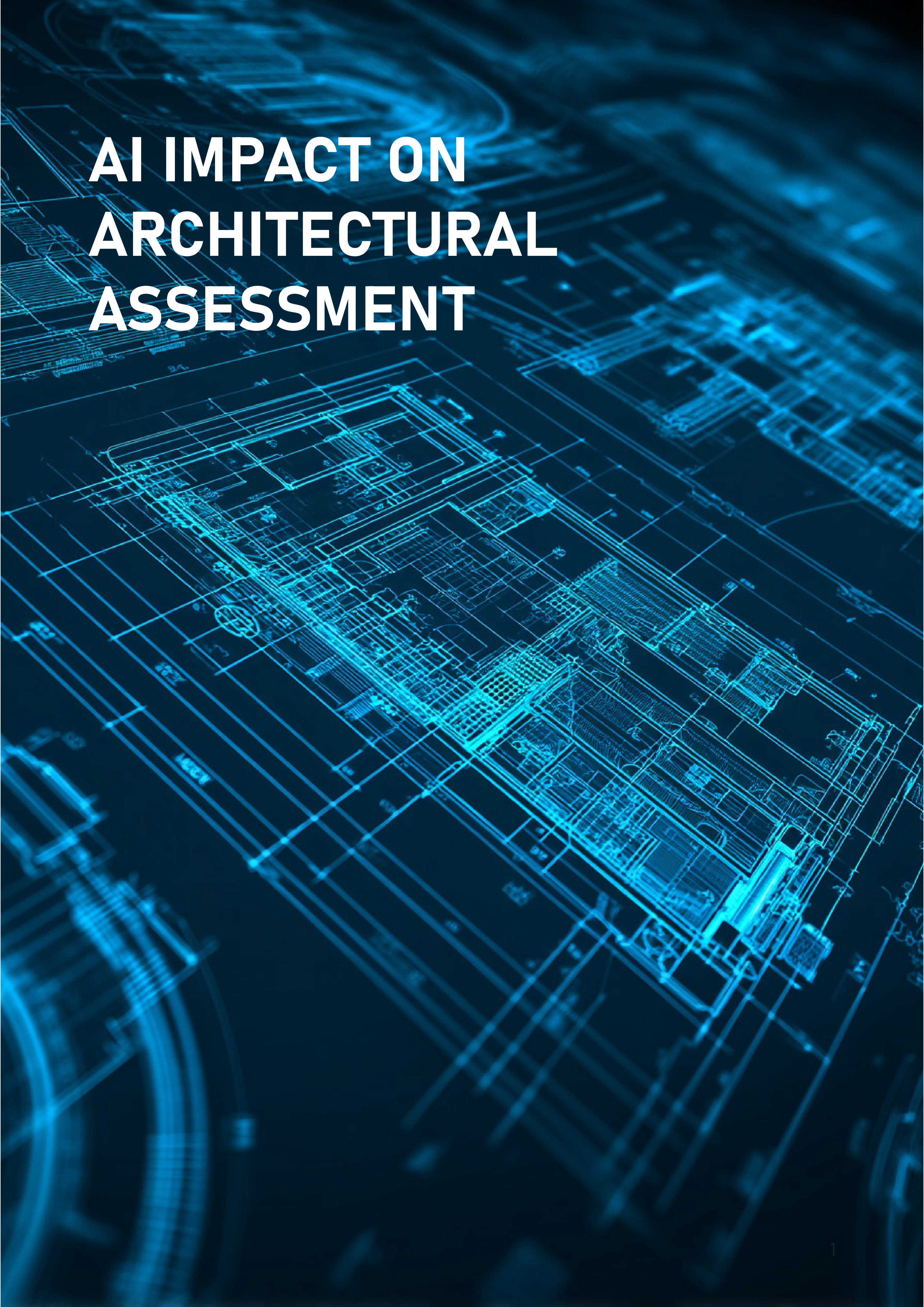
AI IMPACT ON ARCHITECTURAL ASSESSMENT



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AI IMPACT ON ARCHITECTURAL ASSESSMENT

