Evolution and Transformation of the Computational Design Ecosystem

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Abstract
This paper presents a structural topic modeling analysis of the computational design literature spanning from 2000 to 2024. By analyzing 12,550 scientific publications from diverse disciplines, this research maps the thematic structure, temporal evolution, interdisciplinary knowledge migration, and geographical distribution of research in computational design. The findings reveal 15 distinct topics that characterize the field, with significant shifts over time from architectural generative design and optimization towards artificial intelligence-based approaches and creative coding. Notable patterns of knowledge migration between disciplines are identified, particularly in the adoption of AI techniques from computer science into design, and digital fabrication methods from engineering into architecture. The analysis also highlights geographical specializations, with Nordic countries focusing on sound design and user experience, East Asian countries on visual design and interactive narrative, and North America on AI-based approaches. This research reveals that the rise of artificial intelligence-based approaches is fundamentally altering not only the technological toolset of the field but also the very nature of interdisciplinary knowledge flow.

Keywords
computational design, topic modeling, interdisciplinary research, knowledge migration

1. Introduction

As the digital transformation driven by the Fourth Industrial Revolution fundamentally reshapes creative practices, computational design stands at the center of this change. In this context, understanding how the knowledge and methods of different disciplines interact and transform one another is of critical importance for mapping the future trajectory of the field.The integration of computational methods into design processes has transformed creative practices across different disciplines. From architecture to product design, visual arts to music, computational design approaches have enabled new forms of expression, expanded the boundaries of what is creatively possible, and facilitated innovative workflows that combine human creativity with algorithmic processes. This intersection of design, computation, and creativity has given rise to a rich interdisciplinary landscape that continues to evolve rapidly with technological advancements [1, 2].

Computational design serves as a bridge, connecting knowledge and practices across disciplinary boundaries. Architects utilize generative algorithms to shape physical spaces [3], product designers integrate optimization techniques into their design processes [4], and artists incorporate artificial intelligence methods into their creative work [5]. These diverse applications underscore the interdisciplinary nature of computational design.

Recent advances in artificial intelligence and machine learning have opened new horizons in computational design and creativity. Generative adversarial networks (GANs), transformer models, and other deep learning techniques have expanded the toolset of designers and creators, enabling new forms of human-machine creative collaboration [6, 7]. These developments have offered new possibilities that enhance and extend human creativity, rather than merely automating design processes [8].

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However, this rapid integration of AI into creative processes has raised fundamental questions about the future of computational design. Concerns about job displacement in creative industries, debates over authorship and authenticity in AI-assisted work, and the need to preserve human creative agency while leveraging computational capabilities have become central to contemporary discourse in the field.

Despite the growing literature on computational design, systematic analyses of how knowledge and methodologies transfer across different disciplinary domains remain limited. Goel and Davies [9] note that much of the work in computational creativity remains isolated, with the opportunities for interdisciplinary exchange not fully realized. Similarly, Bhattacharjee et al. [10] emphasize the need for better understanding of knowledge sharing patterns to promote interdisciplinary collaboration in computational design.This paper addresses this need by using a data-driven approach to map the thematic evolution and interdisciplinary migrations within computational design research over the past two decades.

2. Methodology

To define the research scope, this study examined review articles published in reputable journals and conferences (ICCC, EvoMUSART, ACM Creativity & Cognition, SIGGRAPH, CAAD Futures, etc.) over the past fifteen years. Based on this systematic approach, the following methodological framework was implemented to ensure comprehensive coverage and analytical rigor. Following Kitchenham and Charters [11], a systematic literature search strategy was developed.

Keywords were determined along three axes: computational/generative design terms (e.g., "computational design", "generative design"), creativity terms (e.g., "computational creativity"), and application domains (e.g., art, architecture, music). Additional terms reflecting technological developments (e.g., "artificial intelligence", "deep learning") were included [12, 13, 14].

Scopus database was selected for its interdisciplinary coverage [15, 16]. Boolean search yielded 17,000 records, filtered to 12,550 publications [17, 18, 19]. Geographical analysis was based on the institutional affiliation of the first author of each publication. While this approach may not fully capture international collaborations, it provides a systematic basis for mapping primary research origins.

The title and abstract fields of the final dataset were combined to create a text corpus, which was processed following standard natural language processing steps [20, 21]: lowercase conversion, punctuation removal, stopword removal, and stemming. The processed corpus was transformed into a document-term matrix representing each document as a vector of word frequencies [22].

