

A BIBLIOMETRIC REVIEW OF SPATIAL INTELLIGENCE (2005 – 2025): RESEARCH HOTSPOTS, TECHNOLOGICAL EVOLUTION, AND FUTURE DIRECTIONS

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ABSTRACT

This study conducts a bibliometric analysis of research trends and applications in spatial intelligence from 2005 to 2025. Driven by artificial intelligence, the Internet of Things, and digital twin technologies, spatial intelligence has become a key topic across design, architecture, and human – computer interaction. Data were collected from the Web of Science Core Collection using the search terms “Spatial Intelligence” and “Spatial AI,” resulting in 509 publications. VOSviewer and CiteSpace were employed to analyze publication trends, country – institution and author collaboration networks, journal co-citation patterns, keyword co-occurrence and citation bursts, as well as clustering and timeline structures. The results reveal a rapid increase in publications over the past five years, with research paradigms evolving from cognitive-oriented approaches toward machine learning and deep learning, and further advancing toward explainable and hybrid intelligence. “Machine learning” and “artificial intelligence” form the methodological backbone, while “spatial intelligence” serves as a conceptual bridge between cognitive science and spatial computing. This study uncovers the staged evolution of spatial intelligence research, providing quantitative insights into its interdisciplinary integration and technological trajectory.

Keywords: Spatial Intelligence, Bibliometric Analysis, Spatial AI, Spatial Computing

1 INTRODUCTION

Since the early 21st century, the rapid development of technologies such as Artificial Intelligence [1], the Internet of Things [2], Virtual Reality [3], and Digital Twin [4], along with the continuous expansion of spatial concepts, has transformed the traditional notion of space from a static physical setting to a dynamic, perceptive, and interactive entity known as Spatial Intelligence [5]. At its core, spatial intelligence refers to the integrated capability of AI systems to perceive, comprehend, reason, and interact within three-dimensional environments, enabling intelligent agents to autonomously sense, understand, and act within both physical and virtual contexts.

The concept of spatial intelligence originated from research on Intelligent Environments and Context-Aware Computing [6], which emphasized how technology can endow spaces with the abilities to perceive, respond, and learn—turning them into platforms for information exchange and human–machine collaboration. Since the 2010s, the study of spatial intelligence has progressively expanded into domains such as design, architecture, geographic information science, and human–computer interaction (HCI), marking a paradigm shift from technology-driven spaces to intelligence-driven spatial experiences [7].

From a disciplinary perspective, the early theoretical foundations of spatial intelligence emerged from psychology and cognitive science. Eliot’s definition of the components of spatial intelligence [8] and Van Rooy et al.’s exploration of its physiological correlation with spatial working memory [9] provided critical theoretical grounding for subsequent research on spatial cognition–environment interaction. With the integration of spatial data and machine learning methods, Zhang and She proposed a spatial intelligence framework based on geographic information and spatial statistics [7], [10], advancing its applications in environmental monitoring and decision support.

In the contexts of design and architecture, spatial intelligence represents more than the automation of physical environments—it reflects an integrated system of perception, cognition, and action within

space. Scholars generally regard it as an extension of embodied intelligence [11], enabling spaces to learn, adapt, and interact autonomously [12]. In recent years, the incorporation of AI technologies into architectural spatial configuration, urban perception, and mobility or health analytics [13], [14], [15] has further expanded the practical boundaries of spatial intelligence.

As AI technologies become increasingly embedded and interdisciplinary, the connotation and boundaries of spatial intelligence continue to evolve. Fei-Fei Li argues that its essence lies not only in perception and data processing but also in realizing embodied intelligence: intelligent agents learn and reason through physical interaction with their environments, transforming space into an integrated platform for understanding, reasoning, and behavior generation. Supporting this process, large-scale annotated datasets and hierarchical classification models form the foundation for perception and representation [16], [17]; cross-modal semantic alignment and generative representations strengthen the closed loop from perception to understanding and action [18]; scene and relational knowledge graphs provide spatial semantic constraints [19]; and group trajectory prediction enables operable spatiotemporal modeling [20]. Together, these elements establish a coherent mechanism linking perception, cognition, and action.

Overall, the theoretical evolution of spatial intelligence can be viewed as the convergence of cognitive psychology and spatial information science. Early studies centered on spatial cognition, focusing on how humans perceive and interpret their environments, and sought to reconstruct spatial thinking through computational models. With the integration of artificial intelligence and design computation, research expanded from cognitive mechanisms to algorithmic frameworks for spatial learning, forming a dual foundation of Design Informatics and Intelligent Environment Theory [21]. In the mid-development stage, scholars embedded cognitive mechanisms into spatial perception systems via machine learning and pattern recognition methods, facilitating the transition from environmental responsiveness to autonomous decision-making [22], [23].

