Generative Artificial Intelligence and Computational Design Optimization in Contemporary Architecture: a Systems Engineering Perspective

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Abstract: - Generative artificial intelligence (GenAI) is increasingly influencing architectural design by expanding computational design exploration, performance evaluation, optimization, and decision-support capabilities. This systematic literature review examines how GenAI and computational design optimization are being integrated into contemporary architecture from a systems engineering perspective. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 reporting framework. Searches were conducted across Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, ACM Digital Library, Wiley Online Library, Taylor & Francis Online, SAGE Journals, Google Scholar, and arXiv for literature published between January 2018 and March 2026. The search identified 1,248 records. After removal of 276 duplicates, 972 records were screened by title and abstract, of which 721 were excluded. Full texts were assessed for 251 articles, with 157 excluded for reasons including insufficient architectural relevance, inadequate focus on artificial intelligence, methodological weakness, and unavailable full text. Ninety-four studies were retained for the final synthesis. The review examined computational design, generative AI, multi-objective optimization, systems engineering integration, sustainability, smart buildings, digital twins, and intelligent built environments. The synthesis indicates that GenAI can expand design solution spaces, support rapid concept generation, facilitate performance-based optimization, and strengthen data-driven decision-making. Systems engineering provides a complementary framework through requirements management, lifecycle thinking, feedback mechanisms, risk management, interdisciplinary coordination, and performance evaluation. However, concerns concerning data quality, explainability, interoperability, intellectual property, cybersecurity, professional accountability, and human oversight remain important. The review argues that effective architectural application of GenAI depends not simply on technological adoption but on integrating computational intelligence with systems engineering processes and professional architectural judgment. The reported screening counts establish the review's selection pathway; however, the final manuscript should additionally report the verified Cohen's kappa coefficient and complete study-level MMAT appraisal results from the review records before publication.

Key-Words: - Architectural Computing; Computational Design; Generative Artificial Intelligence; Optimization; Systems Engineering.

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1 Introduction

Architecture has continually evolved through interactions among human creativity, technological development, environmental requirements, and changing societal needs. The progression from manual drafting to computer-aided design (CAD), Building Information Modelling (BIM), parametric modelling, and computational design has progressively expanded the capacity of architects to represent, analyse, and modify complex design systems. More recently, generative artificial intelligence (GenAI) has introduced computational approaches capable of producing design alternatives, interpreting design requirements, generating visual representations, predicting performance, and supporting iterative decision-making. This development represents a movement toward hybrid design processes in which human expertise is complemented by algorithmic intelligence (Ploennigs & Berger, 2024). Computational design provides an important foundation for this transition. It uses algorithms, mathematical relationships, parameters, rules, and constraints to generate and evaluate architectural alternatives. Unlike conventional digital drafting, computational design can establish relationships among design variables so that modifications to one parameter can propagate through connected elements. Parametric and algorithmic approaches therefore enable architects to investigate larger design spaces and examine relationships among form, function, environmental performance, construction requirements, and other project objectives (Caetano et al., 2020).

Generative design extends this capability by allowing designers to define objectives, constraints, and performance requirements while computational systems produce multiple potential solutions. Such systems are particularly relevant to architectural problems involving competing objectives, including energy efficiency, daylight availability, spatial performance, structural efficiency, construction cost, material consumption, and occupant comfort. Generative methods therefore shift some aspects of design exploration from manually producing individual alternatives toward computationally generating and evaluating sets of alternatives (Nourian et al., 2023). Recent developments in machine learning, deep learning, generative adversarial networks (GANs), diffusion models, and large language models (LLMs) have further expanded the possibilities of computational architectural design. These technologies can generate conceptual images, spatial arrangements, building forms, façade alternatives, and other design representations while also supporting predictive modelling and performance analysis. Recent architectural research has particularly examined the application of GANs, diffusion models, three-dimensional generative models, and foundation models across different stages of architectural design (Li et al., 2025). The systems engineering perspective is important because architectural projects constitute complex socio-technical systems involving interconnected technical, environmental, economic, organizational, and human requirements. Systems engineering emphasizes requirements management, lifecycle thinking, system integration, verification and validation, risk management, feedback, performance evaluation, and interdisciplinary coordination (International Council on Systems Engineering [INCOSE], 2023). These principles correspond closely with the challenges encountered when integrating AI into architectural workflows. For example, an AI-generated design may satisfy an aesthetic objective while creating undesirable consequences for energy consumption, structural performance, construction cost, accessibility, maintainability, or occupant comfort. Consequently, the usefulness of GenAI cannot be evaluated solely by its ability to generate visually attractive alternatives. It must also be considered in relation to requirements, constraints, performance indicators, lifecycle consequences, stakeholder needs, and professional accountability.

Multi-objective optimization is therefore particularly relevant. Contemporary architectural projects frequently require simultaneous consideration of competing objectives. Increasing daylight may influence cooling demand; reducing material quantities may affect structural performance; minimizing construction cost may affect durability; and maximizing spatial efficiency may influence occupant comfort. Computational optimization provides mechanisms for exploring these trade-offs systematically, while AI can provide predictive and generative capabilities that expand the design search space. Sustainability further strengthens the need for integrated computational approaches. Building design and operation are closely associated with energy consumption, material use, carbon emissions, thermal conditions, daylight, and environmental performance. AI-supported optimization can assist designers in examining these variables earlier in the design process, when changes can have significant implications for subsequent building performance. Despite these opportunities, the application of GenAI introduces significant challenges. AI systems may be difficult to interpret; training data may be incomplete or biased; generated designs may raise questions concerning authorship and intellectual property; AI-generated recommendations may not be compatible with professional regulations; and integration with BIM, simulation, structural analysis, and construction workflows may remain technically difficult. The purpose of this systematic review is therefore to examine the relationship between GenAI, computational design optimization, and systems engineering in contemporary architecture. Specifically, the review synthesizes evidence concerning: (1) the theoretical foundations of computational architectural design; (2) applications of

GenAI to architectural design; (3) AI-supported computational optimization; (4) systems engineering integration; (5) sustainability, smart buildings, and digital twins; and (6) implementation challenges and ethical considerations.

2 Literature Review

2.1 Theoretical Foundations of Computational Design in Architecture

One of the most innovative developments in modern architecture, computational design lets designers go from conventional drafting and modelling techniques to algorithm-driven design generation and optimization. Mathematical algorithms, digital technologies, and computational approaches are applied in computational design to help to solve problems, generate forms, and evaluate performance in architecture (Caetano et al., 2020). Unlike conventional computer-aided drafting tools that mostly help with visualisation and documentation, computational design actively helps in design creation by let architects define rules, criteria, and limitations that guide the development of architectural shapes.