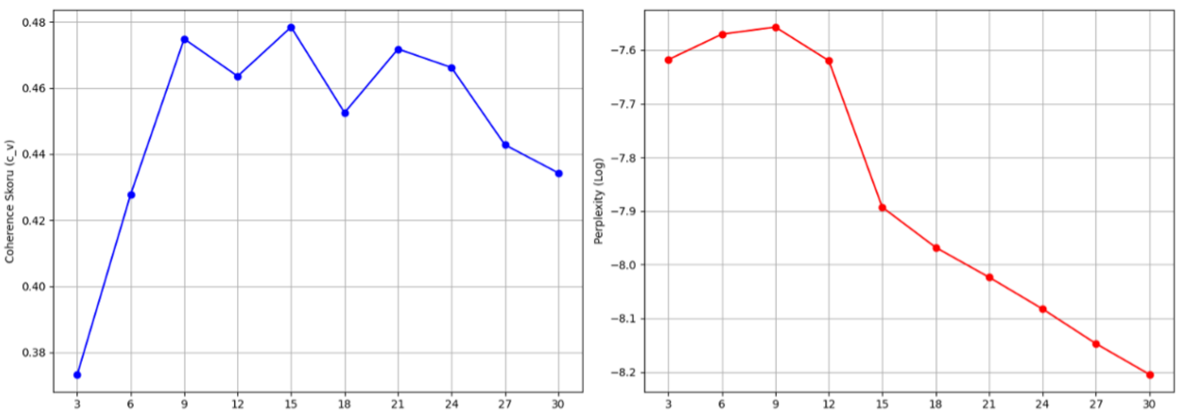

Figure 1. Changes in semantic coherence, exclusivity, and perplexity for different numbers of topics (K).

Structural Topic Modeling, developed by Roberts et al. [23], was used for text analysis. Unlike traditional topic modeling methods, STM allows document characteristics (covariates) to influence both topic content and topic prevalence. Through diagnostic measures including semantic coherence and exclusivity metrics, K=15 topics was determined as the optimal number providing balance between interpretability and granularity [24, 25].

Three main covariates were incorporated: temporal (publication year, 2000-2024), disciplinary (field categorization), and geographical (country of first author affiliation) [26, 27, 28]. The model formulation expressed these covariates as: topic prevalence ~ s(Year) + Discipline + Country where s(Year) is a non-linear (spline) function of year [29].

For analyzing interdisciplinary knowledge transfers, the analysis identified the dominant topic for each document, calculated topic distributions for each discipline-year slice, and modeled transitions between consecutive time slices as a weighted directed network [30, 31, 32]. This approach allowed visualization of topic migrations between disciplines over time.

Geographical distribution analysis utilized scientific mapping methodology [33], calculating country-based topic distributions. Temporal analyses examined changes in topic probabilities over time in annual and 2-year slices [34]. All analyses and visualizations were performed using R programming language with specialized packages [35, 36, 37]. All analyses used R programming [35, 36, 37]. Limitations include English-only publications and Scopus coverage, potentially underrepresenting Global South research and non-Western academic traditions

3. Results

3.1. Thematic Structure of Computational Design

The Structural Topic Modeling (STM) analysis identified 15 fundamental topics within the computational design literature. These topics and their most distinctive terms are presented in Table 1. The analysis revealed that the topics with the highest prevalence are Architectural Generative Design (T1) (14.3%), AI-Based Design (T3) (11.7%), Manufacturing and Fabrication (T4) (9.8%), and Creative Coding (T2) (9.1%).

Table 1
15 topics identified by STM analysis and their most distinctive terms.

Topic ID	Label	Most Distinctive Terms
T1	Architectural Generative Design	parametric, geometric, algorithmic, façade, architect, form, optimization, script, pattern, generative
T2	Creative Coding	code, program, creative, software, interact, artist, tool, platform, interface, develop
T3	AI-Based Design	ai, learn, generate, neural, gan, deep, network, intelligent, model, train
T4	Manufacturing and Fabrication	print, manufacturing, fabrication, 3d, material, additive, product, structure, layer, robot
T5	Visual Design and Typography	graphic, typography, visual, layout, font, composition, create, image, element, text
T6	Sound and Music Production	sound, music, audio, composition, instrument, generate, acoustic, perform, signal, frequency