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Abstract

This thesis investigates the rapid enterance of Artificial intelligence (AI) to the architectural practice, reshaping not only how buildings are designed, but also how architecture , as a practice is being assessed. Asking whether AI expands architects' evaluative capacity or reduces professional control by automating decisions that require human judgment. Architecture , by its complex nature is often slow and with the integration of new technologies is now standing on the brink of a change which has a revolutionary scale. Using a qualitative, and a non-linear methodology with combining literature review, historical analysis, industry review, and project-based case studies the research traces the transition from traditional drafting to CAD/BIM and toward AI-driven, data-intensive workflows.

Through an investigative research and experimenting with some of these AI tools, the thesis explores AI's role in conceptual and operational phase. This role is examined by the related case studies and investigating how the leading firms in the field of architecture are using and integrating these tool to their workflows and operational projects.

Ultimately, the thesis suggests that integrating AI is a helpful agent to architects in their repetitive and data heavy tasks but AI may also increase the professional responsibility by introducing new demands for validation, accountability, and transparency creating a demand for an advanced set of skills mainly the digital literacy.

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Introduction

Architecture has gone through a significant transformation over the past decades. Technological advancements have reshaped the way architects think, design, and assess. Since the 1980s, when Computer-Aided Design (CAD) was introduced, and later with the rise of Building Information Modeling (BIM) in the 2000s, digital tools and advancements have made architecture more precise, efficient, and collaborative.Allowing all the parts to be involved in the process in a more effective way. As of 2020s the pattern is rapidly evolving with the introduction and the active use of the Artificial Intelligence in the architectural practice. These new AI tools and systmes are capable of learning, reasoning, and optimizing in ways that human would but act at the speeds unachievable by people. AI technologies, such as machine learning, deep learning, generative AI and evolutionary algorithms are increasingly integrated into the architectural workflows, allowing data-driven decision-making, predictive simulations, and automated optimizations and fast visualization outcomes. This integration is more visible in areas like parametric design, performance analysis, and material computation, where AI enhances the architect's capability of handling complex issues and making them more prepared and active in the process.

But despite all the benefits and capabilities , this rapid integration of AI into architecture raises some critical challenges.Traditionally architecture has been a human cetered practice relying on projudgment, experience, and ongoing feedback to find the right balance between aesthetics, function, and ethics. AI challenges this by using algorithms that focus on measurable data, which can sometimes overlook important factors like cultural context or social structures The problem lies in understanding how AI impacts this assessment process. Does AI help architects by giving them more ways to evaluate their work making them more capable on different assessment steps, or does it take away their control by automating choices that need human judgment? And as AI becomes more autonomous, questions rise about accountability, ethical implications, and environmental sustainability. This is the core question that we will ask and discover "What is the scale of AI's impact on architecture?". This thesis explores how AI is changing the way architectural assessments are done. It highlights the importance of working together with AI so that new technologies support the archiectural practice.

Objectives

1-To explore the theoretical foundations of artificial intelligence with a focus on their relevance to architectural practice.

2-To trace the technological evolution from traditional drafting and digital architecture to AI-driven design.

3-To analyze the changing role of the architect in the age of AI.

4-To investigate the adoption of AI in leading architectural firms, providing evidence from case examples to understand integration strategies and outcomes.

5-To examine specific case studies of AI-applied projects, evaluating how AI influences the design.

6-To refine the findings into conclusions that address how AI transforms architectural assessment and offer recommendations for human-AI collaboration in future practice.

Research Questions

1-How does artificial intelligence transform the processes of architectural design and assessment?

2-What are the implications of AI for the role and responsibilities of architects, including potential expansions or restrictions in creativity, ethics, and decisionmaking?