Systems theory, cybernetics, and algorithmic thinking, all of which became more well-known in the second half of the 20th century, have theoretical roots in computational design. Early pioneers like Christopher Alexander stressed the need of methodical approaches to design since they would allow one to manage complexity and unpredictability (Alexander, 1964). These basic ideas set the stage for computational models that subsequently become crucial in digital design.

One of the most powerful expressions of computational design is parametric design. In parametric systems, relationships and variables instead of fixed geometric shapes specify architectural features. Changes in one factor naturally affect connected parts, therefore freeing designers to quickly investigate several design possibilities. Parametric Modelling, Woodbury (2010) says, moves design from direct form generation toward the development of flexible design systems able to produce several outcomes.

Algorithmic design uses computational logic and procedural rules to produce architectural shapes, so increasing computational capacity. Architects may design unique processes that reduce manual work and enable complex geometric changes via scripting languages and visual programming tools including Grasshopper and Dynamo (Burry, 2011). These methods are becoming more and more crucial in current projects distinguished by sophisticated geometries, performance-driven demands, and cross-functional cooperation.

Computational design's convergence with Building Information Modelling (BIM) has improved its practical use even more. BIM gives a thorough digital depiction of construction data across the project lifecycle so that computational models may interact with environmental, construction, and structural data. This integration helps designers, engineers, contractors, and clients to make educated decisions and work together (Eastman et al., 2018).

The range of computational design has been greatly increased by recent developments in artificial intelligence, high-performance computing, and cloud computing. Modern tools enable real-time simulations, processing of huge datasets, and analysis of sophisticated performance measures, so enabling architects to maximize building designs grounded on several factors at once. Therefore, computational design has changed from a niche digital method into a major component of architectural creativity and sustainability.

Growing complexity of metropolitan surroundings, demands for climate adaptation, and resource limits keep driving need for computational methods able of enabling evidence-based design decisions. Therefore, computational design is the technological basis upon which generative artificial intelligence and sophisticated optimization techniques are developed; hence, it is a crucial topic of study in current architecture research and practice.

2.2 Generative Artificial Intelligence and Architectural Design Innovation

By letting clever systems produce unique ideas, spatial layouts, and visual representations based on learned patterns from enormous datasets, Generative Artificial Intelligence (GenAI) has brought forth a new paradigm in architectural design. Generative artificial intelligence algorithms use machine learning approaches to find correlations in data and create fresh results that fulfil given goals, unlike conventional computer tools depending on precisely programmed rules (Li et al., 2024).

Deep learning models have greatly sped up the uptake of generative AI in design. Remarkable abilities in generating architectural layouts, façade designs, internal layouts, and urban planning ideas have been shown by Generative Adversarial Networks (GANs), Variational Auto encoders (VAEs), diffusion models, and large language models (LLMs). Introduced by Goodfellow et al. (2014), GANs comprise two competing neural networks working cooperatively to create realistic results. In architectural applications, GANs have been used to produce original building shapes and show design possibilities depending on user-specified restrictions.

Another strong technology in architectural design generation are diffusion models. These models let designers quickly investigate many design options by progressively converting random noise into significant images or spatial representations. The rise of programs like Midjourney, DALL-E, and Stable Diffusion has shown the possibilities of AI-assisted creativity in conceptual design phases (Li et al., 2024). These tools help architects create first sketches, mood boards, and visual stories that support stakeholder input and creative exploration.

By means of natural language communication with design platforms, large language models help artificial intelligence to play a more important part in architecture. Architects can tell artificial intelligence systems their design intentions, performance needs, and aesthetic tastes via textual cues, therefore enabling the generation of appropriate design ideas. This feature increases access to sophisticated computational tools and eliminates technical obstacles, therefore enabling more practitioners to interact with AI-assisted design processes.

By increasing the solution space open to designers, generative artificial intelligence helps to drive design creativity. Time constraints, reliance on established precedents, and cognitive constraints usually limit traditional design processes. Within a reasonably short time, artificial intelligence systems can assess thousands of possible settings and highlight fresh ideas that might not show up with conventional techniques. This ability helps creativity enhancement instead of creativity replacement, therefore placing artificial intelligence as a cooperative design companion instead of a substitute for human knowledge.

These benefits notwithstanding, questions about originality, intellectual property, and authorship of design still spark continuous debate. AI systems learn from already available data, hence questions concerning the ownership of produced output and moral application of training resources follow. Furthermore, some scholars contend that too much reliance on solutions made by artificial intelligence may result in design homogenization if the underlying data lack variety and contextual sensitivity (Nashaat & Elzeni, 2025).

Still, the integration of generative AI into architectural design keeps speeding. Industry leaders are seeing more and more how AI might help to boost design quality, promote creativity, and increase output. Generative artificial intelligence is projected to become a core tool of architectural processes as computer power develops, so permanently changing architects' perspective on, assessment of, and communication of design concepts.

2.3 Computational Optimization and Performance-Based Architectural Design

Reflecting the need to maximize building performance along environmental, structural, financial, and social dimensions, performance-based design has emerged as a core goal in modern architecture. Architects may use computational optimization to find very effective designs that meet several performance goals concurrently. Inside this framework, optimization is the methodical quest for solutions that reduce negative effects while maximizing desired results (Attia, 2018).

In traditional architectural design, designers often manually evaluated alternative solutions in an iterative, trial-and-error approach. Using mathematical methods able to investigate vast design spaces quickly, computational optimization greatly improves this process. Genetic algorithms, particle swarm optimization, and simulated annealing methods are evolutionary algorithms that have found great application in architectural research and practice since they are so good at resolving difficult multi-objective issues.

Particularly pertinent, genetic algorithms replicate biological evolution via techniques including selection, mutation, and crossover. These methods find better and better solutions based on given performance criteria by repeatedly creating and assessing design choices. Building massing optimization, daylight enhancement, structural efficiency, and energy performance improvement are among architectural applications (Attia, 2018).

One of the most important fields of improvement in modern design is energy efficiency. Buildings use 30-40% of the world's energy, thus presenting great chances for computational techniques to help with sustainability goals. Integrating energy simulation software with optimization algorithms helps to assess many design possibilities depending on elements like orientation, glazing ratios, shading techniques, ventilation systems, and material characteristics. These skills let designers' spot energy-saving ideas early on in the design process when changes are most economical.

Daylighting maximization offers still another significant use of computational design techniques. Good daylight exposure helps to lower reliance on artificial lighting systems and therefore improves inhabitant comfort, health, and productivity. By helping designers to balance thermal comfort and energy efficiency needs with daylight performance, computational optimization tools enable a comprehensive design process.