Topic ID	Label	Most Distinctive Terms
T7	User Experience in Design	user, experience, interact, interface, product, evaluate, design, human, usability, test
T8	Knowledge-Based Systems	ontology, semantic, knowledge, inference, rule, database, represent, reason, schema, query
T9	Optimization and Simulation	optimization, simulation, algorithm, performance, function, solution, constraint, objective, efficiency, search
T10	Computational Creativity Theory	creativity, cognitive, computational, process, human, theory, conceptual, automation, intent, system
T11	Design Tools and Workflows	workflow, tool, bim, process, collaboration, integration, platform, management, project, implementation
T12	Computational Design in Education	education, pedagogy, learn, teach, student, curriculum, skill, course, academic, workshop
T13	Data-Driven Design	data, visual, analysis, model, structure, information, extract, pattern, cluster, set
T14	Urban and Spatial Design	urban, spatial, city, plan, space, map, environment, model, analysis, geographic
T15	Games and Interactive Narrative	game, play, narrative, interact, virtual, character, scene, environment, player, story

3.2. Temporal Evolution of Topics

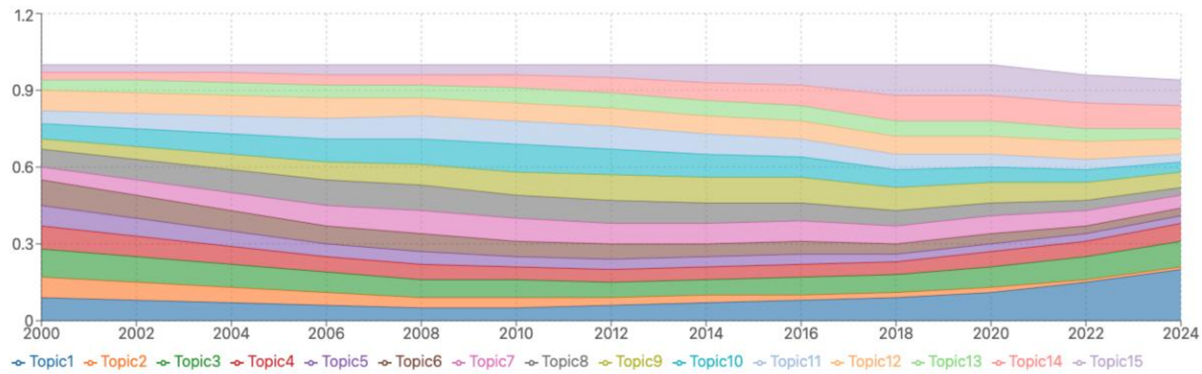

Figure 2: Temporal evolution of topics (2000-2024): relative prevalence of topics in four time periods.

The analysis revealed significant temporal shifts in topic prevalence between 2000 and 2024 (see Figure 2). The most pronounced changes manifested as a rise in the popularity of some topics and a decline in others. Notably, AI-Based Design (T3) exhibited the most remarkable growth, increasing its share from 5.2% in the early 2000s to 18.7%. Similarly, Creative Coding (T2) gained prominence, rising from 4.9% to 12.3%. In contrast to this growth, the prevalence of Architectural Generative Design (T1), which was dominant in the field's early years, decreased from 18.5% to 11.4%. During the same period, Optimization and Simulation (T9) also lost its earlier popularity, falling from 12.1% to 7.3%. On the other hand, topics such as Sound and Music Production (T6) and Computational Design in Education (T12) maintained relatively stable shares throughout the analyzed period. The introduction of artificial intelligence and deep learning techniques into the design field, especially post-2017, has significantly affected this topic distribution. The rise of generative models (GANs and diffusion models) explains the dramatic increase in the prevalence of AI-Based Design

3.3. Interdisciplinary Topic Migrations

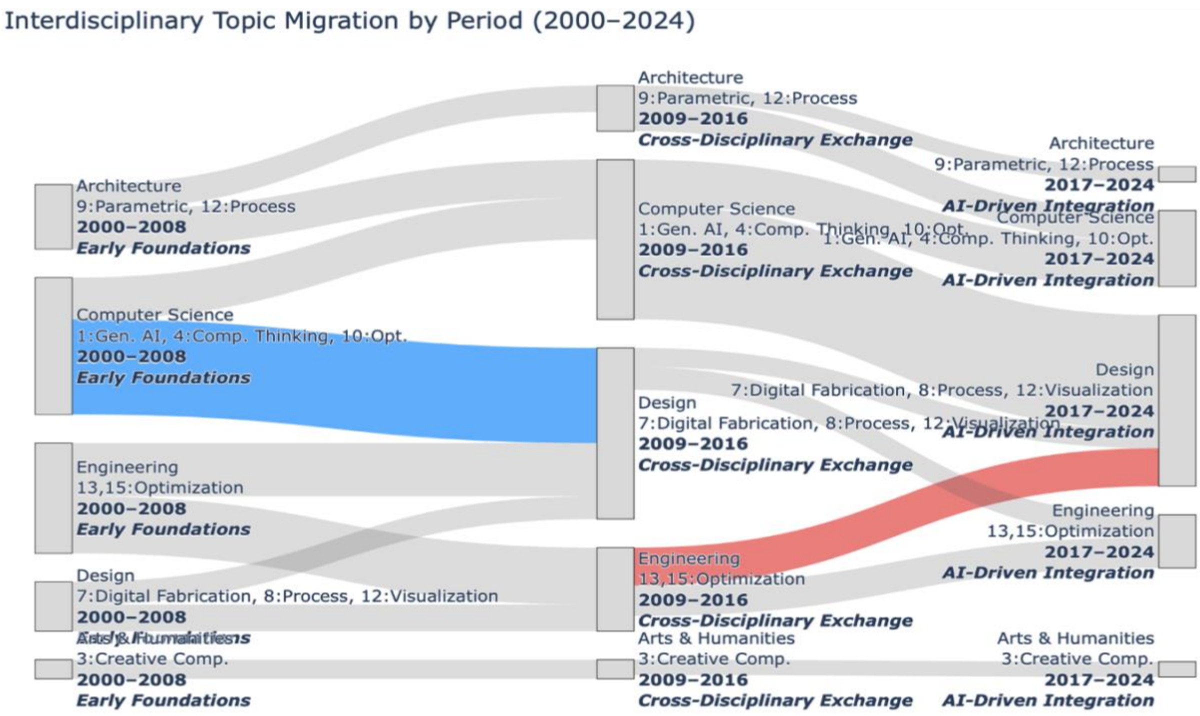

Figure 3: Interdisciplinary topic migrations: Sankey diagram showing the transition of topics from one discipline to another.

The examination of interdisciplinary topic migrations reveals prominent patterns that highlight the direction and nature of knowledge flow within the field (see Figure 3). One of the most significant transitions, becoming particularly evident after 2015, is the transfer of the AI-Based Design (T3) topic from Computer Science to Design, which demonstrates how the design discipline has adopted and adapted artificial intelligence techniques. A similar dynamic was observed in the continuous flow of the Manufacturing and Fabrication (T4) topic from Engineering to Architecture, reflecting the integration of computational design with physical production processes. Other important migrations include the adaptation of Creative Coding (T2) from Design to Arts & Humanities and the way problems in Architectural Generative Design (T1) from Architecture have opened new research areas for Computer Science. These migration patterns reflect the dynamic nature of interdisciplinary interaction in the computational design field, with a bidirectional flow of knowledge observed, particularly in the topics of AI-Based Design and Creative Coding.

3.4. Geographical Distribution

The geographical analysis revealed distinctive regional research focuses, as shown in Table 2. This geographical distribution reflects unique regional research traditions and priorities. For instance, Nordic countries (Sweden, Finland, Denmark) stand out in Sound and Music Production (T6) and User Experience in Design (T7). East Asian countries (Japan, South Korea) exhibit a strong focus on Visual Design and Typography (T5) and Games and Interactive Narrative (T15). In contrast, North America (USA, Canada) dominates in technology-intensive topics such as AI-Based Design (T3), Optimization and Simulation (T9), and Data-Driven Design (T13).

Table 2
Geographical distribution of topics: The top three countries where each topic is most prominent.

Topic ID	Label	Prominent Countries
T1	Architectural Generative Design	Switzerland, Austria, Italy
T2	Creative Coding	Germany, Netherlands, Japan
T3	AI-Based Design	USA, China, Canada
T4	Manufacturing and Fabrication	Singapore, Switzerland, Germany
T5	Visual Design and Typography	Japan, UK, South Korea
T6	Sound and Music Production	Sweden, Finland, UK
T7	User Experience in Design	Denmark, Finland, Norway
T8	Knowledge-Based Systems	Portugal, Spain, Italy
T9	Optimization and Simulation	USA, Canada, China
T10	Computational Creativity Theory	UK, Australia, USA
T11	Design Tools and Workflows	Australia, Hong Kong, Singapore
T12	Computational Design in Education	UK, Australia, Canada
T13	Data-Driven Design	USA, Israel, Canada
T14	Urban and Spatial Design	Netherlands, Australia, UK
T15	Games and Interactive Narrative	Japan, South Korea, Canada

4. Discussion

The identification of 15 distinct topics reveals computational design as a field encompassing both theoretical exploration and practical application across multiple domains. The temporal analysis demonstrates that architectural generative design dominated the field's early development, establishing computational methods that subsequently influenced other disciplines. This finding validates Woodbury's [38] observations about parametric design's transformative effect while documenting its role as a foundational element in the field's evolution. This foundational stability underwent significant change in the field's later development.