3-In what ways do leading architectural firms adopt AI technologies, and what specific outcomes do they achieve?

4-To investigate the adoption of AI in leading architectural firms, providing evidence from case examples to understand integration strategies and outcomes.

5-How do selected case studies illustrate the practical impacts of AI on architectural assessment?

Methodology

This thesis uses a non linear methodology that includes qualitative methods, including a literature review, historical analysis, case studies of firms, and project-specific reviews to explore how AI affects architectural assessment. AI in architecture is a relatively new and rapidly changing field. So using a flexible approach works better than following a strict, step-by-step process, since the field of AI keeps evolving. The approach begins with a theoretical framework created by the key texts in AI, cognitive science, and architectural theory. Then connecting it to the evolution of the tools that are essential to modern day architecture following the inevitable integration of AI to them (and emergence of new AI tools) and using them as parctical elements in the architectural practice.Thus changing the role of architect and how the architectural practice is being executed. This analysis takes an interpretive approach, looking at patterns of integration, ethical issues, and performance results. It does not include experiments or quantitative models.

Structure

Chapter 1 establishes the conceptual foundation of artificial intelligence and its theoretical framework within architecture. It defines intelligence and AI, traces historical developments from early computational models to modern advancements, and explores subfields.

Chapter 2 examines the technological evolution and architecture of AI in design practices. Starting with the transition from traditional drafting to digital architecture through CAD and BIM, highlighting the architect's evolving role.

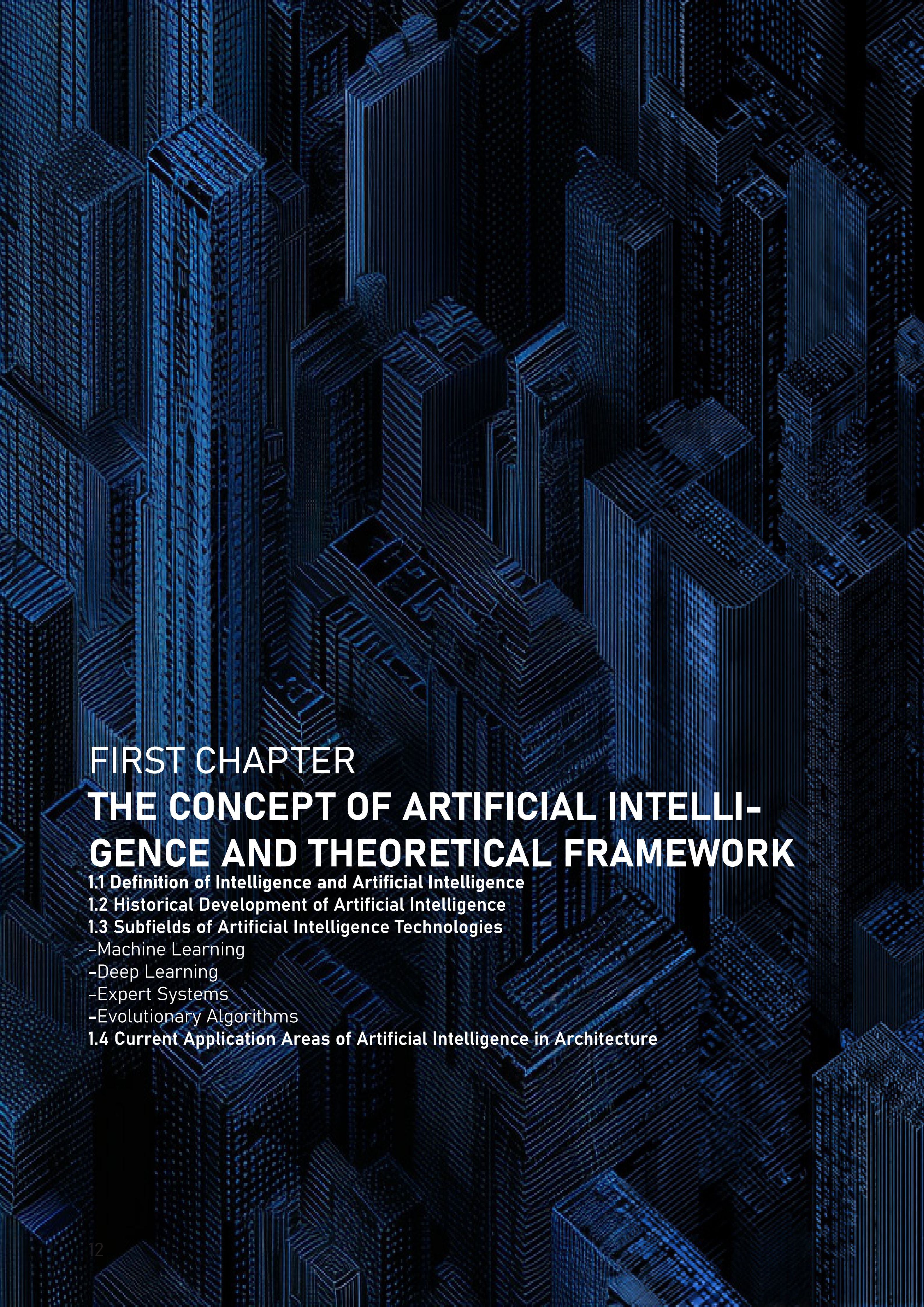
Chapter 3 investigates the role of the architect in the context of artificial intelligence. It explores the changing role digital transformation and the architect's position in the age of AI, that includes impacts on practice. Asking crtitical questions like whether AI expands or restricts architectural capabilities,covering ethical, social, and environmental dimensions.