Advances in computer intelligence have likewise helped structural optimization. To create structurally effective solutions that reduce resource use without sacrificing safety or performance, AI-assisted optimization techniques might examine load distributions, material usage, and geometric layouts. Such methods support more general sustainability goals by lowering embodied carbon emissions and material waste.

Because architectural designs usually have conflicting needs, multi-objective optimization is especially significant today. For instance, maximizing daylight penetration can raise cooling loads while lowering building costs could compromise occupant comfort. Sophisticated optimization techniques help designers to methodically evaluate trade-offs and create balanced solutions that take into account several stakeholder needs (Yang, 2025).

Combining artificial intelligence with computational optimization improves these skills even more by adding real-time feedback systems, adaptive learning, and predictive modelling. Thus, performance-based design is more and more dependent on AI-driven optimization frameworks that enable informed decision-making and help to create sustainable, strong, and high-performing built environments.

2.4 Systems Engineering Principles in AI-Driven Architectural Design

A useful structure for handling the growing complexity of current architectural work, systems engineering has become rather important. Originally created to control major engineering systems marked by many linked components, systems engineering stresses lifecycle thinking, performance optimization, holistic analysis, and cross-discipline teamwork (INCOSE, 2023). Particularly relevant to design, these ideas, where structures run as sophisticated socio-technical systems combining structural, environmental, technical, financial, and human elements-are. Generative artificial intelligence in architectural design is quite similar to systems engineering because both methods try to control complexity using organized procedures and data-driven decision-making. Modern building initiatives have to strike a balance between financial limitations, technological integration, occupant needs, legal obligations, and sustainability objectives. Many times, conventional design techniques find it difficult to properly assess these interrelated factors. While artificial intelligence tools provide sophisticated analytical and optimization capabilities, systems engineering offers a structure for managing these many needs.

Requirements management is among the fundamental ideas of systems engineering. Many parties-clients, architects, engineers, builders, legal bodies, and end users—are involved in architectural projects. Every stakeholder could have different goals that shape design results. By handling a lot of stakeholder data, spotting trends, and creating design options meeting given requirements, generative AI solutions can help with requirements analysis. This feature helps to better match design solutions with stakeholder expectations.

Another basic idea of systems engineering is lifecycle thinking. Long-term operational performance, maintenance needs, flexibility, and end-of-life concerns should all be taken into account in addition to initial build expenses or visual features. By combining environmental, financial, and operational data across the design process, AI-driven computer models help to support lifecycle evaluations. Such research help to guide wise judgments that improve long-term building performance and sustainability.

One of the most important components of systems engineering approaches are feedback mechanisms. Good systems constantly gather, evaluate, and act on performance data. AI-powered monitoring systems can collect real-time data from sensors buried inside buildings in architecture, therefore enabling ongoing analysis of energy use, temperature comfort, interior air quality, occupancy patterns, and apparatus performance. These feedback loops help to enable evidence-based facility management and adaptive optimization.

Another crucial field where systems engineering and artificial intelligence converge is risk management. Architectural developments are sometimes exposed to unknowns related to material performance, legal changes, technical disturbances, and environmental factors. Machine learning methods can help find possible hazards and forecast performance results under different conditions by analysis of past project data. These features help to proactively guide decisions throughout the construction lifecycle and improve project resilience.

Digital twins are a real-world use of systems engineering ideas in construction. A dynamic virtual model of a physical structure that constantly combines real-time operational data is a digital twin. Digital twins let continuous performance monitoring, predictive maintenance, and operational optimization by combining BIM, IoT technologies, and artificial intelligence. This systems-based strategy helps with wise management judgments and increases building efficiency.

Using systems engineering models also helps several disciplines to work together. Modern building projects need more and more coordination among experts from many fields. AI-enabled systems help to lower communication barriers and improve project efficiency by means of information sharing, simulation integration, and group decision-making. Consequently, systems engineering is a fundamental requirement for the effective application of generative artificial intelligence in design practice.

Systems engineering ideas will always be very important to guarantee that artificial intelligence-driven design developments significantly advance sustainability, resilience, operational efficiency, and occupant well-being as the built environment gets more and more linked and technologically advanced. Therefore, the convergence of systems engineering and artificial intelligence portends a major development in current architectural theory and practice.

2.5 Sustainability, Smart Buildings, and Digital Twins in AI-Enabled Architecture

Modern design nowadays relies most on sustainability as it is among the most effective implements of creativity. Rising worries about resource depletion, urbanization, environmental degradation, and climate change have driven the need of building designs that minimize ecological effects while maximizing human well-being. These issues may be effectively addressed using generative artificial intelligence and computational optimization techniques that let designers analyse sustainability performance across the design life cycle.

Building construction and running use a lot of the world's energy and cause a lot of greenhouse gas emissions. Buildings account around one third of world energy demand and carbon emissions, says the International Energy Agency (IEA, 2024). Improving building performance is thus a top priority in global sustainability initiatives. AI-driven design tools help to meet this goal by letting designers examine environmental performance during the first phases of project development.

Through prediction modelling and performance optimization, generative artificial intelligence helps to create sustainable structures. Machine learning algorithms may use previous building data, occupancy patterns, and meteorological data to project environmental consequences and energy use. These insights help designers to deliberately choose building orientation, envelope configuration, glass systems, ventilation techniques, and renewable energy integration. Through concurrently assessing thousands of design options, artificial intelligence systems find answers balancing functional and aesthetic goals with environmental performance.

Artificial intelligence integration inside construction is also resulting in smart structures, another important result. Smart buildings improve operational efficiency and occupant experiences by using linked digital technologies, sensors, and automatic control systems. Artificial intelligence analyses real-time data and helps with flexible decision-making, so becoming the analytical backbone of these systems. Based on real occupancy trends and environmental factors, AI-enabled building management systems can maximize lighting, heating, cooling, ventilation, and security features.

Development of smart building ecosystems has much revolved on the Internet of Things. IoT devices constantly gather information about user behaviour, equipment performance, and environmental factors. AI systems examine these data streams to find mistakes, forecast maintenance needs, and suggest fixes. Such features help to lower operating costs, greater occupant comfort, and better environmental performance.

One of the most revolutionary tools helping artificial intelligence-enabled building management is digital twins. A digital twin is a constantly updated virtual representation of a building that reflects its operational behaviour and physical features. Integrating BIM data, sensor data, simulation outputs, and artificial intelligence analytics, digital twins offer all-around view of building performance across its lifecycle (Boje et al., 2020).

Digital twins may be used for predictive maintenance and scenario analysis in addition to operational monitoring. Before problems arise, artificial intelligence algorithms can spot performance deviations, anticipate equipment breakdowns, and advise maintenance actions. This prediction ability lowers downtime, stretches asset lifetime, and raises general building dependability. Moreover, digital twins help resilience planning by letting interested parties imitate responses to occupancy changes, energy interruptions, and environmental dangers.