In recent years, spatial computing and spatial intelligence have emerged as pivotal concepts that emphasize the integration of spatial data, artificial intelligence, and design thinking to enable a paradigm shift from passive perception to active learning. The rise of generative AI and the metaverse has further propelled spatial intelligence toward multidimensional transformations across domains such as design, urban systems, and healthcare. For instance, Kent et al. proposed constructing generative smart city models through Spatial AI [24], while Baresi revealed potential risks of spatial inequality induced by AI technologies from the perspective of social space [25]. Meanwhile, AI-driven spatial analysis has been increasingly applied to complex system identification, significantly enhancing data interpretability in spatial health information retrieval [26], geoclimatic pattern decoding [23], and spatial competitive intelligence analysis [22].

Overall, research on spatial intelligence is evolving from a technology-centric focus toward a multidimensional integration of cognition, data, and design, reflecting a systematic deepening from theoretical construction to multi-scenario application. Although related studies have proliferated in recent years, most existing reviews focus on single technological pathways—such as the Internet of Things (IoT) or Deep Learning—while lacking systematic quantitative analyses of research evolution, knowledge structure, and technological co-occurrence within the field [22]. Early studies primarily concentrated on spatial data mining and knowledge discovery [27]; however, in the era of multimodal perception and AI-generated content (AIGC), research paradigms have shifted from static analysis to dynamic intelligence recognition and decision generation [28]. Moreover, disciplinary fragmentation remains: AI, design, and architecture have yet to converge into a unified analytical framework, particularly regarding the explainability and trustworthiness of spatial intelligence systems [29].

To address these gaps, this study conducts a bibliometric analysis of spatial intelligence research from 2005 to 2025 using CiteSpace and VOSviewer. Specifically, the research aims to answer the following questions:

1. What are the major research themes and hotspots of spatial intelligence in design, architecture, and human–computer interaction?
2. How have spatial intelligence technologies evolved and converged across disciplines?
3. What trends characterize the evolution of spatial intelligence research, and what are its future directions?

Through systematic mapping and quantitative analysis, this study seeks to provide theoretical insights into the interdisciplinary integration of spatial intelligence and offer methodological implications for future design practices and the construction of intelligent environments.

2 DATA SOURCE AND RESEARCH METHOD

2.1 Data Source

This study employs the Web of Science Core Collection as the primary data source, encompassing the SCI-EXPANDED, SSCI, and ESCI sub-databases. Web of Science was selected for its broad disciplinary coverage, high academic quality, and reliable peer-reviewed data. The advanced search query used was:

TI = ("Spatial Intelligence") OR TI = ("Spatial AI") with the time span set from 2005 to 2025.

To ensure comprehensive coverage, no restrictions were imposed on document type; journal articles, conference papers, and review articles were all included. The retrieved records were exported in the Full Record and Cited References format, containing metadata such as author, institution, country, keywords, and cited references.

During the data cleaning process, duplicates and irrelevant records were removed through cross-verification of titles, authors, and publication years. Institution and country names were standardized, author name ambiguities were resolved, and keywords were normalized through lowercasing, lemmatization, and synonym merging (e.g., Spatial Intelligence and Spatial AI were treated as equivalent). After processing, a total of 509 valid publications were retained for analysis.

2.2 Research Method

This study employs two bibliometric and visualization tools—VOSviewer and CiteSpace—to conduct a comprehensive analysis.

VOSviewer, developed by the Centre for Science and Technology Studies at Leiden University, is a Java-based visualization software designed for constructing and exploring bibliometric networks. It analyzes information such as titles, keywords, authors, and citations to generate cluster, label, and density visualizations, effectively illustrating the structure, evolution, and collaboration patterns within a research field. Its strong graphical capability makes it particularly suitable for analyzing large-scale datasets [30].

CiteSpace, developed by Dr. Chaomei Chen, is a scientific visualization software widely used for bibliometric and co-citation analyses. It reveals the knowledge structure, research hotspots, and emerging frontiers within a domain [31].

Data analysis was performed using both VOSviewer and CiteSpace in combination. In VOSviewer, the minimum keyword occurrence was set to 5, with fractional counting applied. In CiteSpace, the time slicing was set from 2005 to 2025 (1 year per slice), and the node types included keywords and journals. Co-citation analysis employed the g -index ($k=25$) as the selection criterion, the LLR algorithm for clustering, and Kleinberg's burst detection algorithm ($\gamma=1.0$) for identifying citation bursts.

The analysis dimensions included publication trends, collaboration networks, journal co-citation, keyword co-occurrence, and citation burst analysis, collectively revealing the structural patterns and evolutionary trajectory of research on spatial intelligence.

3 RESULTS

Through a systematic bibliometric analysis of publications from 2005 to 2025, this study identifies the major development trends and research hotspots in the field of spatial intelligence. Using tools such as VOSviewer and CiteSpace, analyses of keyword co-occurrence, citation bursts, and timeline evolution were conducted.

3.1 Publication Trends

Between 2005 and 2025, the annual number of publications on spatial intelligence shows a steady upward trajectory, with particularly rapid growth in the past five years (see Figure 1). From 2005 to 2013, publication output remained low—ranging between 1 and 13 papers per year—indicating a nascent research stage. Between 2014 and 2017, publication numbers began to rise gradually from 4 to 11, reflecting growing academic attention. From 2018 to 2021, the field entered a phase of stable growth, increasing from 21 to 34 papers annually. After 2022, publication output accelerated sharply, rising from 50 papers in 2022 to 96 in 2024, reaching a temporary peak of 100 papers in 2025.

Overall, the trend demonstrates a clear transition over the past two decades—from initial accumulation to rapid expansion—highlighting the increasing maturity and interdisciplinary influence of spatial intelligence research.

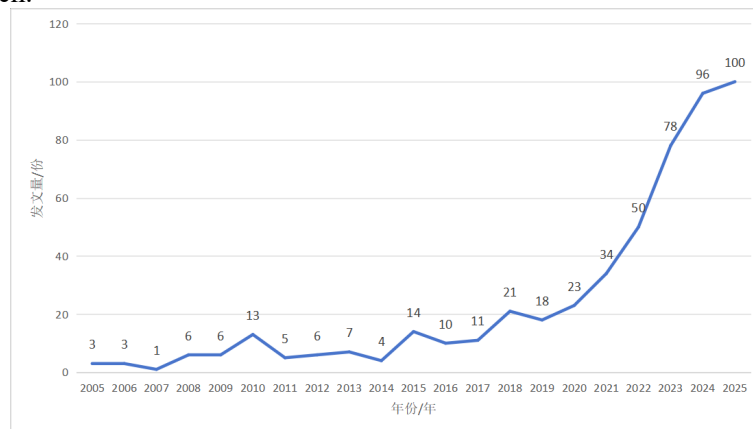


Figure 1. Annual publication trend

3.2 Research Themes and Knowledge Structure: Keyword Co-occurrence and Clustering

As illustrated in Figures 2 and 3, the thematic structure of spatial intelligence research exhibits a hierarchical pattern characterized by methodological foundation, cognitive integration, and applied implementation. The keyword co-occurrence network reveals that artificial intelligence and machine learning serve as core high-frequency nodes, densely connected with methodological terms such as deep learning, neural networks, artificial neural network, random forest, decision tree, and classification, thereby forming the technical backbone of the field. Meanwhile, spatial intelligence is closely associated with task-oriented terms like model, prediction, and identification, reflecting its central role in classification, prediction, and recognition practices.

The clustering analysis further highlights the structural organization of research themes. Cluster #0 “machine learning” occupies the central position with the highest node density, radiating connections to #1 “artificial intelligence” and #2 “spatial intelligence.” Cluster #2 is adjacent to #4 “working memory” and #5 “intelligence,” indicating the sustained integration between cognitive research and spatial intelligence. Cluster #3 “adaptive neuro-fuzzy inference system” links to #0, representing a trend toward hybrid reasoning and explainable intelligence. Clusters #6 “simultaneous localization and mapping,” #9 “spatial analysis,” and #16 “spatial decision support systems” constitute the application and decision-making layer. In contrast, #17 “density index” and #10 “gifted” exhibit smaller nodes and sparse connections, reflecting peripheral topics.

Overall, the dense interconnections and evident cross-cluster linkages demonstrate a deep integration among algorithmic methods, cognitive frameworks, and applied scenarios, underscoring the multidisciplinary evolution of spatial intelligence research.

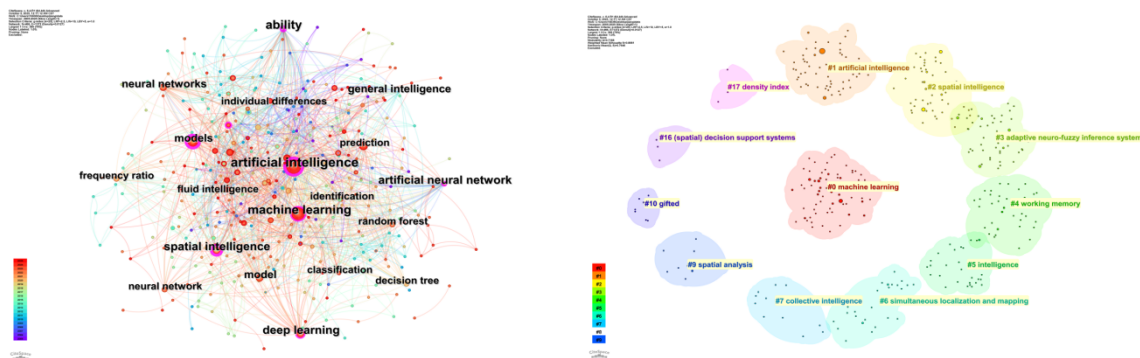


Figure 2. Keyword co-occurrence diagram Figure 3. Keyword clustering diagram

3.3 Thematic Evolution and Research Frontiers: Timeline and Citation Bursts

The timeline analysis (Figure 4) reveals a systematic evolution of research themes—from cognitive intelligence to deep learning—over the past two decades. Between 2005 and 2012, studies were primarily rooted in cognitive psychology, with frequent keywords such as working memory, general intelligence, and spatial intelligence. This phase focused on ability measurement and intelligence mechanisms, emphasizing theoretical exploration of cognitive capacity.

From 2013 to 2018, research methods gradually incorporated machine learning and spatial analysis techniques. Keywords like neural networks, support vector machine, and frequency ratio began to intersect with cognition-related themes, marking a transition from psychometric assessment to computational modeling and spatially oriented tasks.

During 2019–2025, keywords such as deep learning, machine learning, and artificial intelligence dominate the network and persist into recent years. Parallel developments in random forest, classification, and prediction indicate a paradigm shift toward data-driven modeling and performance optimization. Emerging themes such as explainable AI and adaptive neuro-fuzzy inference system highlight a growing research interest in model transparency and reasoning mechanisms, reflecting an increasing emphasis on interpretability and hybrid intelligence.

Overall, the results demonstrate that machine learning and artificial intelligence constitute the methodological core of the field, while spatial intelligence and spatial decision support systems represent its cross-disciplinary extensions. This progression delineates a coherent evolutionary trajectory—from cognitive foundations, through algorithmic development, to integrated applications—illustrating the maturation of spatial intelligence as both a theoretical and technological paradigm.

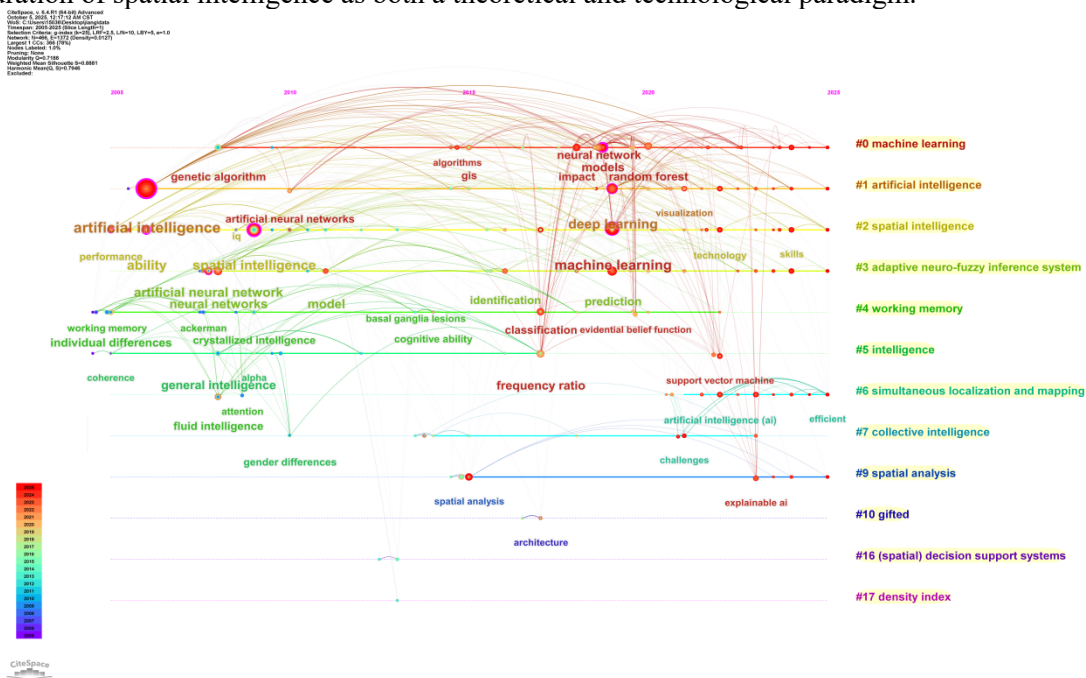


Figure 4. Keyword clustering timeline

The citation burst analysis (Figure 5) reveals a phased evolution of research keywords in spatial intelligence.

In the first phase (2008–2015), terms related to cognition and intelligence dominated—such as working memory, general intelligence, fluid intelligence, spatial intelligence, mental rotation ability, and cognitive ability. These bursts were generally short in duration, with moderate intensities ranging from 1.0 to 2.6, indicating an early research focus on cognitive mechanisms and ability measurement.

The second phase (2016–2021) marks a methodological shift toward modeling and evaluation, characterized by the emergence of keywords such as land cover, decision tree, logistic regression, frequency ratio, and analytical hierarchy process. Burst peaks were concentrated between 2019 and 2021, reflecting the widespread adoption of traditional statistical models and machine learning methods, as well as growing attention to multi-criteria decision-making.

The third phase (2021–2025) shows a clear transition to technology-driven paradigms. Keywords including deep learning, machine learning, neural network, artificial intelligence, classification, prediction, and explainable AI exhibit long-duration bursts extending through 2025. Among them, artificial intelligence (burst strength ≈ 4.34) and deep learning (≈ 4.28) recorded the highest intensities in the dataset. Shorter bursts for random forest and identification between 2022 and 2023 further illustrate the accelerated progression from traditional models to deep learning and interpretability-oriented approaches.

A cross-phase comparison reveals two key trends. First, methodological terms have increased markedly since 2019, while task-oriented terms such as classification, prediction, and impact have risen in parallel—emphasizing the shift toward model application and performance evaluation. Second, domain-specific terms remain relatively scarce, with land cover being the only prominent one, suggesting that recent studies have focused more on generalizable algorithms and evaluation frameworks rather than single-domain applications.

In summary, the field has undergone a three-stage transition—from cognitive theory-oriented research, to traditional machine learning, and finally to deep learning and explainable AI. This progression reflects an accelerating technological paradigm shift, with interpretability and evaluability emerging as new focal points in spatial intelligence research.

Top 25 Keywords with the Strongest Citation Bursts

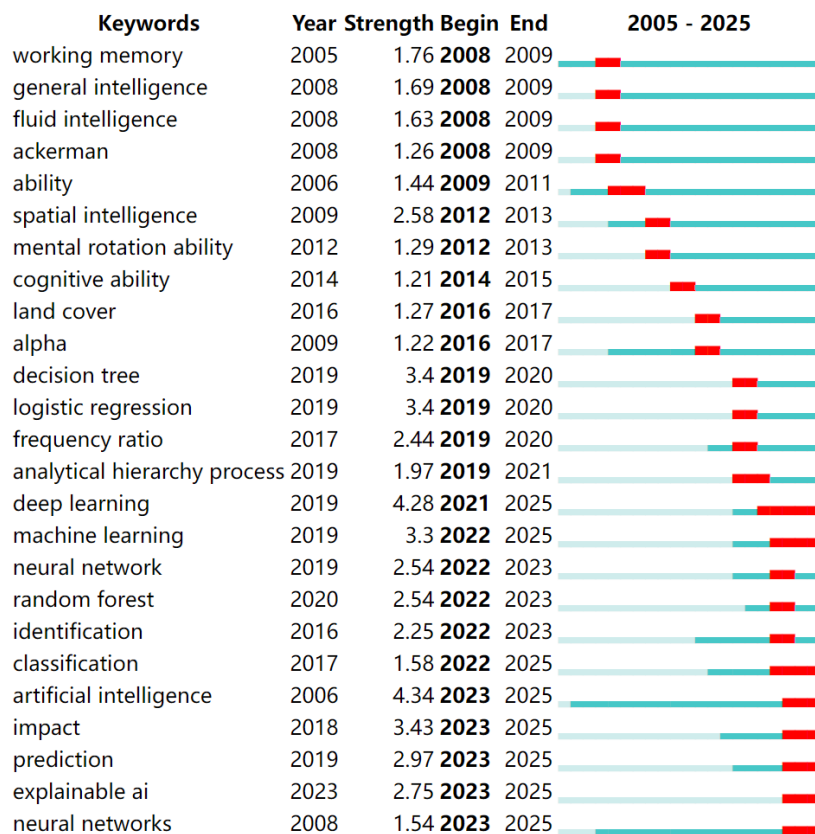


Figure 5. Top 25 Keywords with the Strongest Citation Bursts

3.4 Journal Co-Citation Analysis

The journal co-citation network (Figure 6) reveals that the core of the field is formed by applied and engineering journals such as Sensors, Remote Sensing, and Sustainability, which are tightly connected to multidisciplinary science journals including Science, Nature, PNAS, and Nature Communications, creating a high-density citation hub. Journals such as Science of the Total Environment, Scientific

Reports, and PLOS ONE serve as intermediary nodes, facilitating the diffusion and integration of research outcomes across domains.

NeurIPS and arXiv occupy the methodological frontier, maintaining strong linkages with the central cluster, which underscores the driving role of algorithms and models in advancing spatial intelligence research. The node size reflects co-citation frequency, while red citation rings indicate recent citation bursts—primarily observed in Science of the Total Environment, Remote Sensing, Sensors, and Sustainability—suggesting a surge of interest in environmental monitoring and remote sensing in recent years.

Peripheral nodes, representing smaller or earlier-stage journals, exhibit color gradients that indicate a hotspot shift from traditional environmental and geoscience outlets toward interdisciplinary platforms bridging sensing and artificial intelligence.

Overall, the results reveal a dual-hub knowledge structure in which environmental remote sensing and multidisciplinary science jointly support the methodological and application foundations of spatial intelligence research.

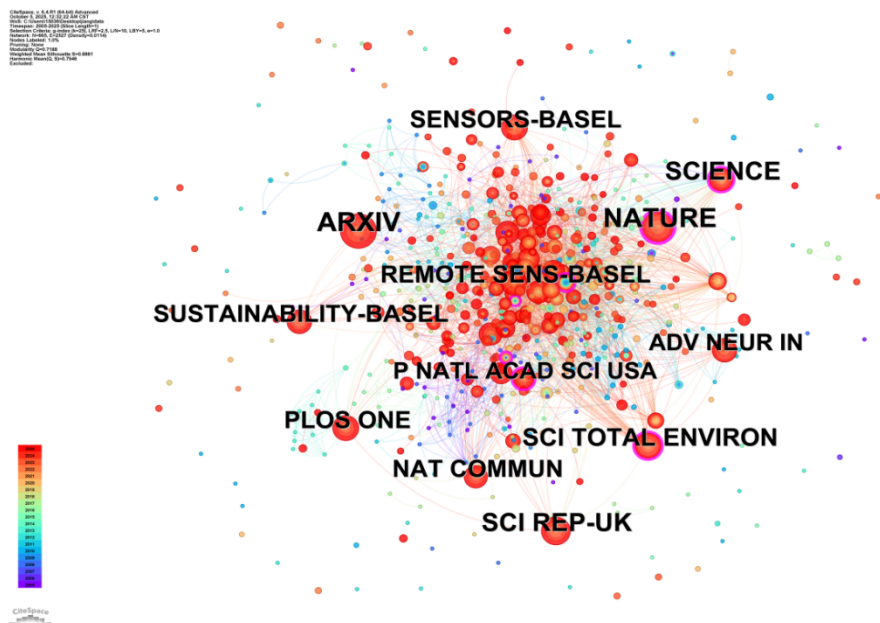


Figure 6. Total citations of journals

3.5 Collaboration Network

As illustrated in Figures 7 and 8, the collaboration landscape of spatial intelligence research demonstrates a multi-layered structure characterized by core clusters, cross-regional bridging, and the emergence of new research forces.

At the institutional level, the network exhibits a tightly connected structure. The Chinese Academy of Sciences, Seoul National University, Samsung Medical Center, University of California System, University of London, and University of Technology Sydney occupy central positions, serving as key nodes for interregional collaboration and knowledge diffusion. Institutions such as Universitas Pendidikan Indonesia, Universiti Kebangsaan Malaysia, Duy Tan University, and Sungkyunkwan University are closely linked to these core entities, reflecting a growing concentration of research activity within the Asia-Pacific region. The prevalence of warm-colored nodes and red citation rings indicates an increase in both collaboration intensity and research output in recent years, with partnerships gradually consolidating around large-scale research universities and medical institutes.

At the national level, the collaboration network reveals a dual-core structure led by the United States and China, with the densest interconnections between them. The United Kingdom, Germany, Australia, and South Korea function as crucial bridges between Western and Asia-Pacific networks, while countries such as India, Iran, and Spain are gradually moving from peripheral to more central positions.

Overall, the results indicate a clear evolution from regional cooperation toward transcontinental collaboration and cross-disciplinary integration. The Asia-Pacific region has emerged as a significant contributor to the global spatial intelligence research network, while European countries continue to play a pivotal role as connective hubs in facilitating global collaboration.

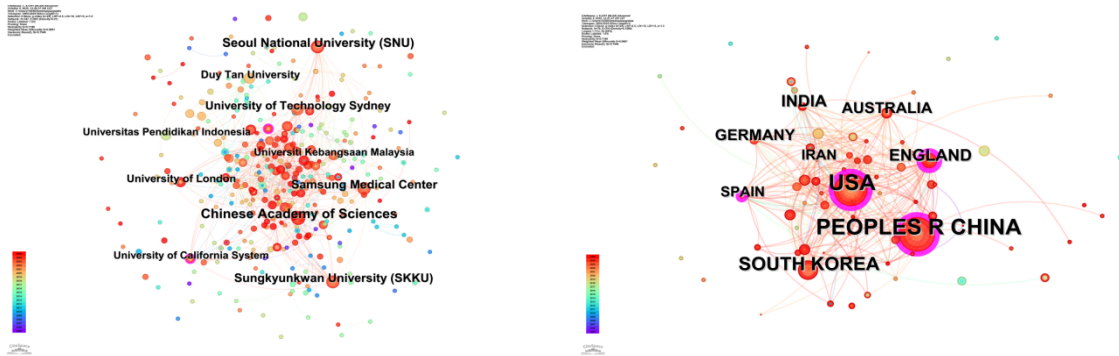


Figure 7. Institutional cooperation network Figure 8. Co-occurrence map of countries

4 DISCUSSION AND IMPLICATIONS

4.1 Research Landscape and Interdisciplinary Integration

The bibliometric findings indicate that research on spatial intelligence has evolved into a multidisciplinary framework supported by artificial intelligence, cognitive science, architecture, and human–computer interaction. Early studies emphasized context awareness and environmental responsiveness, focusing on spatial automation and sensing performance. As theoretical understanding deepened, the research perspective shifted toward a systemic integration of cognition, interaction, and design.

Keyword clustering and citation burst analyses reveal three major research pathways: cognitive computing, spatial information science, and human–AI collaborative design. Cognitive computing has established mechanistic models for spatial perception and reasoning; spatial information science provides the foundation for spatial representation and semantic modeling; and human–AI collaborative design extends the application of spatial intelligence to urban computing, architectural design, and experiential interaction.

Emerging concepts such as embodied intelligence and spatial semantic networks mark a transition from technological control toward semantic understanding and contextual reasoning. Overall, the disciplinary structure of spatial intelligence is shifting from a technology-driven paradigm to an intelligent ecosystem integrating cognition, perception, and design.

4.2 Technological Evolution and Paradigm Shift

The technological development of spatial intelligence has undergone a continuous transformation—from perceptual control, to semantic cognition, and eventually toward active learning. Early research focused on sensor networks and ubiquitous computing, aiming to enhance environmental responsiveness. With the advancement of deep learning and computer vision, space has evolved from a passive environment into an intelligent system capable of learning and reasoning.

The bibliometric results indicate a clear transition of technological hotspots from intelligent environments to spatial intelligence. High-frequency keywords such as machine learning, deep learning, spatial analysis, and SLAM highlight the ongoing reconstruction of the technical framework underpinning spatial intelligence.

Integrating clustering and citation burst analyses, the research structure of spatial intelligence can be summarized as a three-layer system comprising Cognition, Design, and Data (Figure 9). Specifically:

1. Cognitive Layer – focuses on spatial perception and intelligent reasoning mechanisms, encompassing cognitive computing and reinforcement learning, and extending toward explainable and hybrid intelligence.
2. Design Layer – centers on human–computer interaction and experience construction, achieving spatial visualization and interaction optimization through multimodal interfaces and digital twins.

3. Data Layer – manages environmental data acquisition, semantic modeling, and spatiotemporal reasoning, providing dynamic data support for spatial intelligence systems. This triadic framework reveals a paradigm shift in spatial intelligence—from a data-driven model to a cognition-driven one—where technology no longer merely describes space but actively generates spatial meaning.

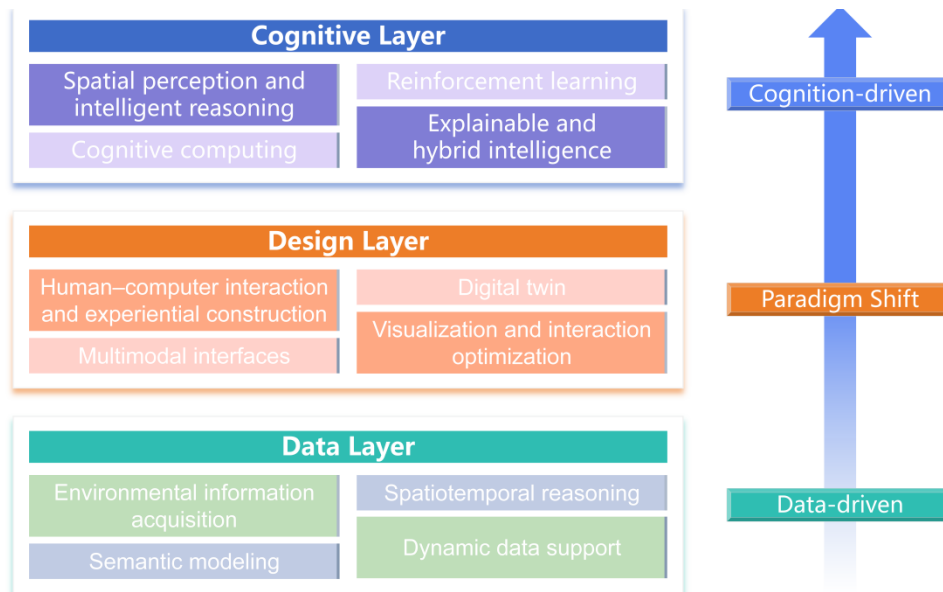


Figure 9. Three-layer Framework of Spatial Intelligence

4.3 Future Trends and Design Implications

The ongoing evolution of spatial intelligence offers new methodological and value orientations for design research. The integration of intelligent technologies is driving a transformation from formal construction to cognitive orchestration, positioning design as a critical interface that connects algorithms, data, and human experience.

At the methodological level, design thinking is shifting from a space-centered to an intelligence-centered paradigm. Designers are now required to possess interdisciplinary integration and systems analysis capabilities to effectively mediate between data logic and human perception. For instance, in urban twins and immersive environments, design extends beyond aesthetic expression to function as a coordinating mechanism for information, behavior, and emotional interaction.

At the social and ethical level, the advancement of spatial intelligence introduces new challenges concerning algorithmic transparency, data privacy, and fairness. Future spatial design should be grounded in human-AI empathy, constructing interpretable and trustworthy spatial systems that balance technological innovation with social responsibility.

At the application level, spatial intelligence opens new design opportunities in urban governance, public services, and cultural heritage preservation. By integrating AIGC, digital twin, and spatial semantic network technologies, designers can dynamically generate and modulate spatial experiences in real time, promoting the intelligent renewal and human-centered reconstruction of urban spaces. Overall, the design implication of spatial intelligence lies in the transition from static form-making to dynamic intelligent collaboration, and from physical spatial shaping to cognitive ecosystem construction.

4.4 Challenges and Future Opportunities of Spatial Intelligence Research

Although spatial intelligence has shown rapid interdisciplinary development, several challenges remain that require further exploration.

First, most existing studies focus on technological development while paying limited attention to the potential risks and limitations of spatial intelligence. Issues such as data bias, spatial inequality, and ethical concerns have not been systematically discussed.

Second, the theoretical foundations of spatial intelligence originated from psychology and cognitive science; however, current research has not fully adapted to the latest advances in cognitive neuroscience, embodied cognition, and human-environment interaction. The integration between cognitive mechanisms and AI-driven spatial models is still fragmented.

Third, with the rise of user-centered design and ubiquitous sensing, the role of user experience and behavioral data is becoming increasingly important. Yet, most studies emphasize algorithmic accuracy rather than experience-driven spatial adaptation and participatory intelligence.

Finally, spatial intelligence models are evolving from static perception models to dynamic, self-learning systems. The transition toward explainable, generative, and hybrid intelligence is still at an early stage, and future research should focus on model transparency, adaptability, and cross-domain scalability.

These challenges point to important future directions: integrating cognitive science and design research, enhancing user-involved spatial intelligence systems, and developing interpretable and trustworthy spatial AI models.

5 CONCLUSION

Based on a bibliometric analysis of studies from 2005 to 2025, this research demonstrates that spatial intelligence has evolved into a rapidly expanding and interdisciplinary domain. Methodologically, the field has progressed from machine learning and deep learning toward explainable and hybrid intelligence; on the application side, research has extended from cognitive assessment to localization, spatial analysis, and decision support. The knowledge structure reveals a dual-hub pattern centered on applied engineering and multidisciplinary science journals, while the international collaboration network exhibits a China – US dual-core with increasing Asia-Pacific convergence.

Overall, spatial intelligence forms a closed-loop system encompassing cognition, semantics, behavior, and simulation, emphasizing a continuous cycle from data acquisition, to understanding, to action and validation. These findings collectively address the study's three core research questions regarding thematic hotspots, technological evolution, and interdisciplinary development trajectories within the spatial intelligence field.

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