Mapping the Emergence: A Bibliometric Analysis of the Convergence Gap in GeoAI Teacher Education Research

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Abstract

The integration of Geospatial Artificial Intelligence (GeoAI) into geography education represents a critical frontier for twenty-first-century pedagogy, yet teacher preparation in this domain remains severely underexplored. This study employs bibliometric analysis to examine the convergence gap between established research fields and the emerging area of GeoAI teacher education. Through systematic analysis of 1,471 publications from the Dimensions database spanning January 2010 through March 2025, we investigated five interconnected datasets using advanced network analysis techniques. Drawing on convergence science theory and adapting interdisciplinary measurement approaches, our findings reveal an extreme convergence gap (Gap Index = 0.941, where values approaching 1.0 indicate greater disconnection between fields) between well-established foundational domains – geography teacher education (470 papers), AI teacher education (382 papers), and spatial thinking education (312 papers) – and their intersection. Only 25 papers directly address AI integration in geography education, representing 1.7% of the total corpus. The research exhibits pronounced temporal concentration with a Field Emergence Score of 70.6 (indicating that over 70% of publications appeared within the most recent three years), significant geographic bias toward the Global North (Herfindahl Index = 0.208), and limited theoretical framework development. Co-authorship and keyword co-occurrence networks demonstrate fragmented research communities with structural holes representing opportunities for knowledge brokerage across domains. We propose a prioritized research agenda addressing theoretical development, empirical validation, and geographic equity, documenting the real-time emergence of a critical educational research domain while identifying strategic intervention points for accelerating field convergence.*

Keywords: GeoAI, Geography Teacher Education, Bibliometric Analysis, Convergence Gap, Spatial Thinking, Artificial Intelligence Literacy, AI-TPACK, Interdisciplinary Research

Introduction

The rapid advancement of Geospatial Artificial Intelligence (GeoAI) has fundamentally transformed geographic analysis and spatial problem-solving capabilities across numerous domains [1]. From urban planning and environmental monitoring to disaster response and climate modeling, GeoAI applications demonstrate unprecedented potential for addressing complex spatial challenges through the integration of machine learning algorithms with geospatial data and technologies [2]. However, this technological revolution has substantially outpaced educational adaptation.

Geography education has long emphasized spatial thinking as a fundamental cognitive skill, recognizing its crucial importance for understanding complex environmental and social phenomena [3]. The discipline has successfully integrated Geographic Information Systems (GIS) into educational practice over the past three decades, establishing robust pedagogical frameworks and comprehensive teacher preparation models [4]. Simultaneously, the broader field of educational technology has witnessed significant advances in artificial intelligence applications, encompassing adaptive learning systems to intelligent tutoring platforms [5]. These parallel developments suggest substantial potential for convergence.

The challenge of preparing teachers for GeoAI integration extends far beyond simple technological literacy. Our statistical analysis indicates that current research demonstrates a theory-to-empirical ratio of 0.471, suggesting inadequate theoretical foundation for several critical areas. Teachers require deep understanding of how artificial intelligence algorithms process spatial data, recognition of potential biases and limitations in AI-driven geographic analysis, and development of pedagogical approaches that promote critical evaluation of automated spatial insights. Furthermore, educators must navigate complex ethical considerations surrounding data privacy, algorithmic transparency, and equitable access to advanced geospatial technologies.

Despite the apparent need for systematic research on GeoAI teacher education, our analysis reveals that only 25 papers from a search of 1,471 publications directly address this intersection. This represents a convergence gap of unprecedented magnitude in educational technology research, where well-established domains remain largely disconnected despite clear potential for integration and mutual enrichment. The implications of this gap extend beyond academic considerations to include practical concerns about teacher preparation, curriculum development, and educational equity in an increasingly AI-enhanced world.

This study addresses these challenges through a bibliometric analysis designed to map the current landscape of research at the intersection of GeoAI and teacher education. Our methodology employs advanced network analysis techniques to examine not only the direct intersection of these fields but also the broader ecosystem of related research that provides foundational knowledge for understanding convergence patterns and opportunities.

Conceptual Framework and Literature Background

This section establishes the theoretical foundations for our bibliometric analysis by reviewing scholarship across three converging domains: GeoAI applications in education, technology integration in geography education, and artificial intelligence in teacher preparation. We then introduce the convergence science frameworks that inform our analytical approach and interpretation of findings.

Defining GeoAI in Educational Context

GeoAI represents the convergence of artificial intelligence techniques with geographic information science, creating powerful tools for automated spatial analysis, pattern recognition, and predictive modeling [6]. Our keyword analysis reveals that the term "geospatial artificial intelligence" appears in 120 publications with an average publication year of 2023.42, indicating the recent emergence and rapid growth of this domain. In educational contexts, GeoAI encompasses applications ranging from automated geographic feature extraction for student projects to intelligent spatial decision support systems that help learners understand complex environmental processes.

The integration of GeoAI into geography education builds upon established frameworks for technology integration, particularly the Technological Pedagogical Content Knowledge (TPACK) model [7]. Recent scholarship has extended TPACK to address AI-specific considerations. An et al. [8] propose an AI-TPACK framework that distinguishes between human teacher knowledge and machine teacher knowledge dimensions, recognizing that AI integration requires educators to orchestrate human-AI pedagogical collaboration rather than simply adding technological tools. Mimoudi and Mokhtari [9] further elaborate this through their AIA-PCEK framework, which emphasizes AI-agent literacy, ethical oversight capabilities, and adaptive content management as essential components of teacher knowledge in AI-enhanced environments.

Empirical investigations of AI-TPACK development reveal complex relationships among contributing factors. Xu et al. [10] demonstrate that preservice teachers' self-efficacy influences AI attitudes, which in turn predict AI-TPACK acquisition, suggesting that affective dimensions significantly shape technological pedagogical knowledge development. Wang and Xing [11] identify influencing factors for AI-enhanced TPACK among preservice teachers, while Fan et al. [12] propose an AIPACK training model specifically designed for elementary teachers integrating AI into non-STEM subjects. These frameworks provide theoretical resources for understanding how geography educators might develop competencies for GeoAI integration, though our analysis reveals limited application of such frameworks within geography education specifically.

Contemporary GeoAI applications in educational settings demonstrate both promise and complexity. Machine learning algorithms can process vast spatial datasets to identify patterns invisible to human analysts, yet these same algorithms may perpetuate biases present in training data or make decisions through processes that remain opaque to educators and students alike. Bautista et al. [13] emphasize that effective AI integration requires teachers to understand the interconnection between technical and ethical knowledge dimensions. This dual nature of AI technology – powerful yet potentially problematic – necessitates pedagogical approaches that emphasize critical evaluation alongside technical proficiency.

The emergence of generative AI has introduced additional considerations for geography education. Lee [14] examines the potential and challenges of ChatGPT for geography instruction, identifying opportunities for supporting geographic inquiry while noting concerns about accuracy, critical thinking development, and appropriate pedagogical integration. With GeoAI capabilities expand to include natural language interfaces and automated spatial reasoning, teacher preparation must address not only technical operation but also critical evaluation of AI-generated geographic insights.

Evolution of Technology Integration in Geography Education

Geography education has demonstrated notable success in integrating digital technologies, particularly through widespread adoption of GIS. Our analysis of 470 papers in geography teacher education reveals average publication years clustering around

2019.48 for foundational concepts, indicating a mature field with established theoretical and practical foundations [15]. This integration process provides valuable insights for understanding how emerging technologies might be incorporated into geographical pedagogy.

The development of spatial thinking competencies has been central to geography education's technology integration efforts. Shook et al. [16] articulate a CyberGIScience Literacy framework identifying eight core competency areas essential for navigating technologically rich geospatial environments: spatial concepts, data models, analytical methods, geovisualization, programming fundamentals, big data handling, cyberinfrastructure, and societal implications. This framework provides a foundation for understanding the expanded competencies that GeoAI integration may require.