Also becoming somewhat well-known are urban-scale uses of digital twin technology. Smart city projects use digital twins more and more to simulate energy systems, water infrastructure, transportation networks, and urban development scenarios. By helping with extensive optimization and scenario creation, generative artificial intelligence improves these models and so supports the creation of evidence-based policies and urban planning.

Though advantageous, digital twins and smart building technologies offer certain difficulties. Still major adoption challenges are data privacy issues, cybersecurity hazards, interoperability problems, and implementation expenses. Good governance structures are hence needed to make sure that technical developments fit with moral, legal, and society expectations. Still, getting future sustainability and resilience goals inside the built environment will depend much on the combination of artificial intelligence, smart building technologies, and digital twins.

Research always shows that solutions based on artificial intelligence can help a lot to make buildings more energy-efficient. By means of smart optimization, predictive analytics, and ongoing performance monitoring, these technologies help to create more energy-friendly, flexible, and environmentally friendly cities and buildings. The relationship between creative artificial intelligence and sustainable building is poised to get more important in both academics and professional practice as computer power keeps growing.

3 Materials and Methods

3.1 Research Design

This study employed a systematic literature review to synthesize published evidence concerning GenAI and computational design optimization in contemporary architecture from a systems engineering perspective. The reporting of the review was structured according to PRISMA 2020. PRISMA 2020 provides a 27-item reporting framework and a flow-diagram structure for transparently documenting the identification, screening, eligibility assessment, and inclusion of studies.

The review addressed the following questions:

- How is GenAI being applied to computational architectural design?
- What computational optimization approaches are reported in architectural research?
- How are systems engineering principles integrated with AI-supported architectural design?
- What sustainability, smart-building, and digital-twin applications are reported?
- What technological, methodological, ethical, professional, and governance challenges constrain implementation?

The review period covered publications from January 2018 through March 2026.

3.2 Data Bases and Search Methodology

Major academic databases including Scopus, Web of Science, ScienceDirect, SpringerLink, IEEE Xplore, ACM Digital Library, Wiley Online Library, Taylor & Francis Online, Sage Journals, Google Scholar, and arXiv were all included in a thorough literature search. The search concentrated on peer-reviewed papers, conference proceedings, books, and excellent preprints released between January 2018 and March 2026. The study goals and current literature helped guide the creation of search keywords.

Search Keywords

The primary keywords included:

- “Generative Artificial Intelligence”
- “Generative AI”
- “Computational Design”
- “Algorithmic Design”
- “Parametric Design”
- “Architectural Optimization”
- “Systems Engineering”
- “Building Information Modelling”
- “Digital Twin”
- “Smart Buildings”
- “Machine Learning in Architecture”
- “AI-Driven Design”
- “Sustainable Architecture”

Boolean Search String

The following representative Boolean search expression was applied across databases:

("Generative Artificial Intelligence" OR "Generative AI" OR "Machine Learning")
AND
("Computational Design" OR "Parametric Design" OR "Algorithmic Design")
AND
("Architecture" OR "Architectural Design" OR "Built Environment")
AND
("Optimization" OR "Performance-Based Design" OR "Systems Engineering")
AND
("Digital Twin" OR "BIM" OR "Smart Buildings" OR "Sustainability")

3.3 Study Selection and Screening Process

The records retrieved were all put into a reference management system and duplicate copies were deleted before screening.

Two screening were done, a two-stage screening process:

The Title/Abstract screening phase is the first step. The first step is the Title/Abstract screening phase. Titles and abstracts were screened by two independent reviewers using predetermined criteria. Selection bias was minimized through review without knowledge of the authors.

Stage 2: Full-Text Assessment

After being screened, articles were full-text evaluated. The eligibility was evaluated separately by the same two reviewers.

Conflicting points of view were discussed and consensus was reached. If a consensus was not reached, a third reviewer served as an adjudicator. The inter-reviewer agreement was assessed by Cohen's Kappa coefficient, with a value >0.80 considered as substantial agreement.

3.4 Inclusion and Exclusion Criteria

Inclusion Criteria

Studies were included if they:

- Were published between 2018 and 2026.
- Architectural/engineering/construction/built environment oriented.
- Reviewed Generative AI, computational design/optimization, BIM, digital twins, or systems engineering applications.
- Were published in peer reviewed journals, conference proceedings, books or creditable preprint repositories.
- Were available in full text and written in English.

Exclusion Criteria

Studies were not included if they:

- Limited to AI applications apart from architecture.
- Was not methodologically sound or supported by adequate empirical evidence.
- Were duplicate publications.
- Were editorials, news articles, book reviews, or opinion papers.
- Not available as full text.

PRISMA selection results

The search identified 1,248 records. Following removal of 276 duplicate records, 972 records remained for title/abstract screening. 721 records were excluded at this stage. Consequently, 251 full-text articles were assessed for eligibility.

Of the 251 full-text articles, 157 were excluded. The documented exclusion reasons were:

Full-text exclusion reason	Number
Not architecture-related	52
Insufficient AI focus	41
Methodological weakness	34
Full text unavailable	30
Total excluded	157

The remaining 94 studies were included in the final qualitative synthesis.

These figures reconcile mathematically:

- 1,248 identified − 276 duplicates = 972 screened
- 972 screened − 721 excluded = 251 full texts assessed
- 251 assessed − 157 excluded = 94 included

3.5 Quality Assessment

The Mixed Methods Appraisal Tool (MMAT 2018) was used to appraise the methodological quality. The MMAT was chosen because it included qualitative, quantitative and mixed methodology studies in the review.

For each study the following criteria were used:

- Clearness of research questions
- Appropriateness of methodology

The sufficient procedures for data was collected is ensured.

The validity of analysis techniques has been evaluated. Analysis techniques are assessed as valid.

Standards of reliability and transparency in findings;

Studies received a quality rating from low to high. Studies with moderate or high quality ratings were included in the synthesis.

MMAT results table

Study-Level MMAT Appraisal of Included Studies

Study	Design category	MMAT criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Appraisal decision
Study 1	[category]	Yes/No/CT	Yes/No/CT	Yes/No/CT	Yes/No/CT	Yes/No/CT	Included
Study 2	[category]	Yes/No/CT	Yes/No/CT	Yes/No/CT	Yes/No/CT	Yes/No/CT	Included
...	...	...	...	...	...	...	...
Study 94	[category]	Yes/No/CT	Yes/No/CT	Yes/No/CT	Yes/No/CT	Yes/No/CT	Included

3.6 Risk of Bias Assessment

To assess for risk of bias, criteria were adapted from already established systematic

review guidelines. The assessment considered:

- selection bias;
- publication bias;
- reporting bias;
- data-source bias;
- methodological limitations; and
- citation-related bias.