Chapter 4 investigates of AI adoption in the architecture industry through leading firms, key actors like Zaha Hadid Architects (ZHA), Foster + Partners, MVRDV, and Arup, analyzing their integration of AI in workflows, from generative design to performance simulation. The chapter highlights strategies, tools, and outcomes, demonstrating how these firms use AI to enhance their works.

Chapter 5 presents detailed case studies shwoing AI's practical application in architecture. it examines projects such as the MX3D Smart Bridge (Amsterdam), Al Wasl Plaza (Dubai), Morpheus Hotel (Macau), DFAB House (Switzerland), The Vessel (New York), Google Bay View Campus (California), and the Smog Free Tower (Rotterdam). Each case evaluates AI involvement across phases, using radar diagrams to assess design generation, analysis, fabrication, and operation, culminating in an overall analysis of patterns and implications.

Chapter 6 synthesizes the thesis findings into a conclusion, reflecting on how AI reshapes architectural assessment as a continuous, data-driven process. It addresses key themes from previous chapters, such as human-AI balance, ethical considerations, and future trajectories, offering final recommendations for the profession.

Disclaimer
Certain parts of this thesis has been enhanced with the use of AI and for some examples od visualization GenAI was used to demonstrate the current use of AI in the field. Some conceptual models from the previosu year design studios such as an axonometric view of a "belvedere" concept for the architecture and structural forms atelier (ACC AY. 2021-2022). Located in the Nanjing Hehua Tang city & the wall was used in this manner.



FIRST CHAPTER

THE CONCEPT OF ARTIFICIAL INTELLIGENCE AND THEORETICAL FRAMEWORK

1.1 Definition of Intelligence and Artificial Intelligence
1.2 Historical Development of Artificial Intelligence
1.3 Subfields of Artificial Intelligence Technologies
-Machine Learning
-Deep Learning
-Expert Systems
-Evolutionary Algorithms
1.4 Current Application Areas of Artificial Intelligence in Architecture

01

1.1 Definition of Intelligence and Artificial Intelligence

The concept of intelligence has long been a central topic in philosophy, psychology, and cognitive science. It was understood as the ability to learn from experience, reason, adapting to new situations, and applying acquired knowledge to solve problems. Psychologists often define intelligence as a combination of perception, memory, understanding, and abstract thinking that enables individuals to respond effectively to their environment. Early studies by Alfred Binet and later theoretical developments by researchers such as Charles Spearman and Howard Gardner laid the foundation for understanding human intelligence as a multilayered construct cotaining analytical, creative, and practical dimensions (Gardner, 1983).

Theory of multiple intelligences by Gardner has expanded the traditional views by proposing that the intelligence cannot be down graded to a single numerical value, but comes out through a linguistic and, personal capacity. This multi layered perspective highlighted that the intelligence is not just a fixed entity but an adaptive system that is responding to certain context and experience (Sternberg, 1985)

From a philosophical point of view, intelligence has been associated with the capacity and the ability to direct thought and action to the reach set goals. The understanding of intelligence as goal-oriented problem-solving has been central in both cognitive science and artificial intelligence research area. Intelligence, whether human or machine, is fundamentally dealing with with making decisions under uncertain condtions, learning from outcomes, and optimizing behavior within constraints (Russell & Norvig, 2010).

As we understand and discover more of the effects of AI there are six main pieces that come out for us to truly understand and operate with it as architects. This is a framework of balance which defines the how AI can be an operational partner rather than just a tool and a computer agent that can possibly replace the professionals. Each of the six subtopics represents a distinct yet interconnected dimension of architectural intelligence that can be in use of both efficiently and ethically. One without another would not be abe to operate fully. This synthesis captures the evolving nature of the architect's role in the age of artificial intelligence and how the adaptaion must take place within the set framework.

1. Understanding the Concept of Artificial Intelligence (AI)

Artificial intelligence (AI) refers to computational systems designed to do tasks associated with human cognition, such as reasoning, learning, and problem-solving. In architecture, AI is integrated with algorithmic systems capable of analysing data, simulating performance conditions, and generating design alternatives based on multiple parameters.

2.Redefining Problem-Solving Approaches

Architectural problem-solving has traditionally relied on linear, rule-based processes structured around analysis, design, and evaluation. AI challenges this concept by bringing a non-linear, exploratorion models of reasoning, allowingdesigners to create greater solution spaces generated through computation and predictive analysis.

3.Balancing the Human Factor in AI-Assisted Design

Despite the capabilities of AI, human role is central to architectural design. Designers contribute contextual understanding, ethics, and aesthetics that cannot be fully generated algorithmically. The critical challenge lies in balancing computational efficiency with human intentionality and responsibility.

4.Enhancing the Iterative Design Process

Iteration is fundamental to architectural practice. AI enhances this process by accelerating feedback loops between design generation, evaluation, and optimisation, allowing designers to test and refine solutions through fast analysis and simulations.

5.Augmenting Creativity with AI

Creativity has traditionally been considered a distinctly human cornerstone of the design process. AI challenges this by contributing to the generation of form, pattern, and conceptual variation, enabling designers to explore new horizonsderived from thee computational processes.

6.Leveraging Data-Driven Insights

Architectural practice operates inside a data rich environment. AI enables the translation of complex datasets into usable insights, supporting predictive and evidence based decisions throughout the design and assessment process.

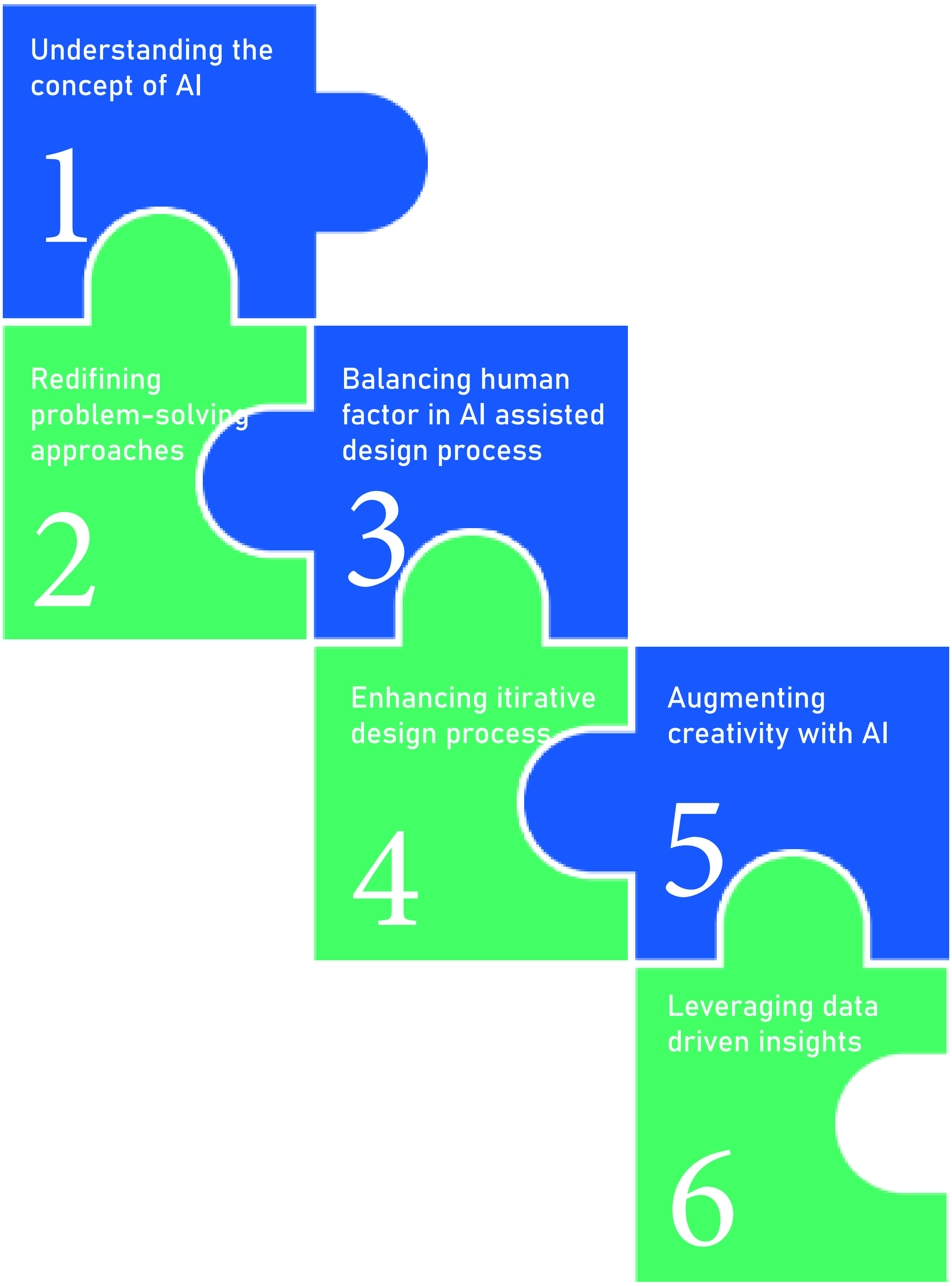


Figure 1. Created by the autor (2025). Pieces of Human AI collaboration

From Human to Artificial Intelligence

The term of Artificial Intelligence (AI) was first introduced in the year 1956 during the Dartmouth Conference by John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon. They have defined AI as “the science and engineering of making intelligent machines” (McCarthy et al., 1955). Since then, many scholars have refined the definition to reflect both technological and theoretical advancements. Stuart Russell and Peter Norvig (2010) define AI as “the study of agents that receive info from the environment and take actions that affect that environment,” making remark that interaction and adaptation are fundamental to intelligent behavior. