drive advancements in the broader field of GIScience. As an initial effort, this study introduces the concept of the machine guidance approach in supporting geospatial analysis as well as its design opportunities and potential. Our ongoing efforts are focused on refining these guidance design strategies and evaluating their feasibility in real-world scenarios. We seek to foster further academic discussion and social engagement around the role of machine guidance in facilitating geospatial analysis. Ultimately, we hope this work sparks further investigation and encourages the development of innovative approaches along the way.

REFERENCES

Ahasan, R. and Hossain, M. M. (2021). Leveraging gis and spatial analysis for informed decision-making in covid-19 pandemic. *Health policy and technology*, 10(1):7.

Armstrong, M., De, S., Densham, P., Lolonis, P., Rushton, G., and Tewari, V. K. (1990). A knowledge-based approach for supporting locational decisionmaking. *Environment and Planning B: Planning and Design*, 17(3):341–364.

Baars, B. J. (1997). Some essential differences between consciousness and attention, perception, and working memory. *Consciousness and cognition*, 6(2-3):363–371.

Baddeley, A. (1992). Working memory: The interface between memory and cognition. *Journal of cognitive neuroscience*, 4(3):281–288.

Badea, A.-C. and Badea, G. (2013). The advantages of creating compound gis functions for automated workflow. *International Multidisciplinary Scientific Geo-Conference: SGEM*, 1:943.

Bailey, T. C., Gatrell, A. C., et al. (1995). *Interactive spatial data analysis*, volume 413. Longman Scientific & Technical Essex.

Bednarz, S., Heffron, S., and Huynh, N. (2013). A road map for 21st century geography education. *Washington, DC: Association of American Geographers*.

Bednarz, S. W. (2004). Geographic information systems: A tool to support geography and environmental education? *GeoJournal*, 60:191–199.

Ceneda, D., Andrienko, N., Andrienko, G., Gschwandtner, T., Miksch, S., Piccolotto, N., Schreck, T., Streit, M., Suschnigg, J., and Tominski, C. (2020). Guide me in analysis: A framework for guidance designers. In *Computer Graphics Forum*, volume 39, pages 269–288. Wiley Online Library.

Ceneda, D., Arleo, A., Gschwandtner, T., and Miksch, S. (2021). Show me your face: towards an automated method to provide timely guidance in visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, 28(12):4570–4581.

Ceneda, D., Gschwandtner, T., May, T., Miksch, S., Schulz, H.-J., Streit, M., and Tominski, C. (2016). Characterizing guidance in visual analytics. *IEEE transactions on visualization and computer graphics*, 23(1):111–120.

Ceneda, D., Gschwandtner, T., May, T., Miksch, S., Streit, M., and Tominski, C. (2018). Guidance or no guidance? a decision tree can help. In *EuroVA@ EuroVis*, pages 19–23.

Ceneda, D., Gschwandtner, T., and Miksch, S. (2019). A review of guidance approaches in visual data analysis: A multifocal perspective. In *Computer Graphics Forum*, volume 38, pages 861–879. Wiley Online Library.

Cohen, P. R., Johnston, M., McGee, D., Oviatt, S., Pittman, J., Smith, I., Chen, L., and Clow, J. (1997). Quickset: Multimodal interaction for distributed applications. In *Proceedings of the fifth ACM international conference on Multimedia*, pages 31–40.

Collins, C., Andrienko, N., Schreck, T., Yang, J., Choo, J., Engelke, U., Jena, A., and Dwyer, T. (2018). Guidance in the human–machine analytics process. *Visual Informatics*, 2(3):166–180.

Couclelis, H. (2003). The certainty of uncertainty: Gis and the limits of geographic knowledge. *Transactions in GIS*, 7(2):165–175.

Council, N. R. et al. (2005). *Learning to think spatially*.

Creem-Regehr, S. H., Willemsen, P., Gooch, A. A., and Thompson, W. B. (2005). The influence of restricted viewing conditions on egocentric distance perception: Implications for real and virtual indoor environments. *Perception*, 34(2):191–204.

Curtis, J. W. (2012). Integrating sketch maps with gis to explore fear of crime in the urban environment: A review of the past and prospects for the future. *Cartography and Geographic Information Science*, 39(4):175–186.

De Smith, M. J., Goodchild, M. F., and Longley, P. (2007). *Geospatial analysis: a comprehensive guide to principles, techniques and software tools*. Troubador publishing ltd.

Dörner, D. and Kreuzig, H. W. (1983). Problemlösefähigkeit und intelligenz. *Psychologische Rundschau*.

Downs, R. M. (1997). The geographic eye: Seeing through gis? 1. *Transactions in GIS*, 2(2):111–121.

Downs, R. M., Liben, L. S., and Daggs, D. G. (1988). On education and geographers: The role of cognitive developmental theory in geographic education. *Annals of the Association of American Geographers*, 78(4):680–700.

Dramowicz, K., Wightman, J. F., and Crant, J. S. (1993). Addressing gis personnel requirements: A model for education and training. *Computers, Environment and Urban Systems*, 17(1):49–59.

Dungan, J. L., Perry, J., Dale, M., Legendre, P., Citron-Pousty, S., Fortin, M.-J., Jakomulska, A., Miriti, M., and Rosenberg, M. (2002). A balanced view of scale in spatial statistical analysis. *Ecography*, 25(5):626–640.

Fischer, A., Greiff, S., and Funke, J. (2011). The process of solving complex problems. *Journal of Problem Solving*, 4(1):19–42.

Freksa, C., Barkowsky, T., Dylla, F., Falomir, Z., Olteţeanu, A.-M., and van de Ven, J. (2017). Spatial problem solving and cognition. In *Representations in mind and world*, pages 156–183. Routledge.

Gao, S. and Goodchild, M. F. (2013). Asking spatial questions to identify gis functionality. In *2013 Fourth International Conference on Computing for Geospatial Research and Application*, pages 106–110. IEEE.

Goodchild, M. and Longley, P. (1999). The future of gis and spatial analysis. *Geographical information systems*, 1:567–580.

Goodchild, M. F. (1992). Geographical information science. *International journal of geographical information systems*, 6(1):31–45.

Goodchild, M. F. (2000). Part 1 spatial analysts and gis practitioners: The current status of gis and spatial analysis. *Journal of Geographical Systems*, 2:5–10.

Goodchild, M. F. (2006). The fourth r? rethinking gis education. *ESRI ArcNews*, 28(3):1.

Goodchild, M. F. (2009). Geographic information systems and science: Today and tomorrow. *Annals of GIS*, 15(1):3–9.

Goodchild, M. F., Anselin, L., Appelbaum, R. P., and Harthorn, B. H. (2000). Toward spatially integrated social science. *International Regional Science Review*, 23(2):139–159.

Goodchild, M. F. and Janelle, D. G. (2010). Toward critical spatial thinking in the social sciences and humanities. *GeoJournal*, 75:3–13.

Grekousis, G. (2020). *Spatial analysis methods and practice: describe–explore–explain through GIS*. Cambridge University Press.

Haining, R. (1994). Designing spatial data analysis modules for geographical information systems. *Spatial analysis and GIS*, pages 45–64.

Hayes-Roth, B. and Hayes-Roth, F. (1979). A cognitive model of planning. *Cognitive science*, 3(4):275–310.

Hofer, B., Mäs, S., Brauner, J., and Bernard, L. (2017). Towards a knowledge base to support geoprocessing workflow development. *International Journal of Geographical Information Science*, 31(4):694–716.

Huisman, O., de By, R. A., et al. (2009). Principles of geographic information systems. *ITC Educational Textbook Series*, 1:17.

Johnson, A. B. and Sullivan, D. (2010). Geospatial education at us community colleges: Background, challenges, and opportunities. *Journal of the Urban & Regional Information Systems Association*, 22(2).

Kang, J.-Y., Michels, A., Lyu, F., Wang, S., Agbodo, N., Freeman, V. L., and Wang, S. (2020). Rapidly measuring spatial accessibility of covid-19 healthcare resources: a case study of illinois, usa. *International journal of health geographics*, 19:1–17.

Kendoul, F. (2012). Survey of advances in guidance, navigation, and control of unmanned rotorcraft systems. *Journal of Field Robotics*, 29(2):315–378.

Kruiger, J. F., Kasalica, V., Meerlo, R., Lamprecht, A.-L., Nyamsuren, E., and Scheider, S. (2021). Loose programming of gis workflows with geo-analytical concepts. *Transactions in GIS*, 25(1):424–449.

Kurland, K. S. and Gorr, W. L. (2007). *GIS tutorial for health*. ESRI, Inc.

Li, M., Imou, K., Wakabayashi, K., and Yokoyama, S. (2009). Review of research on agricultural vehicle autonomous guidance. *International Journal of Agricultural and biological engineering*, 2(3):1–16.

Li, Z. and Ning, H. (2023). Autonomous gis: the next-generation ai-powered gis. *International Journal of Digital Earth*, 16(2):4668–4686.

Lieberman, H., Fry, C., and Rosenzweig, E. (2015). The New Era of High-Functionality Interfaces. In Duval, B., Van Den Herik, J., Loiseau, S., and Filipe, J., editors, *Agents and Artificial Intelligence*, volume LNAI 8946, pages 3–10. Springer International Publishing, Cham.

Lim, K. J., Engel, B. A., Tang, Z., Choi, J., Kim, K.-S., Muthukrishnan, S., and Tripathy, D. (2005). Automated web gis based hydrograph analysis tool, what 1. *JAWRA Journal of the American Water Resources Association*, 41(6):1407–1416.

Liu, S., Andrienko, G., Wu, Y., Cao, N., Jiang, L., Shi, C., Wang, Y.-S., and Hong, S. (2018). Steering data quality with visual analytics: The complexity challenge. *Visual Informatics*, 2(4):191–197.

Maes, P. (1995). Agents that reduce work and information overload. In *Readings in human–computer interaction*, pages 811–821. Elsevier.

Miller, H. J. and Wentz, E. A. (2003). Representation and spatial analysis in geographic information systems. *Annals of the Association of American Geographers*, 93(3):574–594.

Mollalo, A., Mohammadi, A., Mavaddati, S., and Kiani, B. (2021). Spatial analysis of covid-19 vaccination: a scoping review. *International journal of environmental research and public health*, 18(22):12024.

Nyerges, T. L. (1995). Cognitive issues in the evolution of gis user knowledge. In *Cognitive aspects of human-computer interaction for geographic information systems*, pages 61–74. Springer.

Pérez-Messina, I., Ceneda, D., El-Assady, M., Miksch, S., and Sperrle, F. (2022). A typology of guidance tasks in mixed-initiative visual analytics environments. In *Computer Graphics Forum*, volume 41, pages 465–476. Wiley Online Library.

Perry, J., Liebhold, A., Rosenberg, M., Dungan, J., Miriti, M., Jakomulska, A., and Citron-Pousty, S. (2002). Illustrations and guidelines for selecting statistical methods for quantifying spatial pattern in ecological data. *Ecography*, 25(5):578–600.

Pretz, J. E., Naples, A. J., and Sternberg, R. J. (2003). Recognizing, defining, and representing problems. *The psychology of problem solving*, 30(3):3–30.

Ramírez, I. J. and Lee, J. (2020). Covid-19 emergence and social and health determinants in colorado: a rapid spatial analysis. *International journal of environmental research and public health*, 17(11):3856.

Roche, S. (2014). Geographic information science i: Why does a smart city need to be spatially enabled? *Progress in Human Geography*, 38(5):703–711.

Rogers, Y. (2004). New theoretical approaches for hci. *Annual review of information science and technology*, 38(1):87–143.

Scheider, S., Ballatore, A., and Lemmens, R. (2019). Finding and sharing gis methods based on the questions they answer. *International journal of digital earth*, 12(5):594–613.

Scheider, S., Nyamsuren, E., Kruiger, H., and Xu, H. (2021). Geo-analytical question-answering with gis. *International Journal of Digital Earth*, 14(1):1–14.

Schulze, U. (2021). "gis works!"—but why, how, and for whom? findings from a systematic review. *Transactions in GIS*, 25(2):768–804.

Shin, E. E., Milson, A. J., and Smith, T. J. (2016). Future teachers' spatial thinking skills and attitudes. *Journal of Geography*, 115(4):139–146.

Slocum, T. A., Blok, C., Jiang, B., Koussoulakou, A., Montello, D. R., Fuhrmann, S., and Hedley, N. R. (2001). Cognitive and usability issues in geovisualization. *Cartography and geographic information science*, 28(1):61–75.

Smith, T., Peuquet, D., Menon, S., and Agarwal, P. (1987). Kbgis-ii a knowledge-based geographical information system. *International Journal of Geographical Information System*, 1(2):149–172.

Sperrle, F., Ceneda, D., and El-Assady, M. (2022). Lotse: A practical framework for guidance in visual analytics. *IEEE Transactions on Visualization and Computer Graphics*, 29(1):1124–1134.

Sun, F., Matthews, S. A., Yang, T.-C., and Hu, M.-H. (2020). A spatial analysis of the covid-19 period prevalence in us counties through june 28, 2020: where geography matters? *Annals of epidemiology*, 52:54–59.

Terveen, L. G. (1995). Overview of human-computer collaboration. *Knowledge-Based Systems*, 8(2-3):67–81.

Thomas, J. J. (2005). *Illuminating the path:the research and development agenda for visual analytics*. IEEE Computer Society.

Traynor, C. (1998). Putting power in the hands of end users: a study of programming by demonstration, with an application to geographical information systems. In *CHI 98 conference summary on Human factors in computing systems*, pages 68–69.

Verma, K. and Estaville, L. (2018). Role of geography courses in improving geospatial thinking of undergraduates in the united states. *International Journal of Geospatial and Environmental Research*, 5(3):2.

Wang, Q., Chen, Z., Wang, Y., and Qu, H. (2021). A survey on ml4vis: Applying machinelearning advances to data visualization. *IEEE Transactions on Visualization and Computer Graphics*.

Ward, T. B., Smith, S. M., and Finke, R. A. (1999). Creative cognition. *Handbook of creativity*, 189:212.

Yeo, I.-A. and Yee, J.-J. (2016). Development of an automated modeler of environment and energy geographic information (e-gis) for ecofriendly city planning. *Automation in Construction*, 71:398–413.