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Artificial Intelligence in Spatial Design: A Bibliometric Analysis of Research Trends, Thematic Structure, and Future Directions (2018–2025)

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ABSTRACT

Artificial intelligence, particularly generative AI, is reshaping spatial design, but research remains fragmented. This study maps 434 topic-screened Lens.org publications (2018–2025) using bibliometrix and VOSviewer to analyse publication trends, authorship, citations, disciplinary composition, and title–abstract term co-occurrence. Of these, 365 (84%) were published in 2023–2025; mean annual output rose from 13.8 in 2018–2022 to 121.7 in 2023–2025. Three interconnected clusters emerged: generative and visual AI; architectural design, process, and education; and performance optimisation and sustainability. Highly cited studies focused on generative and optimisation approaches, while collaboration remained fragmented across small author groups. Although design education was prominent, a post-hoc corpus search identified only four records (0.92%) containing child-related terms, indicating that children's and early-childhood spaces are under-represented. The study maps the field across the generative-AI transition and highlights priorities for human-centred, performance-aware, and context-specific research.

1. Introduction

Artificial intelligence (AI) has moved from a peripheral computational aid to a central agent in the design of physical space. Machine learning, deep learning, and—most recently—generative models such as diffusion systems and large language models now support tasks ranging from automated floor-plan and furniture layout [27] and code-compliance checking [10] to photorealistic visualisation and concept ideation [11], [12]. The public release of text-to-image and conversational AI tools after 2022 accelerated this shift, prompting a surge of scholarship across architecture, interior design, urban design, and design education.

This expansion, however, has produced a fragmented body of knowledge. Existing reviews fall into several narrow streams: interior design and interior architecture [1], [5], architectural conceptual design [2], machine learning in the inner built environment [3], and AI applications in smart buildings [4]. These studies establish important domain-specific evidence, but they either concentrate on a single spatial-design subfield or emphasise technological and performance applications rather than the field's wider thematic structure. Moreover, reviews bounded by earlier time windows do not fully capture the sharp post-2022 shift toward text-, image-, and language-driven generative systems. A holistic, up-to-date mapping across spatial design that spans this generative-AI inflection is therefore still lacking.

To address this gap, this study conducts a bibliometric analysis of AI research in spatial design from 2018 to 2025. "Spatial design" is treated as an umbrella encompassing interior, architectural, environmental, and related space-making disciplines. The analysis maps publication dynamics, leading sources and authors, disciplinary composition, and the thematic structure of the field, and identifies under-researched areas. Three research questions guide the study:

RQ1. What are the publication trends of AI in spatial design across time, sources, and authors?

RQ2. What are the research hotspots, thematic clusters, and intellectual structure of the field, and how have they shifted with the rise of generative AI?

RQ3. What research gaps remain, particularly regarding AI in children's, art, and educational spaces?

This study makes three contributions:

(i) It provides a field-wide map of publication, collaboration, citation, disciplinary, and thematic patterns across the post-generative inflection.

(ii) It identifies and substantiates a critical research gap in children's, art-education, and early-childhood spaces.
(iii) It documents a reproducible workflow for screening, harmonising, and mapping a multidisciplinary spatial-design corpus.

2. Methodology

2.1 Research design

This study adopts a bibliometric approach to map the intellectual structure and developmental trends of AI research in spatial design. Bibliometric analysis [7] enables an objective and reproducible overview of a research field through the quantitative analysis of publication metadata, and is well suited to identifying hotspots, intellectual bases, and gaps in a rapidly growing literature.

2.2 Data source and search strategy

Bibliographic records were retrieved from the Lens.org scholarly database in a single search conducted on 14 June 2026; the dataset was not updated after that date. Lens.org is an open, integrative database that aggregates sources including Crossref, PubMed, and Microsoft Academic, and provides exportable metadata suitable for bibliometric analysis. The search was applied to the title and abstract fields and combined two concept groups: an AI group ("artificial intelligence", "machine learning", "deep learning", "generative design", "generative AI", "AI-generated") and a spatial-design group ("spatial design", "space design", "interior design", "interior architecture", "environmental design", "architectural design"). Results were limited to English-language journal articles and conference-proceedings articles published between 2018 and 2025, and to the Fields of Study Art, Visual arts, Architecture, and Interior design. The 2018–2025 publication-year range was the only date restriction applied.

2.3 Inclusion, exclusion, and screening

The initial query returned 1,121 records with no duplicate DOIs. Because the term "architecture" is shared between the built environment and computer science, records were screened on the basis of their titles and abstracts: a study was retained only if it substantively concerned physical, interior, architectural, or environmental design. Records belonging primarily to computational, medical, security, networking, or marketing domains were excluded. After screening, 434 publications were retained for analysis. The selection process is summarised in a PRISMA-style flow diagram [8] (Figure 1).

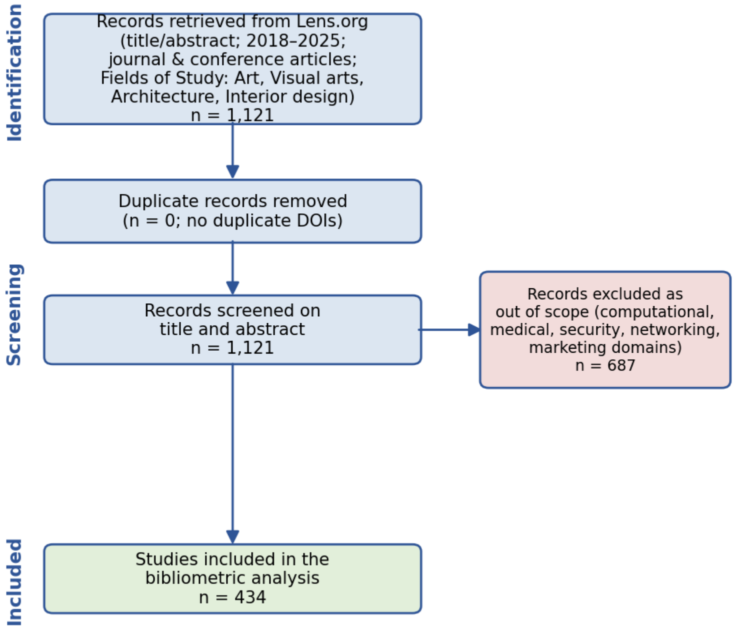

Figure 1. PRISMA-style flow diagram of the study selection process.

2.4 Data cleaning and analysis

Retrieved records were cleaned and terms were harmonised through an iteratively developed thesaurus. The most frequent title and abstract terms were reviewed, after which synonyms, abbreviations, singular/plural forms, hyphenation, and spelling variants were merged (e.g., "A.I." with "artificial intelligence", and "deep-learning" with "deep learning"). Because author keywords were available for only a small share of records, term co-occurrence was derived from titles and abstracts using text mining with binary (per-document) counting; after removing function words and harmonising variants, terms occurring in at least 49 documents were retained, yielding 28 terms for the co-occurrence network. The Fields of Study tags were used to describe the disciplinary structure. Annual publication counts, leading sources, productive authors, disciplinary composition, term co-occurrence, and the most-cited documents were computed. Author statistics were calculated from 430 records with author information; mean authors per publication was the total number of listed authors divided by these records, and the collaboration index was the number of author appearances in multi-authored publications divided by the number of multi-authored publications. Network mapping and clustering were performed using VOSviewer [6], complemented by the bibliometrix R-package [9]; thematic clusters were identified through association-strength normalisation and modularity-based clustering. As post-hoc checks, weighted Newman–Girvan modularity was calculated on association-strength weights, and a silhouette coefficient was calculated from the exported two-dimensional VOS map.

3. Results

3.1 Publication trends

The volume of research on AI in spatial design grew almost exponentially over the study period, from 5 publications in 2018 to 214 in 2025—a more than 40-fold increase (Figure 2). Growth was modest until 2021 and then accelerated sharply: the three years 2023–2025 alone account for 365 publications, or 84% of the corpus. Mean annual output increased from 13.8 publications in 2018–2022 to 121.7 in 2023–2025, an 8.8-fold increase. This temporal break coincides with, but does not by itself establish causation from, the public emergence of generative AI tools.

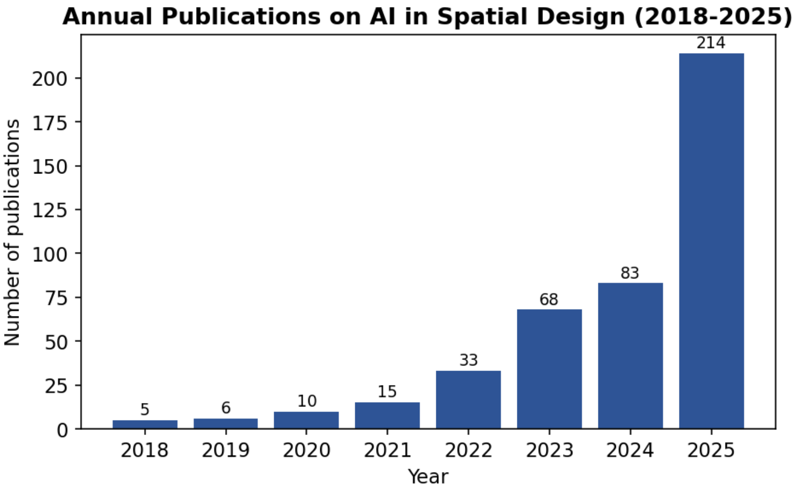

Figure 2. Annual publications on AI in spatial design (2018–2025). The sharp rise after 2022 marks the temporal inflection associated with the public diffusion of generative AI tools.

3.2 Leading sources

Publications are concentrated in built-environment and computational-design venues (Figure 3). The journal Buildings is the most productive source (13 publications), followed by the open repository Zenodo (10) and the conference series eCAADe (8), with the International Journal of Architectural Computing (7) and Civil Engineering and Architecture (6) also prominent. The presence of both archival journals (e.g., Automation in Construction, Sustainability) and design-computing conferences (eCAADe, CAADRIA) reflects the field's dual character as an applied and a methodological research domain.

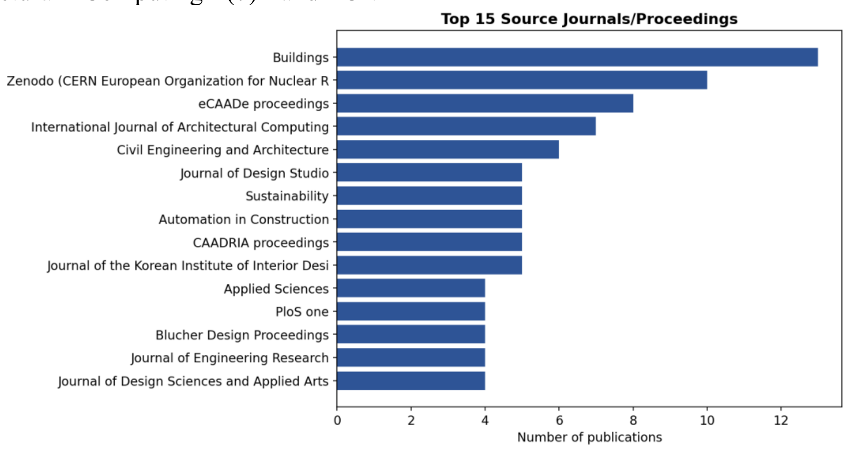

Figure 3. Top 15 source journals and proceedings by number of publications. The spread across journals, proceedings, and repository records indicates a fragmented publication landscape.

3.3 Productive authors and collaboration

Authorship is broadly distributed, with no single dominant author. The most productive author is Jin-Kook Lee (6 publications), followed by Zichun Shao and Junming Chen (5 each); a further group of authors contributed three publications each (Figure 4). Across the 430 records with available author information, the mean was 2.69 authors per publication. Of these records, 296 were multi-authored, yielding a collaboration index of 3.46; four records without author information were excluded from these calculations. Despite multi-authorship within papers, the network is dominated by several small, largely disconnected groups rather than a single integrated community, indicating limited collaboration across research groups.

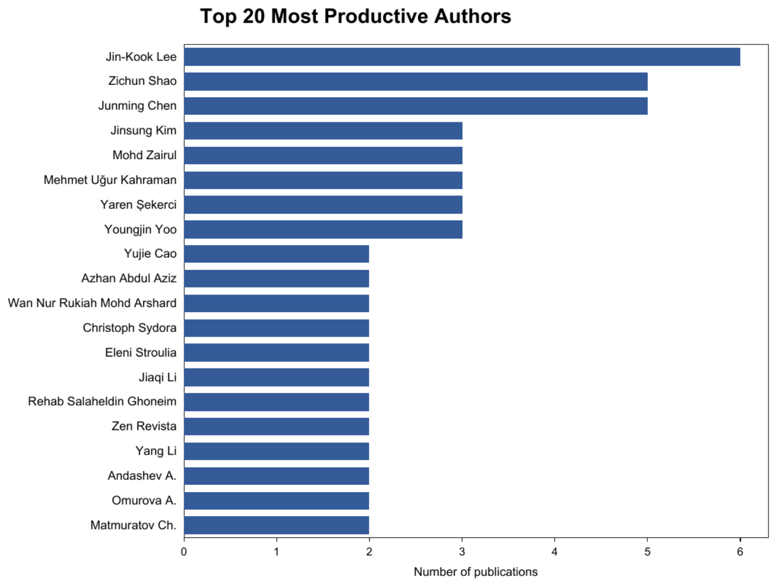

Figure 4. Top 20 most productive authors. Low individual publication counts and small co-authorship groups confirm a dispersed collaboration structure.

3.4 Disciplinary composition

Beyond the expected computational tags, the corpus is anchored in design and built-environment fields (Figure 5): Architecture (298), Art (210), Visual arts (192), Architectural engineering (177), Architectural design (123), and Interior design (108) are the leading design-related fields of study. This confirms that, after screening, the corpus genuinely represents spatial-design scholarship rather than purely technical work, while the strong co-tagging with computer science reflects the interdisciplinary nature of the topic.

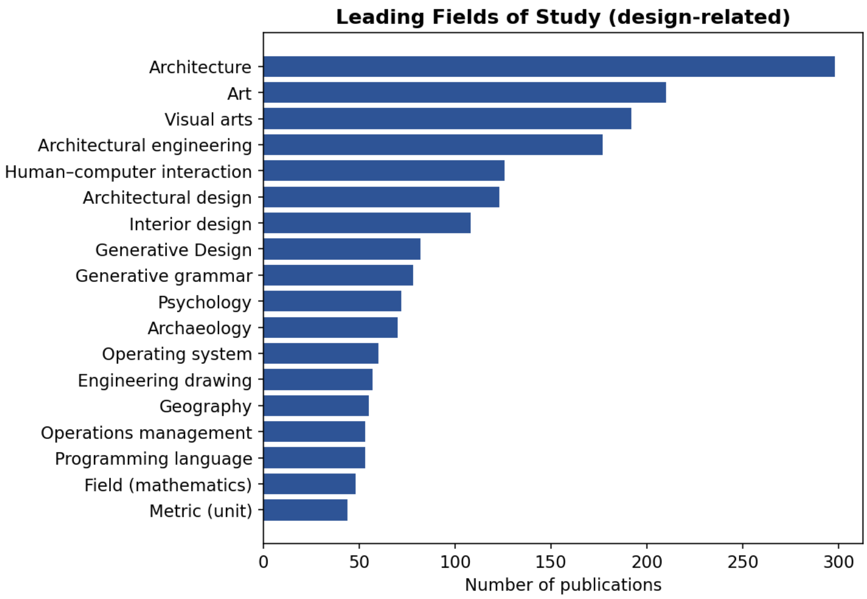

Figure 5. Leading design-related fields of study. The dominance of architecture, art, and visual arts confirms the corpus's built-environment and design orientation.