The results also support Menges and Ahlquist's [39] emphasis on the integration of computational design with material systems and fabrication processes. The high prevalence of T4 (Manufacturing and Fabrication) indicates a close relationship between digital design and physical production.

The substantial growth of AI-Based Design represents the most significant transformation documented in this analysis, accelerating particularly after 2017 with mainstream AI tool availability. This shift suggests reorientation toward human-machine collaboration while raising critical questions about creative agency and professional displacement. The trend validates McCormack et al.'s [40] predictions while indicating implications that extend beyond initial technological adoption.

The documented migration patterns reveal computational design as an active knowledge mediator rather than isolated practice. Three pathways emerged: AI techniques flowing from Computer Science to Design, manufacturing knowledge migrating from Engineering to Architecture, and Creative Coding establishing bidirectional Design-Arts exchange. These patterns challenge Goel and Davies's [9] concerns by demonstrating selective transfer through practical applicability rather than theoretical alignment.

The flow of Manufacturing and Fabrication from Engineering to Architecture supports Kolarevic and Klinger's [43] thesis on the reintegration of architectural design and production processes, linked to the adoption of digital fabrication technologies in architectural practice.

While the rise of AI-based approaches is the most striking trend, other important developments were observed. The increase in Data-Driven Design reflects the growing use of big data in design processes, as emphasized by Offenhuber and Ratti [44], indicating evolution toward evidence-based design approaches.

The relationship between User Experience in Design and Games and Interactive Narrative reflects the "gamification" trend identified by Deterding et al. [45], developing predominantly under the leadership of Nordic research groups.

The stable presence of Computational Design in Education confirms Oxman's [1] predictions regarding the transformation of digital design education, reflecting the institutionalization of computational design in educational curricula.

These converging trends suggest three strategic directions for computational design's evolution. First, AI-driven transformation requires frameworks preserving human creative agency while leveraging computational capabilities. Second, successful migration patterns provide templates for fostering exchange between isolated domains. Third, addressing geographical participation gaps necessitates systematic support for underrepresented regions. These findings indicate that computational design's advancement depends on thoughtful navigation of technological, collaborative, and cultural dimensions

Future research could extend this work with full-text analyses, citation network analyses, and examination of non-textual content (images, codes, models). Deeper analysis of interdisciplinary topic migrations could provide insights into the mechanisms driving these knowledge transfers.

5. Conclusion

This study maps the thematic structure, temporal evolution, interdisciplinary knowledge migrations, and geographical distribution of the computational design field through Structural Topic Modeling analysis of 12,550 scientific publications. The findings show that computational design is a versatile and dynamic interdisciplinary field spanning architecture, computer science, art, and engineering.

This study provides valuable insights for computational design educators, researchers, and practitioners by identifying opportunities for interdisciplinary collaboration, emerging trends, and future research directions. It contributes to a deeper understanding of how computational design has transformed creative applications across different disciplines and how it continues to evolve as a field at the intersection of technology, creativity, and design.

This study acknowledges several limitations. The analysis focuses on English-language publications in Scopus, potentially underrepresenting non-Western research traditions. Additionally, geographical categorization based on first author affiliation may not fully capture international collaborations, and the reliance on titles and abstracts rather than full-text content may limit thematic detail.

Ultimately, this study demonstrates that computational design has evolved beyond a collection of tools and techniques to become a dynamic ecosystem that fundamentally challenges traditional disciplinary boundaries. The documented shift from architectural parametricism to AI-driven creativity, coupled with systematic knowledge migration patterns, reveals a field in profound transformation. As artificial intelligence continues to reshape creative practices, understanding these interdisciplinary dynamics becomes essential for educators developing future curricula, researchers identifying promising directions, and practitioners navigating an increasingly complex technological landscape. Computational design's future lies not in any single discipline but in the spaces between them—where technology, creativity, and human insight converge to expand the boundaries of what is possible.

Declaration on Generative AI

In this study, the author used ChatGPT-4o3 for translation, language checking, and coding processes. All content was subsequently reviewed and edited by the author, who takes full responsibility for the publication.

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