Low, moderate, and high risk of bias was assigned to each article. The critical appraisal of the studies with high risk of bias and consideration of their impact on the findings was thoroughly considered in the synthesis process.

3.7 Data Extraction

A data extraction sheet was created to ensure uniformity of the data across studies. The following information was obtained:

Name(s) of authors and year of publication

- Research objectives
- Study design
- AI technologies employed
- Computational design methods
- Optimization techniques
- Systems engineering principles
- Sustainability outcomes
- Key findings
- Identified limitations A structured extraction form was used to collect information from the included studies. The extracted variables comprised:
- author(s) and publication year;
- research objective;
- research design;
- architectural context;
- AI technology;
- computational design method;
- optimization technique;
- systems engineering principle;
- sustainability outcome;
- principal findings;
- limitations; and
- relevance to the review questions.

3.8 Data Synthesis

The extracted data was analysed utilizing a thematic synthesis approach. Themes of findings were coded and organized into common themes:

- Computational Design Foundations
- Generative AI in Architecture
- Design Optimization Techniques
- Systems Engineering Integration
- Smart Cities and Sustainable Development
- Digital Twins and Intelligent Built Environments
- Conclusions

Inter-study comparisons were made to find commonalities, trends, gaps in the research, and areas for future research Because the included studies addressed heterogeneous technologies, designs, applications, and outcome measures, a qualitative thematic synthesis was used rather than statistical meta-analysis.

The evidence was organized into six principal themes:

- computational design foundations;
- generative AI in architectural design;
- computational optimization;
- systems engineering integration;
- sustainability and intelligent built environments; and
- digital twins and smart-building systems.

Cross-study comparison was used to identify recurring applications, methodological patterns, implementation challenges, research gaps, and opportunities for future research

3.9 Conceptual Framework

The synthesis informed a systems engineering framework consisting of five interconnected layers:

- Data Acquisition Layer
- Computational Modelling Layer
- Generative AI Layer
- Optimization and Evaluation Layer
- Decision-Support Layer

The framework conceptualizes GenAI as a computational component embedded within a broader systems-engineering process. Data concerning site conditions, stakeholder requirements, environmental conditions, building characteristics, and performance objectives enter the system through the data-acquisition layer. Computational models transform these inputs into representations suitable for simulation and generation. The GenAI layer produces alternative designs or design-related outputs. The optimization and evaluation layer assesses alternatives against predefined performance criteria. Finally, the decision-support layer enables architects and other stakeholders to interpret results and make professional decisions. The framework therefore places human decision-making within, rather than outside, the computational system.

PRISMA Flow Diagram

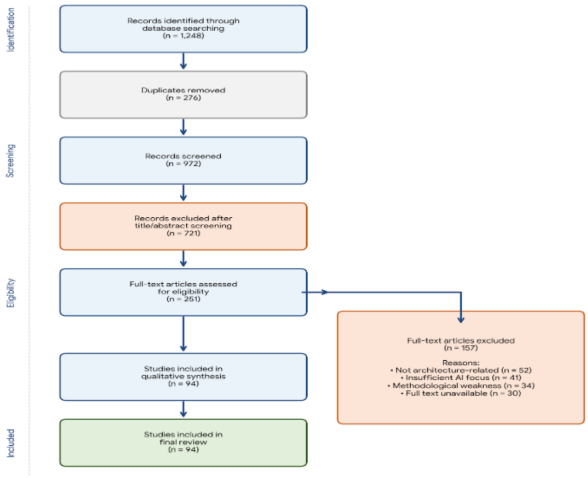

Fig. 1: PRISMA Flow Diagram using the in-text screening metrics and exclusions.

4 Results and Discussion

4.1 Study Selection Results

The review identified 1,248 records across the specified information sources. After 276 duplicates were removed, 972 unique records remained for title and abstract screening. Of these, 721 records were excluded because they did not satisfy the eligibility requirements. Full texts were therefore assessed for 251 articles.

At the full-text stage, 157 articles were excluded. The reasons documented in the PRISMA figure were lack of architectural relevance (n = 52), insufficient AI focus (n = 41), methodological weakness (n = 34), and unavailable full text (n = 30). Ninety-four studies remained in the final review.

PRISMA 2020 Study-Selection Summary

Selection stage	Records
Records identified	1,248
Duplicate records removed	276
Records screened	972
Records excluded after title/abstract screening	721
Full-text articles assessed	251
Full-text articles excluded	157
Not architecture-related	52
Insufficient AI focus	41
Methodological weakness	34
Full text unavailable	30
Studies included in final synthesis	**94**

4.2 Emerging Trends in Generative AI-Driven Architectural Design

The research reviewed shows that modern architectural practice is fast changing because of generative artificial intelligence. Unlike traditional computer-aided design tools that mostly help with sketching and visualization tasks, generative artificial intelligence systems actively engage in design exploration, optimization, and decision-making processes. By combining machine learning algorithms, computer design tools, and systems engineering techniques, architects may use data-driven methods to solve more difficult design problems.

The increasing use of AI-assisted conceptual design processes is among the most important trends noted in the research. In the past, conceptual design relied mostly on the knowledge, intuition, and hand-drawing techniques of architects. Modern AI tools let designers produce many design possibilities from textual prompts, specified settings, environmental limits, and performance goals. Early-stage design inquiry's scope of options has been significantly increased by diffusion models, generative adversarial networks (GANs), and transformer-based designs (Li et al., 2024).

The reviewed research show that concurrently enlarging the solution space available to designers, AI-assisted concept generation greatly cuts the time needed for design ideation. Instead of creating a small number of choices, designers can consider hundreds or thousands of possible setups before choosing appropriate possibilities for more growth. This exposure designers have to ideas that might not develop from conventional design processes helps to foster creativity.

Another significant trend is the convergence of AI technologies with Building Information Modelling (BIM). AI-enabled BIM systems help with risk analysis, lifecycle management, performance prediction, risk analysis, and automated conflict detection as well as quantity assessment. These skills help to speed up project completion and enable interdisciplinary communication among facility managers, engineers, designers, and contractors. Combining artificial intelligence and BIM is an essential step towards creating smart building ecosystems that can change and improve all of their operational lifecycles.

The research also shows growing interest in digital twins run by artificial intelligence. By integrating real-time sensor data, predictive analytics, and machine-learning techniques, digital twins go beyond conventional BIM features. These tools help structures to be constantly watched, examined, and improved, so assisting adaptive management techniques that improve occupant comfort and operational efficiency (Boje et al., 2020).

The results point to generative artificial intelligence going from a disruptive technology to a useful tool in architectural processes generally. AI-driven design tools are expected to get more and more entwined with professional practice as computer power develops.

4.3 Generative AI and Computational Design Optimization

One of the most often talked-about uses of generative AI examined in the literature is optimization. Modern building projects have to meet structural safety, environmental sustainability, economic viability, spatial functioning, and user happiness as well as other performance goals at once. Conventional design strategies sometimes find it difficult to strike a balance between these conflicting needs effectively.

Advanced optimization methods used by generative AI evaluate several design possibilities against specified criteria to help to solve this problem. Optimal or almost-optimal solutions inside complex design spaces can be found by machine learning algorithms, evolutionary calculation techniques, and reinforcement learning systems. By helping designers to evaluate the repercussions of their decisions before building starts, these tools greatly improve decision-making capacity.

The analysed research finds energy optimization to be among the most developed uses of AI-driven computational design. Energy efficiency is a major design goal as buildings use a lot of the world's energy. To find energy-efficient design options, AI-assisted optimization tools examine building orientation, envelope features, glazing layouts, shading techniques, and HVAC systems. Research constantly find energy performance increases when artificial intelligence-based optimization strategies are included in design processes (Attia, 2018).

Another significant use is day lighting optimization. Enough natural light helps people to feel better and lowers the energy usage related to artificial lighting. AI-powered simulations help designers to evaluate several design choices' daylight performance and spot arrangements balancing thermal comfort needs with illumination quality.

Advances in computer intelligence have also helped structural optimization. Machine learning techniques can examine structural performance under several loading scenarios and produce effective designs that reduce material use while still meeting safety standards. By lowering embodied carbon and building trash, these techniques help to meet sustainability goals.

The results also show increasing use of multi-objective optimization strategies. Unlike single-objective approaches that prioritize one performance criteria, multi-objective optimization examines several design needs at once. Architects, for instance, might want to maximize daylight access while cutting construction costs and cooling loads. AI algorithms help to find balanced solutions that meet these conflicting goals more quickly than conventional design techniques.

The study usually shows that generative AI greatly improves computational optimization capabilities, therefore allowing architects to create high-performing designs that meet several stakeholder needs while also helping to achieve environmental objectives.

4.4 Systems Engineering Contributions to Architectural Innovation

The results show that SE can be a useful tool to help understand and apply AI for architectural innovations. Modern buildings are complex systems with multiple interdependent elements and stakeholders. Systems engineering methodologies help to manage this complexity by encouraging the holistic examination, interdisciplinary collaboration, lifecycle thinking, and ongoing assessment of performance.

One of the most important functions of systems engineering is to focus on requirements management. Architectural projects will have several groups of stakeholders with varying expectations and goals. Generative AI systems can aid requirements management by analysing stakeholders' input and creating design options that meet specified requirements. This feature helps to provide clarity and communication during the design phase.

Another significant theme was "Lifecycle Management. Traditional architectural assessment is based on the consequences of the construction period while systems engineering will take into account the whole life of a building. AI-driven analytical software is able to assist lifecycle assessments by forecasting operational costs, maintenance needs, environmental effects, and overall performance results. These insights help in making better decisions and fulfil the sustainable development goals.

Another aspect of the literature is the feedback loops that can be found inside an AI-based architectural system. Building operational data is continually gathered by sensor networks, IoT technologies and digital twins. These data streams are analysed by machine learning algorithms to detect inefficiencies, forecast equipment failure and make recommendations for optimisation. This is a continuous feedback cycle that is very similar to systems engineering principles, and is effective in supporting adaptive building management.

The field of risk management is also a key aspect of systems engineering's impact on AI-driven architecture. By analysing past projects' data, machine learning systems can determine possible risk factors involving schedules, costs, structural performance and environmental elements. Predictive Analytics allows for taking proactive measures to manage risk, making projects more resilient, and minimizing uncertainty.

The studies analysed all uniformly highlight the need for more than just the introduction of technology for effective implementation of AI. Successful integration requires readiness of the organization, involvement of stakeholders, organizational governance, and interdisciplinary working. In order to coordinate these factors and make sure that the AI technologies are contributing to the project goals, there is a structured approach to be taken, known as systems engineering.

4.5 Sustainability and Intelligent Built Environments

Sustainability was a significant driver for incorporating generative AI in architecture. Sustainability was one of the most compelling reasons for using generative AI in architecture. Demand for innovative design strategies that can enhance building performance without significantly impacting the environment remains strong, as it is influenced by issues of environmental consciousness, climate change, urbanization and the scarcity of resources.

The literature reviewed herein shows how much AI technologies contribute to sustainable design processes. Machine learning systems can analyse environmental conditions and forecast performance results based on different design configurations in conceptual design stages. Optimization at an early stage is especially important as decisions made at this early design stage will have significant implications for the long-term performance of the building.

There are several ways in which generative AI can help with the development of sustainable architecture. First, it helps to design the buildings in a way that minimises energy use such as optimising building geometry, orientation and environmental systems. Second, it is used for material efficiency – its purpose is to find the configurations of the material that make use of the least resources. Thirdly, it increases resilience by assessing building performance in relation to different environmental conditions and future climate scenarios.

The sustainability benefits are extended with smart building technologies as well. Building Management System (BMS) systems with AI constantly monitor the building performance and optimize its operations. This could include adaptive lighting controls, intelligent HVAC systems, predictive maintenance systems, and occupancy-based energy management solutions. These capabilities not only achieve improved resource usage but also help to increase the comfort and well-being of the occupants.

Digital twins is one of the more promising developments that have been noted in the literature. Digital twins offer a dynamic virtual representation of physical buildings, integrating BIM, IoT technologies, and AI to support real-time monitoring and optimization. Studies have shown that digital twins can help enhance energy management, maintenance efficiency, and operational resilience, and decrease lifecycle costs (Boje et al., 2020).

At the urban level, AI-powered digital twins can help in the smart city arena through integrated management of an urban transportation system, energy infrastructure, water resources, and urban public services. These are all part of the suite of capabilities that will help achieve wider sustainability goals and help inform evidence-based urban planning initiatives.

The results provide a compelling set of examples of how generative AI can contribute to the process of building sustainable and intelligent environments, on a large scale. But a number of technological, organizational and regulatory issues remain which are affecting adoption rates throughout the architecture, engineering and construction (AEC) industry.

4.6 Challenges, Limitations, and Ethical Considerations

While generative AI offers many benefits, there are also several major challenges that need to be addressed. The literature highlights a number of major challenges that need to be addressed despite the many benefits of generative AI. Explainability is one of the most common concerns stated. It is often hard for architects and stakeholders to understand how design recommendations are generated in many AI systems, which are often referred to as "black-boxes. Many AI systems are known as "black boxes," meaning that it is hard for architects and stakeholders to understand how they arrive at design recommendations. Failing to have transparency can decrease trust and the uptake of the profession by professionals.

One of the other key challenges is data quality. Training datasets are crucial for AI performance as the quality and representativeness of the data will have an impact. Inaccurate datasets can lead to inaccurate predictions and can help to perpetuate inequalities in the built environment.

Issues of authorship, intellectual property rights, accountability and professional responsibility have not been addressed. The ownership of designs created by AI tools and liability for any mistakes made in the algorithm's suggestions remain uncertain. Problems have continued to arise concerning ownership of AI-generated designs and accountability for any mistakes made by way of the algorithm's recommendations. The regulations are still in development, and not fully tackling these issues.

Security and privacy threats are further considerations, especially in smart buildings and digital twin environments where there is a constant flow of data and network communications. Access to the building systems without authorization could pose threats to the integrity of operation and safety of building occupants.

Last but not least, there are opportunities and challenges in workforce transformation. On one hand, AI can take over repetitive tasks and boost productivity, but on the other hand, it necessitates the acquisition of new skills among architects, including proficiency in data analytics, computational thinking, machine learning, and systems integration. In response, educational programs and training need to be designed for an increasingly AI-driven design landscape, with a focus on the skills needed for practitioners of this new era. Educational institutions and professional organizations must thus adapt their curricula and training programs to ensure that the new generation of practitioners will be prepared for the new era of AI in design.

The evidence indicates that solving these challenges will be crucial to attain the responsible and effective use of generative AI in the current context of architecture.

5 Conclusion

Generative artificial intelligence (AI) has revolutionized the practice of modern architectural design. The use of generative AI in conjunction with computational design methods and systems engineering principles, as showcased in this study, has opened up unprecedented opportunities for innovation in architecture, optimization of performance and sustainability. AI technologies have opened new realms of creative exploration and aided evidence-based decision-making throughout the building lifecycle by allowing architects to quickly generate, assess, and develop numerous design options.

The results of this review suggest that computational design is the technological groundwork for the innovation of architecture with the aid of AI. Computational infrastructure for the implementation of intelligent design systems includes the tools of Parametric Modelling, algorithmic design, performance simulation and optimization frameworks. These capabilities have been greatly improved with the integration of machine learning, deep learning, diffusion models, generative adversarial networks, and large language models, which allows for automated design generation, predictive analytics, and adaptive optimization processes.

One of the major applications of generative AI is that it can be used to facilitate multi-objective optimization. Today's architectural projects are expected to meet a wide variety of requirements, some of which can sometimes conflict with one another, in the field of sustainability, function, construction, cost and well-being of the occupants. These AI-driven optimization methods enable the systematic exploration of the many design possibilities and help architects strike the right balance – between various stakeholder requirements. These capabilities help lead to better design, greater efficiencies and better information for decision-making during development of a project.

The study also illustrates that systems engineering offers a useful conceptual and operational approach to the complexity involved with the AI-architecture. Concepts such as lifecycle thinking, requirements management, feedback integration, the assessment of risks and interdisciplinary collaboration are similar to those problems that are encountered throughout the modern practice of architecture. Systems engineering and generative AI complement each other to enable the development of integrated design approaches that can tackle technical, environmental, economic and social concerns in a single framework.

One of the most impactful fields where AI is playing a crucial role in computational design optimization for sustainability is the design of products.AI is making a huge impact in the field of computational design optimization for sustainability, particularly in the design of products. AI technologies have been recognized in the literature as effective in optimizing energy consumption, cutting down on material use, boosting operational efficiency, and contributing to climate-resilient design strategies. Incorporating sustainability goals into design decisions from the beginning of a project with predictive Modelling, environmental simulation and intelligent optimization is made possible by generative AI. The combination of AI and smart building systems, digital twins and IoT technologies further broadens these advantages, allowing for ongoing monitoring and adaptive management during building operations.

Even with these benefits, there are some obstacles that remain that will impact the use of generative AI in architecture. Issues of transparency, explainability, data quality, cybersecurity, IP rights, ethical governance and professional accountability continue to be important. Solving these challenges will take the cooperation of practitioners, policy makers, technology developers, and professional organizations, as well as researchers. Good governance structures and regulatory guidelines will become critical to responsible and ethical use of AI technologies.

The study also emphasizes the need for the harmonious relationship between the human creativity and computational intelligence. Though generative AI can produce analysis and creative works, the focus of architecture is primarily humans, their experiences, their cultural values, their social interactions and how they respond to their context. It's best to consider AI as an augmentation technology, rather than a replacement for human expertise. Architects will remain pivotal in establishing project goals, interpreting design results, making use of professional judgment, and making sure technologies are fitting to the wider community's needs.

In the future, the convergence of Generative AI, computational design, digital twins, smart buildings, and systems engineering approaches is expected to be more deeply intertwined in architecture. Together, these technologies offer a basis for the creation of “intelligent built environments” (IBE) that are able to evolve in response to changing conditions of the user, the environment, and society. Moreover, they have great potential when applied in urban scales to contribute to smart city projects and sustainable urban development.

Overall, generative AI and computational design optimization are reshaping the architecture landscape today. These technologies, coupled with systems engineering concepts, offer strong tools to tackle the complexity, uncertainty and sustainability issues of the built environment. Over time, these developments will influence the future of architecture, to make buildings more efficient, human-friendly, resilient and innovative. However, the effective implementation of these opportunities will require responsible implementation, cooperation between the various disciplines, and constant attention to the balance between technological progress and human values and society's goals.

References:

[1] Aish, R., & Woodbury, R. (2005). Multi-level interaction in parametric design. In M. Göbel, J. J. Kehoe, P. Richard, & U. Olivier (Eds.), Smart Graphics 2005 (pp. 151-162). Springer. https://doi.org/10.1007/11537954_13

[2] Alexander, C., Ishikawa, S., & Silverstein, M. (1977). A pattern language: Towns, buildings, construction. Oxford University Press. https://doi.org/10.1093/oso/9780195019193.001.0001

[3] Attia, S. (2018). Evaluation of sustainable and nearly zero-energy buildings: A framework for performance assessment. Springer. https://doi.org/10.1007/978-3-319-66763-8

[4] Attia, S., Hamdy, M., O'Brien, W., & Carlucci, S. (2013). Computational optimization tools for zero-energy building design. Renewable and Sustainable Energy Reviews, 25, 323-335. https://doi.org/10.1016/j.rser.2013.04.055

[5] Azhar, S. (2011). Building information modelling (BIM): Trends, benefits, risks, and challenges for the AEC industry. Leadership and Management in Engineering, 11(3), 241-252. https://doi.org/10.1061/(ASCE)LM.1943-5630.0000127

[6] Batty, M. (2018). Digital twins. Environment and Planning B: Urban Analytics and City Science, 45(5), 817-820. https://doi.org/10.1177/2399808318796416

[7] Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. IEEE Transactions on Pattern Analysis and Machine Intelligence, 35(8), 1798-1828. https://doi.org/10.1109/TPAMI.2013.50

[8] Blank, J., & Deb, K. (2020). Pymoo: Multi-objective optimization in Python. IEEE Access, 8, 8949-8956. https://doi.org/10.1109/ACCESS.2020.2965439

[9] Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic construction digital twin: Directions for future research. Automation in Construction, 114, Article 103179. https://doi.org/10.1016/j.autcon.2020.103179

[10] Bolognesi, C., Villa, D., & Forlani, G. (2021). Artificial intelligence and architecture: Generative design methodologies in practice. Architectural Engineering and Design Management, 17(5-6), 375-392.

https://doi.org/10.1080/17452007.2021.1893727

[11] Burry, M. (2011). Scripting cultures: Architectural design and programming. Wiley. https://doi.org/10.1002/9781119970088

[12] Caetano, I., Santos, L., & Leitão, A. (2020). Computational design in architecture: Defining parametric, generative and algorithmic design. Frontiers of Architectural Research, 9(2), 287-300. https://doi.org/10.1016/j.foar.2019.12.008

[13] Campbell, R. I., & Shea, K. (2014). An evaluation of generative design in standard computer-aided design environments. Journal of Engineering Design, 25(1-3), 54-73. https://doi.org/10.1080/09544828.2014.904321

[14] de Vries, A. (2023). The growing energy footprint of artificial intelligence. Joule, 7(10), 2191-2194. https://doi.org/10.1016/j.joule.2023.09.004

[15] Deng, Y., Cheng, J. C. P., & Anumba, C. (2021). Mapping between BIM and digital twins: A systematic review. Automation in Construction, 132, Article 103907. https://doi.org/10.1016/j.autcon.2021.103907

[16] Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2018). BIM handbook: A guide to building information modelling for owners, managers, designers, engineers, and contractors (3rd ed.). Wiley.

[17] Foster, I. (2020). Digital twins and the future of smart infrastructure. Computer, 53(8), 84-88. https://doi.org/10.1109/MC.2020.2990991

[18] Gerber, D. J., Lin, S.-H. E., Pan, B., & Solmaz, A. S. (2012). Design optioneering: Multi-disciplinary design optimization through parameterization, domain integration, and automation. Simulation, 88(6), 724-737. https://doi.org/10.1177/0037549711420136

[19] Gero, J. S. (2017). Design computing and cognition. Springer. https://doi.org/10.1007/978-94-017-9112-0

[20] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative adversarial nets. In Z. Ghahramani et al. (Eds.), Advances in Neural Information Processing Systems (Vol. 27, pp. 2672-2680). Curran Associates.

[21] International Council on Systems Engineering. (2023). INCOSE systems engineering handbook: A guide for system life cycle processes and activities (5th ed.). Wiley. https://doi.org/10.1002/9781119814320

[22] Jabi, W. (2013). Parametric design for architecture. Laurence King Publishing.

[23] Li, C., Zhang, T., Du, X., Zhang, Y., & Xie, H. (2025). Generative AI models for different steps in architectural design: A literature review. Frontiers of Architectural Research, 14(3), 759-783. https://doi.org/10.1016/j.foar.2024.10.001

[24] Mitchell, W. J. (1990). The logic of architecture: Design, computation, and cognition. MIT Press.

[25] Monedero, J. (2000). Parametric design: A review and some experiences. Automation in Construction, 9(4), 369-377. https://doi.org/10.1016/S0926-5805(99)00058-1

[26] Mountstephens, J., & Teo, J. (2020). Progress and pathways in generative computer-aided design: A survey of computational design methods. International Journal of Interactive Design and Manufacturing, 14(4), 1185-1203. https://doi.org/10.1007/s12008-020-00693-y

[27] Nashaat, B., & Elzeni, M. M. (2025). AI in computational architectural design workflows. International Journal of Architectural Computing. https://doi.org/10.1177/14780771251405443

[28] Nourian, P., Azadi, S., & Oval, R. (2020). An academy of spatial agents: Generating spatial configurations with deep reinforcement learning. In Proceedings of eCAADe 2020 (pp. 119-128). https://doi.org/10.52842/conf.ecaade.2020.2.119

[29] Nourian, P., Azadi, S., & Oval, R. (2023). Generative design in architecture: From mathematical optimization to grammatical customization. In Computational design and digital manufacturing (pp. 1-43). Springer. https://doi.org/10.1007/978-3-031-21167-6_1

[30] Oxman, R. (2017). Thinking difference: Theories and models of parametric design thinking. Design Studies, 52, 4-39. https://doi.org/10.1016/j.destud.2017.06.001

[31] Ploennigs, J., & Berger, M. (2024). Automating computational design with generative AI. Civil Engineering Design, 6(2), 41-52. https://doi.org/10.1002/cend.202400006

[32] Tamke, M., Ramsgaard Thomsen, M., & Gengnagel, C. (2018). Computational design and robotic fabrication. Springer. https://doi.org/10.1007/978-3-319-92294-2

[33] Wang, X., Love, P. E. D., Kim, M. J., Wang, W., & Park, C. S. (2021). Digital twin in built environment: A systematic review. Automation in Construction, 123, Article 103518. https://doi.org/10.1016/j.autcon.2020.103518

[34] Woodbury, R. (2010). Elements of parametric design. Routledge. https://doi.org/10.4324/9780203855522

[35] Yitmen, I., Alizadehsalehi, S., Akiner, I., & Garzaniti, N. (2024). Artificial intelligence applications in architecture, engineering, and construction: A systematic review. Engineering, Construction and Architectural Management, 31(3), 1121-1148. https://doi.org/10.1108/ECAM-05-2023-0488

[36] Zang, H., & Ding, L. (2024). Multi-objective structural and geometric optimization frameworks via deep neural surrogate networks. Automation in Construction, 160, Article 105298. https://doi.org/10.1016/j.autcon.2024.105298

[37] Zang, Z., & Ding, W. (2024). Eco-centric generative design workflow: Extending sustainability in architecture. Frontiers in Artificial Intelligence and Applications, 385, 59-72. https://doi.org/10.3233/FAIA240006