3.5 Thematic structure (term co-occurrence)

The term co-occurrence network derived from titles and abstracts reveals three thematic clusters (Figure 6 and Figure 7). The first cluster—generative and visual AI—groups terms such as image, generation, visual, deep learning, interior design, space, spatial, user, and evaluation, and reflects work on text-to-image and diffusion-based design generation [11], [12], [23]. The second cluster—architectural design, design process, and education—links architecture, architectural design, design process, designers, architects, students, education, creativity, digital, and construction, capturing studies on how AI reshapes design practice and pedagogy [16], [24], [33]. The third cluster—performance optimisation and sustainability—connects machine learning, algorithms, optimisation, performance, building, sustainable, sustainability, and environmental factors, representing simulation- and optimisation-oriented research [14], [32]. Phase comparison shows that performance-related terms were proportionally more prominent in 2018–2022, whereas the generative/visual cluster increased after 2022; notably, 95.2% of documents containing "generation" and 90.6% containing "visual" were published in 2023–2025. The exported network contained 28 terms and 293 links.

Its association-strength-weighted modularity was Q = 0.111, and the silhouette coefficient based on the two-dimensional VOS layout was 0.241. These values support an interpretable three-cluster solution while also indicating substantial thematic overlap, so the clusters should be understood as interconnected rather than sharply separated. The most frequent terms overall are architecture, architectural design, interior design, building, and space, confirming the field's centre of gravity in built-environment design.

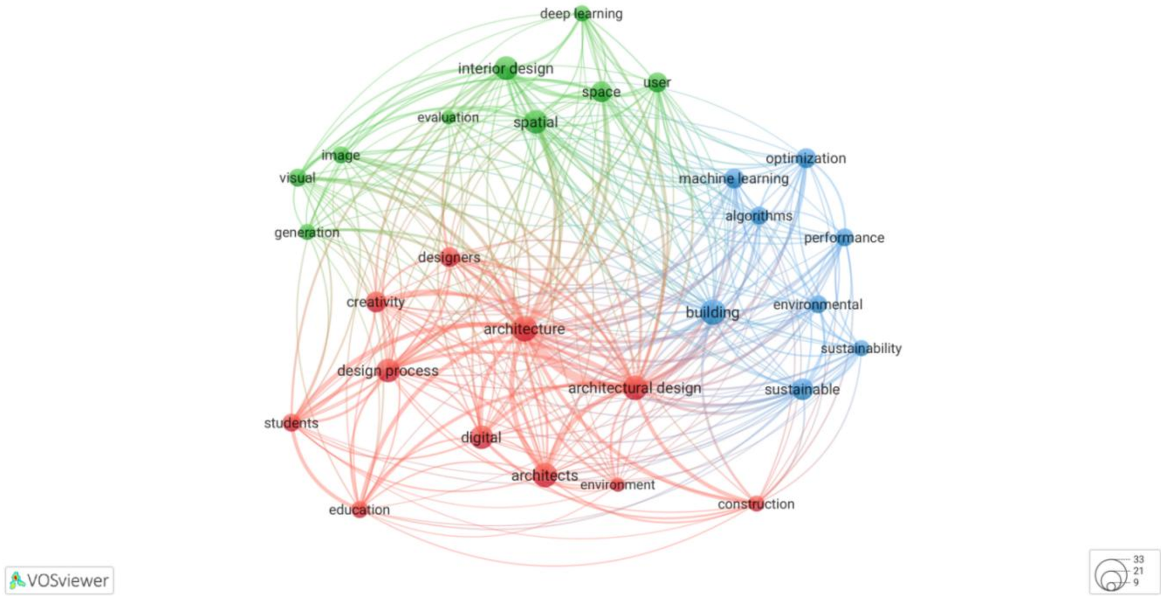

Figure 6. Term co-occurrence network of AI in spatial design (VOSviewer; three thematic clusters). Dense cross-cluster links show that generative, educational, and performance themes are analytically distinguishable but strongly interconnected.

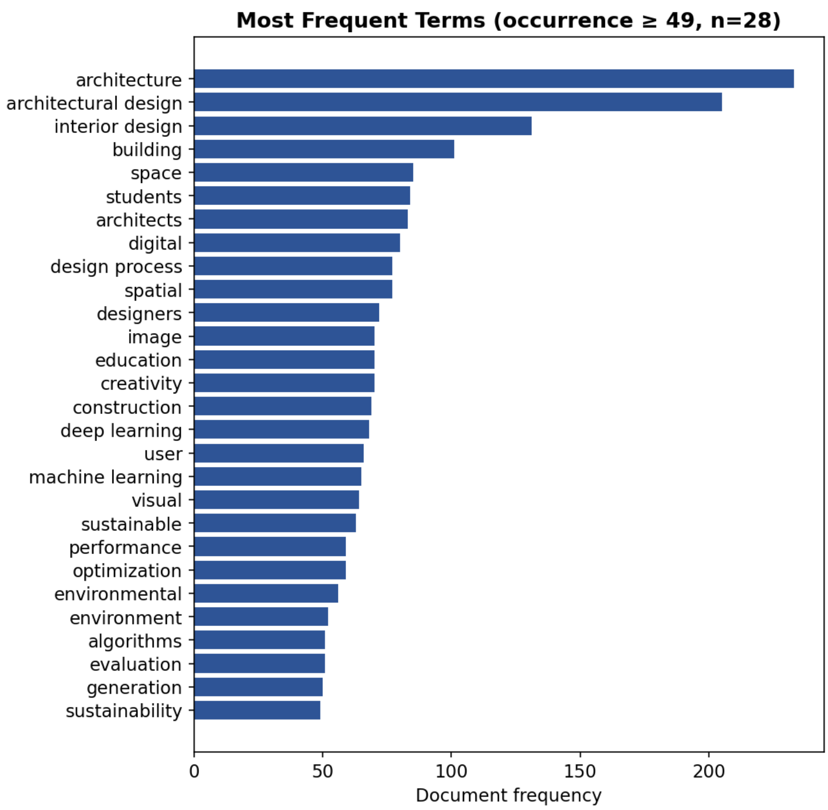

Figure 7. Most frequent terms in titles and abstracts (occurrence ≥ 49; 28 terms). Architecture-related terms dominate, while generation, evaluation, and sustainability form secondary research hotspots.

3.6 Most-cited works

The most-cited publications (Table 1) are dominated by generative and optimisation methods applied to interiors and buildings. Citation counts in Table 1 were obtained directly from the citation metadata provided by Lens.org on 14 June 2026; no separate citation analysis beyond the

434-record corpus was conducted. The single most-cited work, Sydora and Stroulia (2020) on rule-based compliance checking and generative design for building interiors using BIM, has 102 citations [10], followed by studies on generating interior design [11] and architectural designs [12] from text. The prominence of recent (2023–2024) highly cited papers on text-to-design generation again underscores the rapid impact of generative AI.

Table 1. Most-cited publications in the corpus (top 8). Counts are total Lens.org citations as of 14 June 2026, not citations limited to the study corpus.

#	Cit.	Year	Title (abbreviated)	Source
1	102	2020	Rule-based compliance checking and generative design for building interiors (BIM)	Automation in Construction
2	76	2023	Generating interior design from text: a diffusion-model-based method	Buildings
3	64	2023	Using AI to generate master-quality architectural designs from text	Buildings
4	55	2024	Integrating AI design into architectural and interior design education	Civil Eng. & Architecture
5	55	2023	Operative generative design using NSGA-II	Automation in Construction
6	52	2023	Potential of AI as a tool for architectural design (Gaudí study)	Buildings
7	47	2024	Enhancing architectural education through AI (case study)	Buildings
8	46	2020	Multi-objective interior design optimization for temporary housing	Building and Environment

4. Discussion

4.1 A field defined by the generative-AI inflection

The trend and citation evidence converge on a single conclusion: research on AI in spatial design has been reconstituted by generative AI. The 40-fold growth concentrated in 2023–2025, the dominance of text-to-design methods among recent highly cited works [11], [12], [19], [23], and the centrality of generative and visual terms in the co-occurrence network all indicate a shift from earlier optimisation- and rule-based paradigms toward generative, language- and image-driven design. This positions the present analysis to capture a phase that earlier reviews, bounded by pre-2022 windows or narrower scopes, could not fully represent.

4.2 Three pillars and their integration

The thematic structure suggests three analytically distinguishable but interconnected pillars—generative and visual AI; architectural design, process and education; and performance optimisation and sustainability. The modest validation values and dense cross-cluster links indicate substantial overlap, which is consistent with an interdisciplinary field rather than three isolated sub-communities. The temporal evidence further suggests that optimisation and performance provided an earlier methodological base, while image- and language-driven generation became more prominent after 2022. A promising direction is therefore to bridge the generative and performance pillars (e.g., coupling text-to-design generation with performance-based evaluation), and to connect both to the education pillar through evidence on learning outcomes.

4.3 Research gap: children's, art, and educational space

Although design education is well represented (124 of 434 studies, 28%) [13], [16], [20], [24], attention to specific user groups and spatial contexts is highly uneven. To examine an emergent gap identified during the thematic interpretation, a post-hoc, case-insensitive search of the titles and abstracts of all 434 retained records was conducted using the terms “child*”, “kindergarten”, “early childhood”, and “early-childhood”. Only 4 publications (0.92%) matched at least one of these terms, indicating that children’s and early-childhood spatial contexts are substantially under-represented within the retained corpus. These terms were applied only after the corpus had been established and were not part of the original database search strategy or eligibility criteria. Given the developmental and pedagogical importance of children’s art and learning environments, this under-representation warrants focused research on how AI-supported design can address spatial configuration, colour, safety, accessibility, and multisensory experience in these settings.

4.4 Future directions

Three actionable directions follow from the analysis. First, human-centred and context-specific research should investigate participatory AI-assisted design with children, educators, and caregivers, while evaluating accessibility, safety, cultural appropriateness, and multisensory experience in real settings. Second, integrative methods should connect generative models to building-performance simulation, code and safety checks, and post-occupancy or immersive user evaluation so that generated proposals are assessed beyond visual quality. Third, pedagogical research should use controlled and longitudinal comparisons of AI-assisted and conventional design studios, measuring creativity, spatial reasoning, technical competence, ethical judgement, and AI literacy. Pursuing these directions would both consolidate the field and extend it into under-served, socially valuable domains.

4.5 Limitations

Four limitations delimit the findings. First, reliance on Lens.org means that database coverage, source classification, citation counts, and Fields of Study tagging may differ from Scopus or Web of Science. Second, restricting the corpus to English-language records may underrepresent relevant regional scholarship. Third, sparse author keywords required term co-occurrence to be derived from titles and abstracts; this improves coverage but may omit concepts expressed only in full text. Fourth, topical screening and the post-hoc identification of domain-specific gaps involved interpretive judgement despite explicit criteria. Future studies should triangulate databases, include multilingual records, compare author-keyword and full-text networks, and use independent reviewers or agreement statistics during screening.

5. Conclusion

This study mapped the intellectual structure of AI research in spatial design using 434 publications from 2018 to 2025. The field has grown exponentially and is now strongly shaped by the generative-AI wave, organised around three overlapping thematic pillars—generative and visual AI; architectural design, process and education; and performance optimisation and sustainability. The most influential works centre on generative and optimisation-based design of interiors and buildings. Critically, research on AI for children's, art, and early-childhood educational spaces is almost entirely absent, marking a clear gap for future work.

Practically, researchers can use the three clusters to identify cross-domain collaboration opportunities and position new studies at the intersection of generation, performance, and education. Practitioners and educators can use the mapped evidence to select AI applications that pair visual exploration with safety, performance, and learning evaluation. Funding bodies and research institutions may prioritise under-represented domains, particularly children's spatial design and art-education environments, where social value is high but the current evidence base is minimal.

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