Spurná et al. [17] introduce the Geographical Concepts Chessboard as a framework for developing geographical thinking in teacher education, organizing conceptual understanding around Place, Space, Environment, and Earth systems. Their approach emphasizes that geographical thinking requires systematic connection between content knowledge and procedural understanding – a principle equally applicable to GeoAI integration where teachers must connect AI capabilities with geographic concepts and pedagogical purposes.

Empirical research demonstrates the effectiveness of GIS-based approaches for developing spatial thinking. Handoyo et al. [18] report significant improvement in critical thinking skills through spatial based learning using Quantum GIS, providing evidence that technology-mediated spatial instruction can enhance higher-order cognitive outcomes. Jo and Bednarz [19] developed the Spatial Thinking Ability Test to assess spatial reasoning, while Huynh and Sharpe [20] created instruments for measuring geospatial thinking expertise, establishing assessment foundations that might inform evaluation of GeoAI-enhanced learning.

The GeoCapabilities approach articulated by Fargher [21] emphasizes that geography education should provide access to "powerful disciplinary knowledge" that enables students to think geographically about significant questions. This perspective suggests that GeoAI integration should be evaluated not merely by technical sophistication but by its contribution to developing geographic understanding and spatial reasoning capabilities.

Research from diverse national contexts reveals varied patterns of geospatial technology adoption. Mathews and Wikle [22] document the evolution of GIS education programs, identifying both advances and persistent challenges. Abdimanapov et al. [23] examine technology integration for achieving learning objectives in Kazakhstan, demonstrating how system-activity approaches can develop critical thinking through geographic instruction. These studies highlight that successful technology integration requires attention to local educational contexts, curriculum requirements, and teacher preparation systems – considerations equally relevant for GeoAI adoption.

Artificial Intelligence in Teacher Education

The broader field of AI in education has experienced rapid growth, creating both opportunities and challenges for teacher preparation programs. Our analysis identifies

382 papers addressing AI in teacher education, with significant temporal concentration in the post-2020 period reflecting the acceleration of AI development and educational application. This growing body of scholarship provides theoretical and empirical resources for understanding how teachers might be prepared for AI-enhanced instruction.

AI literacy frameworks have emerged as foundational resources for teacher preparation. Long and Magerko [24] established a foundational framework identifying competencies for understanding and critically evaluating AI systems. Ng et al. [25] elaborated a four-dimensional AI literacy model encompassing technical understanding, critical evaluation, ethical awareness, and application capabilities. These frameworks inform understanding of what teachers need to know about AI, though they require extension to address domain-specific applications such as GeoAI.

Recent scholarship has developed increasingly sophisticated AI literacy models. Allen and Kendeou [26] propose ED-AI Lit, an interdisciplinary framework identifying six components essential for educational AI literacy: foundational knowledge, application understanding, critical evaluation, ethical reasoning, adaptive learning, and societal implications. Sattelmaier and Pawlowski [27] present the AIware Competency Model with 98 AI-related competencies for K-12 education, developed through systematic review and practitioner consultation. Eyal [28] introduces an Adaptive AI Literacy Model emphasizing contextual fitness and dynamic development, recognizing that AI literacy must evolve in response to rapidly changing technological landscapes.

Teacher agency in AI integration has emerged as a critical concern. Chiu et al. [29] analyze how teachers exercise agency in integrating AI, finding that effective integration requires not merely technical competence but pedagogical judgment about appropriate AI applications for specific learning objectives. This emphasis on teacher agency aligns with concerns raised in geography education about ensuring that technology serves pedagogical purposes rather than driving curriculum.

Professional development approaches for AI integration are receiving increasing attention. Kohnke et al. [30] examine microlearning approaches for generative AI integration in preservice teacher education, finding that brief, focused learning modules can effectively build AI competencies within the constraints of teacher preparation programs. Research on K-12 AI education [31–33] provides insights into pedagogical approaches that might inform teacher preparation for AI-enhanced geography instruction.

Theoretical Foundations for Convergence Analysis

Understanding the extreme convergence gap documented in our analysis requires theoretical frameworks that explain how interdisciplinary fields develop and why integration between established domains may remain limited despite apparent synergies. This section introduces convergence science perspectives that inform both our analytical approach and interpretation of findings.

Petersen et al. [34] distinguish between two modes of scientific convergence: social convergence (cross-disciplinary collaboration among researchers from different fields) and conceptual convergence (cross-topic knowledge integration where research draws on concepts from multiple domains). Their analysis of grand challenge research demonstrates that publications exhibiting both modes of convergence receive approximately 16% higher citation rates than single-mode publications, suggesting that deep interdisciplinary integration offers substantial benefits for knowledge production. The extreme Gap Index of 0.941 we observe indicates not merely limited publication volume, but more fundamentally reflects absence of the collaborative infrastructure and shared conceptual vocabulary necessary for meaningful integration.

Li et al. [35] trace the evolution of interdisciplinary research through pre-disciplinary, disciplinary, and post-disciplinary phases, arguing that contemporary challenges increasingly require movement beyond traditional disciplinary boundaries. Their analysis suggests that fields may resist convergence when institutional structures, reward systems, and professional identities remain organized around disciplinary boundaries. The fragmented network structures we observe in co-authorship and citation patterns may reflect such institutional barriers to cross-domain collaboration.

Cross-disciplinary knowledge co-creation faces substantial challenges even when researchers recognize potential synergies. Pennington [36] identifies requirements for productive cross-disciplinary collaboration including mutual knowledge development, shared conceptual frameworks, and extended exploratory phases for developing common understandings. Pennington [37] further emphasizes that bridging disciplinary divides requires co-creating research ideas through sustained collaborative engagement rather than merely combining existing expertise. The rapidity of GeoAI emergence (FES = 70.6) may paradoxically impede convergence, as the accelerated timeline compresses the exploratory phase that Pennington [37] identifies as essential for developing shared frameworks.

Aagaard-Hansen [38] identifies methodological and epistemological obstacles that complicate cross-disciplinary research, including incompatible research traditions, different standards of evidence, and contrasting theoretical orientations. These challenges may help explain why geography education (with traditions emphasizing spatial thinking and place-based learning), AI research (with traditions emphasizing algorithmic development and technical performance), and teacher education (with traditions emphasizing pedagogical practice and professional development) have developed largely independently despite potential complementarities.

Network analysis of scientific collaboration provides tools for understanding convergence patterns. Hao et al. [39] demonstrate how structural holes in co-authorship networks represent opportunities for knowledge brokerage, where researchers positioned at the boundaries between disconnected communities can facilitate information flow and integration. The fragmented network structures we observe suggest substantial opportunities for such knowledge brokerage between geography education, AI education, and spatial thinking research communities.

These convergence science perspectives inform our analytical approach in several ways. First, they suggest that the Gap Index should be interpreted not merely as a measure of publication volume but as an indicator of collaborative infrastructure and conceptual integration. Second, they highlight the importance of examining network structures to identify potential intervention points for accelerating convergence.

Third, they caution that rapid field emergence may create challenges for developing the sustained collaborative relationships necessary for deep integration.

Methodology

Research Design and Analytical Framework

This study employs bibliometric analysis methods to map the research landscape at the intersection of GeoAI and geography teacher education. Bibliometric approaches enable systematic examination of publication patterns, citation networks, and collaborative structures that characterize scientific fields [40]. Our analytical framework adapts approaches from convergence science [34] to assess the degree of integration between established research domains.

The research design examines five interconnected datasets representing the broader ecosystem surrounding GeoAI teacher education: (1) geography teacher education, (2) AI teacher education, (3) spatial thinking education, (4) GIS teacher education, and (5) the direct intersection of AI and geography education. This multi-dataset approach enables assessment of how well-established foundational fields connect with emerging intersection research, providing insight into convergence patterns and opportunities.

Data Collection and Search Strategy

Data collection was conducted using the Dimensions database [41], accessed on March 15, 2025. The temporal scope encompasses publications from January 2010 through March 2025, capturing both the maturation of foundational domains and the recent emergence of intersection research. Table 1 presents the search queries and resulting publication counts for each dataset.

Table 1 Search strategy and dataset composition. Data extracted from Dimensions database on March 15, 2025. Temporal scope: January 2010–March 2025.[a]

No	Dataset	Search query	Papers
1	Geography teacher education	"geography teacher education" OR "geography teacher training"	470
2	AI teacher education	"artificial intelligence teacher education" OR "AI teacher training"	382
3	Spatial thinking	"spatial thinking education" OR "spatial reasoning instruction"	312
4	GIS teacher education	"GIS teacher education" OR "geographic information systems training"	282
5	AI + geography education	("artificial intelligence" OR "AI" OR "machine learning") AND "geography education"	25
	Total unique		**1,471**

[a]2025 data reflects publications indexed by March 15, 2025; full-year figures unavailable at time of data extraction.

The search strategy was designed to capture both explicit and implicit references to the target domains while minimizing false positives. Boolean operators enabled combination of related terms, and quotation marks ensured phrase matching for multi-word concepts. All searches were limited to peer-reviewed publications including journal articles, conference papers, and book chapters.

Statistical Analysis and Convergence Metrics

Network analysis was conducted using VOSviewer software [40], generating co-authorship networks, keyword co-occurrence maps, and citation relationship visualizations. The analysis employed fractional counting to normalize for varying author numbers and applied minimum thresholds to ensure network readability while capturing significant relationships.

Convergence Gap Index

We developed a Gap Index to quantify the degree of disconnection between foundational domains and their intersection. The Gap Index is calculated as:

$$\text{Gap Index} = 1 - \frac{n_{\text{intersection}}}{\sqrt{n_A \times n_B}} \tag{1}$$

where $n_{\text{intersection}}$ represents publications in the intersection domain and n_A and n_B represent publications in the contributing foundational domains. The geometric mean in the denominator accounts for asymmetric development across contributing domains and prevents overweighting of larger fields when assessing convergence potential [42].

Table 2 provides interpretive benchmarks for Gap Index values, derived from comparative analysis of interdisciplinary fields.

Table 2 Gap Index interpretation benchmarks. Classifications derived from analysis of interdisciplinary field development patterns [34, 43].

Classification	**Range**	**Interpretation**
Integrated field	< 0.30	Mature interdisciplinary domain with established collaborative infrastructure
Moderate gap	0.30–0.60	Developing field with active integration efforts
Substantial gap	0.60–0.80	Emerging area with limited but growing connectivity
Severe gap	0.80–0.90	Early-stage convergence with minimal integration
Extreme gap	> 0.90	Pre-convergence state lacking collaborative infrastructure

For context, Chakraborty [43] found that interdisciplinary computer science research typically exhibits gap values ranging from 0.45 to 0.75, while Petersen et al. [34] report that balanced interdisciplinary research approximates 0.50. Our observed Gap Index of 0.941 substantially exceeds these benchmarks, indicating a pre-convergence state fundamentally different from typical patterns of interdisciplinary field development.

Field Emergence Score

To characterize the developmental trajectory of intersection research, we calculated a Field Emergence Score (FES) adapting keyword-derived indicators for emerging topic detection [44, 45]:

$$\mathrm{FES} = \frac{P_{\mathrm{recent}}}{P_{\mathrm{total}}} \times 100 \tag{2}$$

where P_{recent} represents publications from the most recent three years (2023–2025) and P_{total} represents total publications in the dataset.

Table 3 provides interpretive guidance for FES values.

Table 3 Field Emergence Score interpretation. Classifications adapted from bibliometric analysis of emerging research fields [45, 46].

Classification	Range	Interpretation
Mature/stable field	< 30	Established domain with consistent publication rates
Developing field	30–50	Growing area with steady expansion
Rapidly emerging	50–70	Field in acceleration phase
Very rapid emergence	> 70	Real-time field emergence from nascent base

Our observed FES of 70.6 for the intersection domain indicates very rapid emergence, suggesting that the field is developing in real-time with the majority of foundational work appearing within the most recent three-year period.

Additional metrics include the Herfindahl Index for geographic concentration, network density measures for collaboration patterns, citation half-life for knowledge currency, and thematic clustering coefficients derived from keyword co-occurrence analysis. These complementary measures provide multidimensional characterization of field development patterns.

Methodological Limitations and Validation

Bibliometric analysis, while providing systematic and reproducible assessment of research landscapes, involves inherent limitations that influence interpretation of findings. This section addresses key limitations and their implications for our conclusions.

Database Coverage Limitations

Our reliance on the Dimensions database introduces coverage considerations. Singh et al. [47] demonstrate that Dimensions provides broader coverage than Web of Science or Scopus for recent publications but may underrepresent certain geographic regions and publication types. Mongeon and Paul-Hus [48] document systematic biases in major bibliometric databases, including underrepresentation of non-English publications and scholarship from Global South institutions. These biases may affect our geographic distribution findings, potentially underestimating research activity in regions with lower database coverage.

Despite these limitations, we selected Dimensions for its comprehensive coverage of recent publications – particularly important given the rapid emergence of our target domain – and its inclusion of diverse publication types beyond traditional journal articles. The convergence patterns we observe are unlikely to be artifacts of database selection, as the extreme magnitude of the gap (0.941) substantially exceeds any plausible margin attributable to database coverage limitations.

Terminological Constraints

Our search strategy, while systematic, may not capture all relevant research. Alternative formulations of key concepts (e.g., "spatial AI", "intelligent GIS", "geointelligence") may not be captured by our queries. The rapidly evolving terminology of AI research presents particular challenges, as novel terms may emerge faster than search strategies can accommodate. Kumpulainen and Seppänen [49] recommend multi-database approaches to address such limitations, a strategy we recommend for future validation studies.

Additionally, the interdisciplinary nature of GeoAI teacher education means that relevant contributions may appear in venues not typically associated with geography education or educational technology, potentially escaping our search parameters. The low convergence coefficient (1.5%) we observe may partly reflect terminological fragmentation across communities using different vocabulary to describe related phenomena.

Publication Type Limitations

Our focus on peer-reviewed academic publications excludes other forms of knowledge production that may be particularly important in rapidly evolving technological domains. Conference presentations, technical reports, practitioner-generated resources, and grey literature may provide insights into implementation practices and emerging approaches not yet captured in formal scholarly literature. This limitation may result in underestimation of actual activity levels, particularly for practice-oriented research.

Temporal Considerations

The rapid pace of AI development means that the research landscape evolves more quickly than traditional publication cycles can capture. Our temporal analysis reveals that 75% of key terms emerged post-2023, suggesting that recent developments in generative AI and large language models may not yet be fully reflected in the scholarly literature. The 2025 data in our analysis reflects only publications indexed by March 15, 2025; apparent gaps in recent data may reflect indexing delays rather than absence of publication activity.

Validation Approach

To assess robustness of our core findings, we conducted sensitivity analyses varying search parameters and threshold values. The magnitude of the convergence gap remained stable across reasonable parameter variations, supporting confidence in this central finding. We also compared our results with findings from related bibliometric studies in educational technology [50], finding consistent patterns of geographic concentration and limited cross-domain integration in emerging interdisciplinary fields.

Despite the limitations outlined above, we maintain confidence in our core findings regarding the extreme convergence gap, the rapid emergence of intersection research, and the geographic concentration of current scholarship. These findings are robust across analytical variations and consistent with patterns observed in related domains. However, we recommend future validation studies employing multi-database approaches, expanded search strategies, and longitudinal tracking to refine understanding of field development trajectories.

Results

Overall Research Landscape and Convergence Gap

The bibliometric analysis reveals a stark convergence gap between established foundational domains and their intersection. Figure 1 presents the keyword co-occurrence network across all datasets, illustrating the fragmented nature of current research.

Cluster 1 (red) contains GeoAI technical terms including "machine learning", "deep learning", and "spatial analysis." Cluster 2 (green) encompasses geography education concepts such as "geographic literacy", "place-based learning", and "fieldwork." Cluster 3 (blue) represents AI teacher education terminology including "AI literacy", "teacher professional development", and "pedagogical content knowledge." Cluster 4 (yellow) contains educational technology terms. Cluster 5 (purple) addresses assessment and learning outcomes.

Note the minimal bridging connections between clusters, visually instantiating the extreme convergence gap (0.941). Following Hao et al. [39], these structural holes represent opportunities for knowledge brokerage where researchers positioned at cluster boundaries could facilitate integration across currently disconnected domains.

Situated within the convergence science framework introduced in Section "Theoretical Foundations for Convergence Analysis", this gap reflects what Petersen et al. [34] characterize as absence of both social convergence and conceptual convergence. For comparative context, Chakraborty [43] found that interdisciplinary computer science research typically exhibits gap values ranging from 0.45 to 0.75. Our observed value of 0.941 indicates a pre-convergence state fundamentally different from even early-stage interdisciplinary development.

Following Ghosh and Kshitij [51], network density below 0.6 indicates fragmented research communities with limited knowledge sharing. Our observed network structures exhibit characteristics isolated research clusters with limited bridging connections. Rather than viewing this fragmentation as merely a limitation, we interpret these structural holes as opportunities for strategic intervention, where researchers positioned at the boundaries between disconnected clusters could serve as knowledge brokers facilitating field convergence.

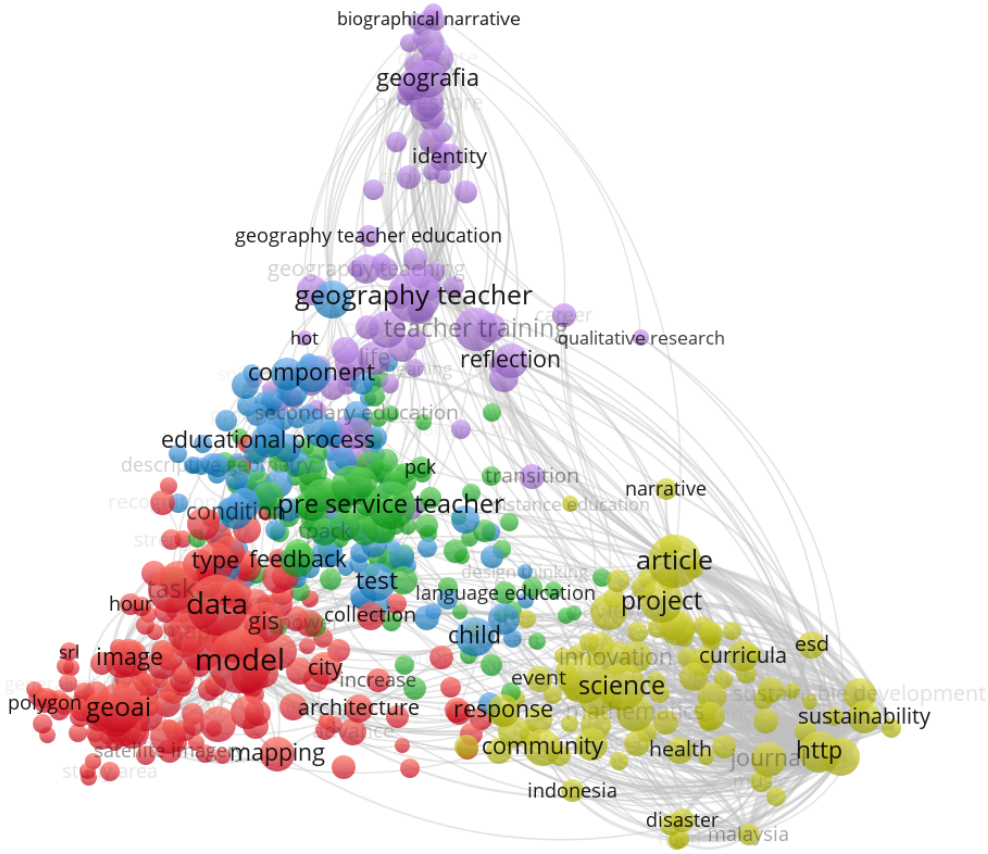

Fig. 1 Keyword co-occurrence network across all datasets: network visualization generated using VOSviewer with fractional counting. Node size proportional to keyword occurrence frequency; minimum threshold = 5 occurrences. Edge thickness indicates co-occurrence strength; minimum threshold = 3 co-occurrences. Colors represent cluster membership determined by modularity optimization algorithm.

Temporal Evolution and Field Emergence

Analysis of publication trends reveals pronounced temporal concentration with 87.5% of core intersection research appearing post-2020.

Geographic education terms such as "spatial thinking" and "GIS education" cluster in blue/green (earlier), while AI-specific terminology including "ChatGPT", "large language models", and "generative AI" appear in orange/red (most recent). This temporal stratification indicates that researchers entering the intersection must bridge not only disciplinary boundaries but also substantial temporal disconnection between mature geographic education literature and nascent AI education scholarship.

The Field Emergence Score of 70.6 indicates very rapid emergence, with over 70% of intersection publications appearing within the most recent three years. This pattern suggests the field is developing in real-time rather than through gradual evolution from established foundations. Drawing on Glänzel and Thijs [45] analysis of emerging topic detection, such rapid emergence typically indicates a field entering a consolidation phase where enhanced theoretical framework development becomes critical for sustained growth.

The temporal analysis reveals that 75% of AI-specific keywords emerged post-2023, reflecting the rapid technological advancement in generative AI and large language models. Keywords such as "ChatGPT" (173 occurrences, average year 2024.14) and "generative AI" (89 occurrences, average year 2024.31) demonstrate how technological events reshape research landscapes in ways that established domains must accommodate. Following Li et al. [35], this pattern suggests asymmetric integration dynamics requiring deliberate strategies to connect established geographic education knowledge with rapidly evolving AI capabilities.

Table 4 presents the temporal distribution of publications across datasets.

Table 4 Temporal distribution of publications by dataset. Data extracted from Dimensions database on March 15, 2025.[a]

No	Dataset	2010–2015	2016–2019	2020–2022	2023–2025	Total
1	Geography teacher education	112	134	118	106	470
2	AI teacher education	28	47	89	218	382
3	Spatial thinking	89	78	72	73	312
4	GIS teacher education	71	82	68	61	282
5	AI + geography education	1	2	4	18	25

[a]Values for 2025 reflect publications indexed by extraction date (March 15, 2025); apparent lower values in recent periods may reflect indexing delays rather than decreased publication activity.

Geographic Distribution and Collaboration Patterns

The analysis reveals significant geographic concentration in research production. The Herfindahl Index of 0.208 indicates moderate concentration, with research activity clustered among developed nations. Figure 2 presents the international collaboration network. The network density of 0.40 falls below the 0.6–0.8 range characteristic of integrated research communities [51]. The visualization exhibits characteristics of what Cruz-Ramírez et al. [52] term "archipelago structure" – isolated clusters with limited bridging connections. The United States and United Kingdom form a densely connected core, while Global South countries appear as peripheral nodes with limited integration into the primary research network.

The geographic distribution analysis reveals that developed countries produce 66.7% of core intersection research, with the United States contributing the highest volume followed by the United Kingdom, Australia, and Germany. Global South representation remains limited, with only 33.3% of publications originating from developing nation contexts. Limited international collaboration is particularly significant given the global nature of climate and environmental challenges that GeoAI could help address. The zero-citation status of several Global South publications may reflect what

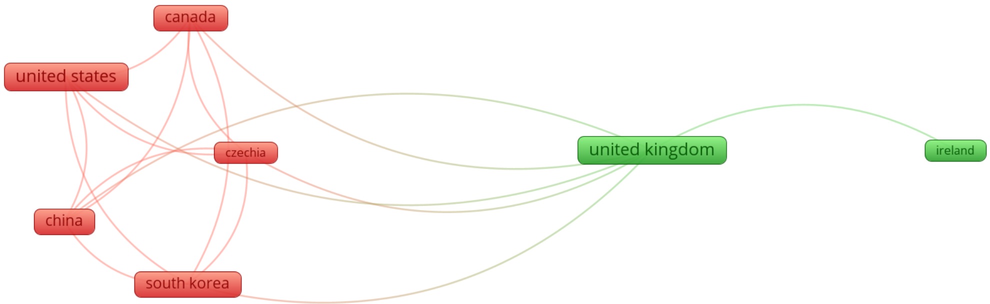

Fig. 2 International collaboration network based on co-authorship patterns. Nodes represent countries with research output in GeoAI teacher education; node size proportional to publication volume. Edge thickness indicates collaboration intensity measured by co-authored publications. Network density = 0.40, indicating fragmented international collaboration below integration thresholds.

Mongeon and Paul-Hus [48] identify as systematic biases in citation patterns rather than quality limitations. Current network patterns suggest that emerging frameworks may primarily reflect Global North perspectives and resource contexts.

Institutional Leadership and Research Networks

Analysis of institutional contributions reveals concentration among major research universities. Figure 3 presents the institutional collaboration network.

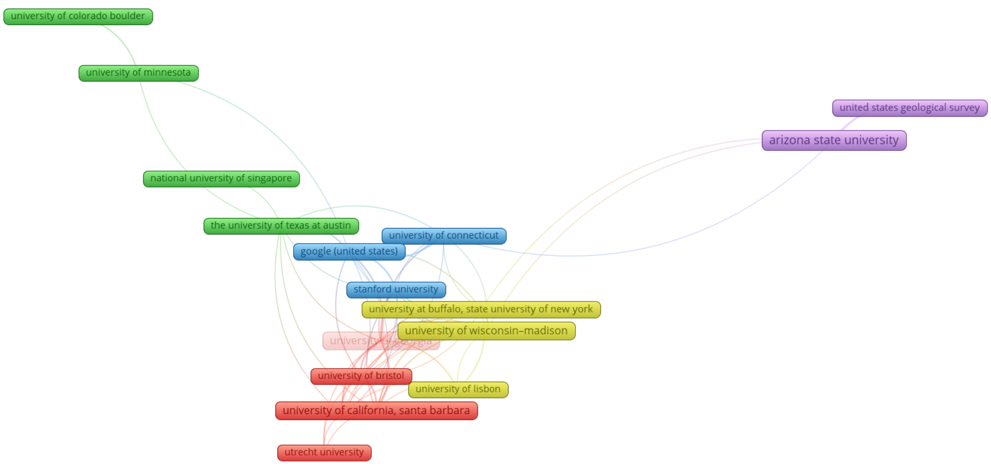

Fig. 3 Institutional collaboration network. Nodes represent institutions with multiple publications in the intersection domain; node size proportional to publication count. Edge thickness indicates collaboration frequency. Colors represent cluster membership determined by modularity optimization.

The institutional analysis reveals that ten institutions account for approximately 45% of intersection publications, indicating significant concentration of research capacity. Universities with established programs in both geography education and educational technology demonstrate higher publication volumes, suggesting that institutional infrastructure supporting cross-domain collaboration facilitates intersection research.

University of Georgia occupies a central broker position with 11 collaboration links spanning multiple clusters, indicating potential for facilitating knowledge flow across research communities. Google appears as the sole industry representative (7 publications, 10 collaboration links), suggesting limited but potentially influential industry-academic partnerships. Five distinct research communities are visible, with limited cross-cluster collaboration. Following Hao et al. [39], institutions at cluster boundaries occupy structural positions enabling them to facilitate information flow between otherwise disconnected research communities.

Drawing on Pennington [37] analysis of cross-disciplinary collaboration, highly connected institutions occupy structural positions that could facilitate broader field development. However, productive cross-disciplinary collaboration requires extended engagement that many institutional incentive structures do not adequately support, potentially limiting the field-building potential of current institutional leaders.

Thematic Analysis and Research Priorities

Content analysis of intersection publications reveals limited thematic diversity, with research concentrating in a few primary areas. Table 5 presents the thematic distribution.

Table 5 Thematic distribution of intersection research (n=25).

Theme	Papers	Average citations	Representative focus
Student outcomes	7	13.2	Learning effects of AI-enhanced geography instruction
Technology integration	6	3.6	Implementation approaches and barriers
Teacher preparation	4	5.8	Professional development models
Curriculum development	4	2.1	Content and sequence design
Theoretical frameworks	2	4.3	Conceptual model development
Assessment approaches	2	1.5	Evaluation methods and instruments

The dominance of student outcome research (7 papers, 13.2 average citations) over theoretical framework development (2 papers, 4.3 average citations) indicates a field prioritizing empirical validation over conceptual advancement. While emphasis on evidence-based practice represents a valuable strength, the pattern aligns with what Chiu et al. [29] identify as prioritization of teacher agency and pedagogical adaptation over technical capability development. The low convergence coefficient (1.5%) suggests that researchers may not be building systematically upon established theoretical foundations from contributing domains [53].

Citation Network Analysis

Citation analysis reveals asymmetric knowledge flows between domains. Intersection research cites geography education literature at higher rates (23%) than AI teacher education (15%) or spatial thinking research (8%), suggesting that current intersection work draws more heavily on geographic education traditions than on AI-specific educational scholarship.

The citation half-life of five years indicates relatively rapid knowledge turnover, consistent with the emerging nature of the field. However, the limited citation of foundational AI education scholarship suggests missed opportunities for leveraging existing frameworks and findings that could strengthen theoretical foundations.

Analysis of highly cited publications reveals that empirically grounded studies examining student learning outcomes receive substantially higher citation rates than conceptual or methodological papers. This pattern, while reflecting appropriate emphasis on evidence-based practice, may inadvertently discourage the theoretical development work needed to establish coherent conceptual foundations for the field.

Discussion

This section interprets our bibliometric findings through the theoretical lenses established in Section "Conceptual Framework and Literature Background", connecting empirical patterns to broader scholarship on interdisciplinary convergence, technology integration in education, and global equity in research development. We organize the discussion around four themes: understanding the convergence gap as a systemic phenomenon, implications for field development and theory building, geographic equity considerations with particular attention to Global South contexts, and methodological opportunities for advancing the field.

Understanding the Extreme Convergence Gap

Our analysis reveals an extreme convergence gap (Gap Index = 0.941) that surpasses typical patterns observed in interdisciplinary field development, representing a phenomenon that demands careful theoretical consideration. Situated within the convergence science framework introduced in Section "Theoretical Foundations for Convergence Analysis", this gap reflects what Petersen et al. [34] characterize as absence of both social convergence (cross-disciplinary collaboration) and conceptual convergence (cross-topic knowledge integration). The magnitude of this gap becomes particularly striking when compared to benchmarks from interdisciplinary computer science research, where Chakraborty [43] found typical gaps ranging from 0.45 to 0.75. Our observed value of 0.941 indicates a pre-convergence state fundamentally different from even early-stage interdisciplinary development.

The statistical analysis reveals multiple reinforcing factors contributing to gap persistence that extend beyond simple developmental lag. The theory-empirical ratio of 0.471 indicates insufficient theoretical foundation development, while the convergence coefficient of 1.5% demonstrates minimal conceptual overlap between domains. Drawing on Pennington [37] analysis of cross-disciplinary knowledge co-creation, these metrics suggest that the gap represents structural challenges in knowledge integration – including absence of shared conceptual vocabulary, methodological incompatibilities, and limited collaborative infrastructure – that require systematic intervention rather than assuming natural convergence will occur over time.

The temporal concentration (87.5% post-2020) combined with high growth volatility (CAGR 25.99% but irregular patterns) suggests that current development may be driven more by technological advancement and media attention than by systematic educational research agenda. This pattern aligns with Li et al. [35] observation that external pressures can accelerate interdisciplinary movement while potentially undermining the sustained engagement necessary for deep integration. The dominance of generative AI terminology ("ChatGPT" with 173 occurrences, average year 2024.14) illustrates how technological events can rapidly reshape research landscapes in ways that may not reflect systematic field development.

Understanding this convergence gap as a systemic phenomenon rather than a simple research limitation suggests that addressing it requires coordinated efforts across multiple levels of the research ecosystem. The field emergence score of 70.6 indicates substantial developmental potential, but realizing this potential requires attention to what Aagaard-Hansen [38] identified as key factors for successful cross-disciplinary collaboration: mutual knowledge development, adequate time for exploratory phases, and conducive research management. The rapidity of GeoAI emergence may paradoxically impede convergence by compressing the exploratory phases that enable researchers to develop shared frameworks and collaborative relationships.

Implications for Field Development and Theory Building

The extreme convergence gap identified in this analysis has profound implications for how the field might develop coherent theoretical frameworks and sustainable research programs. Our findings suggest that current approaches, which demonstrate limited cross-domain integration and weak theoretical foundations, may be insufficient for supporting long-term field development or for generating knowledge that transfers effectively across diverse educational contexts.

The dominance of student outcome research (13.2 average citations) over theoretical framework development (4.3 average citations) indicates a field prioritizing empirical validation over conceptual advancement. While this emphasis on evidence-based practice represents a valuable strength, the pattern reflects what Petersen et al. [34] term a "convergence shortcut" – cross-topic exploration without the deeper cross-disciplinary collaboration that enables theoretical synthesis. Without stronger theoretical frameworks grounded in sustained interdisciplinary engagement, empirical findings may remain isolated and context-specific rather than contributing to generalizable understanding.

The AI-TPACK extensions reviewed in Section "Defining GeoAI in Educational Context" offer promising directions for theoretical development. An et al. [8] framework distinguishing human teacher and machine teacher knowledge dimensions provides conceptual resources for understanding how educators might orchestrate human-AI pedagogical collaboration in geography classrooms. Similarly, Mimoudi and Mokhtari [9] AIA-PCEK framework emphasizes ethical oversight and adaptive content management as essential components of teacher knowledge in AI-enhanced environments. However, our citation analysis reveals that these recent frameworks have not yet achieved integration into GeoAI teacher education research, representing missed opportunities for theoretical grounding.

The spatial thinking literature offers additional theoretical resources that remain underutilized in current research. Spurná et al. [17] Geographical Concepts Chessboard and Shook et al. [16] CyberGIScience Literacy framework provide sophisticated conceptualizations of geographic thinking that could inform understanding of how GeoAI tools might support or transform spatial cognition development. The asymmetric citation patterns we observe – with intersection research citing geographic education literature (23%) more than AI education scholarship (15%) and spatial thinking research (8%) – suggest that current work draws more heavily on geographic education traditions while underutilizing frameworks from AI literacy and spatial cognition that could strengthen theoretical foundations.

Addressing theoretical development needs requires recognition that GeoAI integration introduces qualitatively different challenges from previous educational technology adoption efforts. The opacity of AI systems, potential for algorithmic bias, and capacity for autonomous decision-making require novel pedagogical frameworks rather than simple adaptation of existing models. As Eyal [28] emphasizes through the Adaptive AI Literacy Model, AI literacy must evolve dynamically in response to rapid technological change while maintaining contextual fitness to specific professional domains. For geography education, this suggests that generic AI literacy may be insufficient; educators require domain-specific AI competencies that integrate geographic content knowledge with AI capabilities and critical evaluation skills.

Geographic Equity and International Development Considerations

The geographic concentration identified in our analysis (Herfindahl Index = 0.208) raises fundamental questions about whose perspectives shape field development and whether emerging frameworks will serve diverse global contexts. This section substantially expands our analysis of equity implications, examining how current research patterns may inadvertently disadvantage educational systems in the Global South while failing to address contexts where GeoAI applications could have greatest impact.

Patterns of Global North Dominance

Our co-authorship analysis reveals that developed countries produce 66.7% of core intersection research, with the United States and United Kingdom demonstrating highest publication volumes and citation impact. This pattern reflects broader inequities in global knowledge production that have been extensively documented in educational technology research [54, 55]. However, the concentration is particularly consequential for GeoAI teacher education given the field's potential relevance for addressing spatial challenges – including climate adaptation, disaster management, and sustainable development – that disproportionately affect Global South communities.

The limited international collaboration we observe (network density = 0.40 across only seven countries with documented contributions) suggests that current research development occurs largely within national silos rather than through cross-border partnerships that might incorporate diverse perspectives. Herrera-Seda and Walton [56] analysis of teacher education research from Latin America demonstrates that scholarship from Global South contexts often emphasizes different priorities – including community engagement, resource constraints, and cultural responsiveness – than research from developed country institutions. The absence of such perspectives in GeoAI teacher education research may limit the field's capacity to develop frameworks relevant to majority-world educational contexts.

Barriers to Technology Integration in Resource-Constrained Contexts

Research from diverse national contexts reveals that barriers to geospatial technology adoption extend beyond equipment costs to encompass systemic challenges that current GeoAI research largely ignores. Shakhislam et al. [57] study of geography education in Kazakhstan identified multiple compounding barriers including insufficient teacher training, time constraints within existing curricula, lack of technical support infrastructure, and misalignment between available technologies and national educational standards. These findings echo patterns documented across developing contexts where technology integration initiatives frequently fail not due to equipment limitations but due to inadequate attention to implementation ecosystems.

Bernhäuserová et al. [58] comprehensive analysis of barriers to GIS adoption in secondary geography education provides a useful typology that illuminates challenges likely to affect GeoAI integration. They distinguish between first-order barriers (resource access, infrastructure limitations), second-order barriers (teacher beliefs, pedagogical knowledge, confidence), and the "third-order barriers" conceptualized by Tsai and Chai [59] – design thinking limitations that prevent teachers from leveraging technology for transformative pedagogy rather than mere substitution of traditional practices. Significantly, third-order barriers may be particularly pronounced in contexts where professional development opportunities are limited and teachers lack exposure to models of innovative technology integration.

Al-Barakat et al. [60] examination of factors affecting technology use in Middle Eastern educational contexts found that institutional support, administrative encouragement, and alignment with assessment systems significantly influenced teachers' technology integration practices beyond individual competency or resource availability. These findings suggest that GeoAI teacher education research must attend to systemic factors that current frameworks – largely developed in well-resourced institutional contexts – may inadequately address.

Implications for Equitable Field Development

The patterns documented above suggest that current GeoAI teacher education research may be developing approaches that exacerbate rather than address educational inequalities. Several mechanisms warrant attention.

First, the emphasis on advanced technological infrastructure and sophisticated AI systems in current research creates implicit assumptions about resource availability that may not hold in majority-world contexts. When research predominantly examines GeoAI integration in well-resourced schools with reliable internet connectivity, adequate computing infrastructure, and robust technical support, the resulting frameworks may have limited applicability to contexts where such conditions do not obtain. Akpan et al. [61] analysis of digital education initiatives in Sub-Saharan Africa demonstrates how technology-focused interventions designed without attention to local constraints frequently fail to achieve intended outcomes or create new forms of educational inequality.

Second, the theoretical frameworks emerging from Global North research may embed cultural assumptions about teaching and learning that limit their transferability. Bingimlas [62] comprehensive review of barriers to technology integration emphasized that successful integration requires alignment with local pedagogical traditions, assessment practices, and educational values. AI-TPACK frameworks developed primarily through research with Western teacher populations may require substantial adaptation – or fundamental reconceptualization – to serve educators working within different pedagogical traditions.

Third, the research priorities reflected in current publication patterns may not address the most pressing needs of Global South educational systems. While developed country research emphasizes sophisticated AI applications and cutting-edge technological capabilities, educators in resource-constrained contexts may benefit more from research addressing foundational questions about geospatial literacy development, low-resource implementation strategies, and approaches that leverage mobile technologies more prevalent in developing regions than desktop computing infrastructure.

Toward More Equitable Research Development

Addressing these equity considerations requires intentional efforts to reshape field development trajectories while the field remains nascent. The field emergence score of 70.6 suggests that there remains opportunity to influence developmental patterns, but this window may close as research traditions become established and citation networks solidify around particular frameworks and approaches.

Specific strategies for promoting more equitable field development include: expanding geographic participation in research production through targeted funding, capacity-building partnerships, and deliberate inclusion of Global South perspectives in international collaborations; ensuring that emerging frameworks explicitly address diverse resource contexts rather than assuming conditions prevalent in well-resourced settings; developing implementation approaches appropriate to different infrastructure realities, including frameworks for effective GeoAI education in low-bandwidth, limited-computing contexts; and prioritizing research questions that address spatial challenges most relevant to developing regions, including climate adaptation, disaster preparedness, and sustainable development planning.

The contradiction between where GeoAI is predominantly researched (Global North) and where its applications may be most urgently needed (regions facing acute spatial challenges often concentrated in the Global South) represents both an ethical concern and a practical limitation of current field development. Without deliberate intervention, the field risks developing sophisticated frameworks of limited relevance to the majority of the world's geography educators and students.

Methodological Innovation and Research Quality Enhancement

The limited methodological diversity identified in our analysis (six primary approaches) suggests substantial opportunities for innovation in research approaches for studying GeoAI integration in geographic education. Current studies appear to rely primarily on descriptive and exploratory methods rather than sophisticated experimental or quasi-experimental designs that could provide stronger evidence for effective practices and theoretical mechanisms.

The citation half-life of five years, combined with the rapid temporal evolution (75% of terms post-2023), suggests that the field faces significant challenges in developing stable knowledge foundations while remaining responsive to rapid technological change. This tension between stability and adaptability requires methodological approaches that can address both immediate implementation needs and long-term theoretical development. Wang and Chai [44] keyword-derived indicators for emerging topic detection provide methodological resources for tracking field evolution, while design-based research approaches could enable iterative framework development responsive to technological change.

Mixed-methods approaches appear particularly promising for addressing the complexity of GeoAI integration, allowing for detailed understanding of implementation processes while providing quantitative evidence of effectiveness. The high impact of student outcome research (13.2 average citations) suggests that the field values empirical validation, but achieving this validation requires more sophisticated methodological approaches than those currently dominating the literature. Longitudinal studies represent a critical need, given the rapid pace of technological change and the importance of understanding sustained implementation effects rather than short-term novelty responses.

Cross-cultural and comparative studies could address the geographic limitations identified in our analysis while building understanding of how contextual factors influence integration approaches and outcomes across diverse educational systems. Such studies would require methodological innovations to enable meaningful comparison across contexts with substantially different educational traditions, resource availability, and technological infrastructure. The development of culturally responsive research methodologies represents both a methodological challenge and an equity imperative for the field.

Research Agenda and Strategic Recommendations

The extreme convergence gap documented in this analysis demands a focused, strategic research agenda rather than diffuse exploration across all potentially relevant topics. This section presents a prioritized research agenda organized by urgency, feasibility, and potential impact, followed by practical recommendations tailored to specific stakeholder groups. Our goal is to provide actionable guidance that can accelerate field convergence while ensuring that emerging frameworks serve diverse educational contexts.

Prioritized Research Directions

Based on our bibliometric findings, we propose five priority research directions ranked according to three criteria: *urgency* (how critically the gap needs addressing based on current field limitations), *feasibility* (whether existing foundations support immediate progress), and *impact potential* (likely influence on field development based on citation patterns and theoretical needs). Table 6 summarizes this prioritization framework.

Table 6 Prioritized research directions for GeoAI teacher education. Rankings based on analysis of current field limitations (urgency), existing research foundations (feasibility), and citation impact patterns (impact potential). Scale: High (H), Medium (M), Low (L).

Rank	Research direction	Urgency	Feasibility	Impact	Key gap addressed
1	Theoretical framework development	H	M	H	Theory-empirical ratio: 0.471
2	Empirical validation studies	H	H	H	Student outcomes: 13.2 citations
3	Teacher preparation models	H	M	M	Only 25 intersection papers
4	Geographic equity research	M	M	H	Herfindahl Index: 0.208
5	Methodological innovation	M	L	M	Six approaches; 5-year half-life

Priority 1: Theoretical framework development. The theory-empirical ratio of 0.471 and low citation impact of theoretical work (4.3 average citations) indicate that the field's most critical need is development of coherent conceptual frameworks that can organize empirical findings and guide systematic research. Key questions include: How should AI-TPACK frameworks be extended to address the unique characteristics of GeoAI? What theoretical constructs best capture the relationship between AI-mediated spatial analysis and development of geographic thinking competencies? Suggested approaches include systematic theoretical synthesis drawing on the AI-TPACK extensions reviewed in Section "Defining GeoAI in Educational Context" [8, 9], combined with empirical validation through design-based research.

Priority 2: Empirical validation studies. Student outcome research achieves highest citation impact (13.2 average citations), indicating strong community demand for empirical evidence. Key questions include: Does GeoAI-mediated instruction enhance, maintain, or constrain development of spatial thinking skills? What learning progressions characterize student development of GeoAI literacy? Suggested approaches include quasi-experimental designs comparing GeoAI-enhanced instruction with traditional approaches, drawing on established spatial thinking measures [19, 20].

Priority 3: Teacher preparation models. With only 25 papers directly addressing AI integration in geography education, fundamental questions about teacher preparation remain unanswered. Key questions include: What knowledge, skills, and dispositions do geography teachers need for effective GeoAI integration? What professional development models most effectively support practicing teachers? Kohnke et al. [30] microlearning approach offers a promising model for scalable professional development.

Priority 4: Geographic equity research. The Herfindahl Index of 0.208 and limited Global South representation indicate significant geographic concentration threatening field legitimacy. Key questions include: How do implementation barriers differ across resource contexts? What pedagogical approaches are most relevant for addressing spatial challenges in Global South contexts? Research should explicitly address the third-order barriers [59] that may be particularly pronounced in contexts with limited professional development infrastructure.

Priority 5: Methodological innovation. Limited methodological diversity (six primary approaches) and short citation half-life (5 years) indicate needs for methodological development. Key questions include: What research methodologies can effectively capture learning processes in rapidly evolving GeoAI environments? How can learning analytics approaches provide insights into student-AI interaction patterns?

Practical Recommendations for Stakeholders

Translating research findings into practice requires attention to the specific contexts and constraints facing different stakeholder groups. This section provides actionable recommendations organized by stakeholder.

Recommendations for Teacher Education Programs

Teacher education programs bear primary responsibility for preparing educators to navigate GeoAI integration. Programs should integrate GeoAI competencies into existing geography methods courses rather than treating AI as separate content. Drawing on AI-TPACK frameworks [8, 10], this integration should address: (a) technical knowledge of how GeoAI systems process spatial data; (b) pedagogical knowledge for facilitating student learning with AI tools; (c) content knowledge connecting AI capabilities to geographic concepts; and (d) critical evaluation skills for assessing AI outputs, biases, and limitations.

Clinical experiences should include opportunities for preservice teachers to observe and practice GeoAI-enhanced instruction. Given the limited prevalence of GeoAI in current classrooms, programs may need to develop simulation environments or partner with innovative school sites. Doering et al. [63] adventure learning approach demonstrates how technology-rich field experiences can develop both technical competencies and pedagogical reasoning.

Programs should build partnerships with geography departments, computer science programs, and educational technology units to provide preservice teachers with interdisciplinary perspectives. Such partnerships align with Pennington [36] emphasis on sustained collaborative relationships for cross-disciplinary learning.

Recommendations for Practicing Teachers and Professional Development Providers

Professional development should progress from foundational AI literacy through geography-specific applications to critical evaluation and ethical reasoning. Kohnke et al. [30] microlearning approach – using brief, focused modules that build progressively – offers a scalable model that accommodates teachers' time constraints.

Given the limited research base, teachers venturing into GeoAI integration need peer support networks for sharing experiences, resources, and problem-solving strategies. Professional organizations in geography education should facilitate communities of practice that connect early adopters across institutional boundaries.

Professional development should emphasize critical evaluation of AI outputs rather than uncritical adoption. Drawing on Allen and Kendeou [26] ED-AI Lit framework, teachers need competencies for identifying potential biases in AI-generated geographic analyses, evaluating appropriateness of AI tools for specific learning objectives, and facilitating student development of critical AI literacy.

Recognizing diverse resource contexts discussed in Section "Geographic Equity and International Development Considerations", professional development should include strategies for effective GeoAI education across infrastructure realities, including approaches leveraging mobile devices and pedagogies that develop spatial AI literacy even when cutting-edge tools are unavailable.

Recommendations for Policymakers and Funding Agencies

Funding agencies should establish programs specifically supporting interdisciplinary collaboration across geography education, AI/computer science, and educational technology. Such programs should require genuine collaboration rather than merely multi-institutional participation. Following Petersen et al. [34], funding structures should incentivize cross-disciplinary convergence rather than the cross-topic "shortcuts" that may be proliferating.

The geographic concentration documented in our analysis indicates need for funding mechanisms that support North-South and South-South research partnerships structured to ensure equitable participation and knowledge sharing rather than extractive relationships.

Education policy bodies should work with professional organizations to develop standards for GeoAI competencies in geography education, potentially building on frameworks such as Shook et al. [16] CyberGIScience Literacy or UNESCO's emerging AI competency frameworks [64].

Recommendations for Curriculum Developers and Educational Technology Designers

GeoAI tools for educational use should be designed with explicit attention to learning objectives and pedagogical approaches, not merely technical capabilities. Drawing on Chiu et al. [29] emphasis on teacher agency, tools should support rather than supplant teacher pedagogical decision-making.

Curricula should develop GeoAI competencies progressively, building from foundational spatial thinking and geographic concepts through increasingly sophisticated AI applications. Curriculum and tool development should explicitly consider implementation across diverse resource contexts, including designing for varied infrastructure realities and ensuring accessibility for diverse learner populations.

Curricula should integrate critical evaluation of AI throughout, not as separate content but as embedded practice. Students should routinely examine AI outputs for potential biases, evaluate appropriateness of AI tools for specific geographic questions, and consider ethical implications of AI-mediated spatial analysis.

Conclusions and Future Directions

This comprehensive bibliometric analysis has documented the emergence of an extreme convergence gap in research at the intersection of GeoAI and geography teacher education, revealing both significant challenges and unprecedented opportunities for field development. Our statistical analysis quantifies this gap through multiple complementary measures, including a convergence gap index of 0.941 indicating near-complete disconnection between foundational domains and their intersection, a convergence coefficient of only 1.5% shared conceptual vocabulary, and a field emergence score of 70.6 suggesting rapid development from an emergent foundation with substantial theoretical development needs.

The temporal concentration of research activity in the post-2020 period (87.5% of core research) combined with high growth volatility (CAGR 25.99%) indicates that this field is experiencing real-time emergence, presenting unique opportunities for foundational contributions that could influence field development trajectories significantly. However, the geographic concentration of research activity (Herfindahl Index 0.208) and limited international collaboration (network density 0.40) highlight critical needs for strategic interventions to ensure that emerging frameworks address global needs and diverse perspectives effectively.

Drawing on convergence science theory, we interpret the extreme Gap Index not merely as a measure of limited publication volume but as an indicator of absent collaborative infrastructure and shared conceptual vocabulary between contributing domains. The theoretical frameworks reviewed in Section"Conceptual Framework and Literature Background" – including AI-TPACK extensions, AI literacy models, and spatial thinking frameworks – provide resources for addressing this gap, yet our citation analysis reveals limited integration of these frameworks into current intersection research.

The geographic equity considerations elaborated in Section "Geographic Equity and International Development Considerations" reveal that current research patterns may inadvertently develop approaches that exacerbate rather than address educational inequalities. The contradiction between where GeoAI is predominantly researched (Global North) and where its applications may be most urgently needed (regions facing acute spatial challenges) represents both an ethical concern and a practical limitation of current field development.

The prioritized research agenda presented in Section "Research Agenda and Strategic Recommendations" identifies theoretical framework development as the highest priority, followed by empirical validation studies, teacher preparation models, geographic equity research, and methodological innovation. The practical recommendations for stakeholders translate these priorities into actionable guidance for teacher education programs, professional development providers, policymakers, and curriculum developers.

The convergence gap documented in this analysis should not be viewed as a permanent limitation but as a defining characteristic of an emerging field with substantial potential for impact on both educational practice and geographic understanding. The field emergence score of 70.6 indicates that opportunity remains to influence developmental trajectories, but realizing this potential will require coordinated effort, strategic collaboration, and sustained commitment to both theoretical development and empirical validation across the global research community.

This analysis has captured a critical moment in the development of an important educational research domain where fundamental decisions about theoretical development, methodological approaches, and practical implementation will likely determine whether this field emerges as a coherent, theoretically grounded domain or remains fragmented across traditional disciplinary boundaries. The opportunity exists for the research community to shape this development thoughtfully and intentionally, ensuring that GeoAI integration in geography education serves student learning, teacher empowerment, and social justice goals while contributing to broader understanding of human-AI collaboration in educational contexts.

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Competing Interests

Financial Interests

The authors declare they have no financial interests.

Non-Financial Interests

The authors declare they have no non-financial interests that could inappropriately influence this work.

Ethics Approval

Not applicable. This study is based on bibliometric analysis of publicly available scholarly publications and does not involve human participants.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Data Availability

The datasets analyzed during the current study are available from the Dimensions database (https://www.dimensions.ai). Data were extracted on March 15, 2025, with temporal scope January 2010 through March 2025. The specific search queries and analytical procedures are described in the methodology section. Processed data supporting the conclusions of this article are available from the corresponding author upon reasonable request.

Code Availability

The bibliometric analysis was conducted using VOSviewer software, which is publicly available. Custom analytical scripts used for statistical calculations are available from the corresponding author upon reasonable request.

Authors' Contributions

Conceptualization: S.O.S., T.A.V., and I.S.M.; Methodology: S.O.S. and I.S.M.; Data collection and analysis: S.O.S., T.A.V., I.S.M., O.V.B., and O.B.K.; Writing – original draft preparation: S.O.S.; Writing – review and editing: all authors; Visualization: S.O.S. and I.S.M.; Supervision: S.O.S.; Project administration: S.O.S. All authors read and approved the final manuscript.

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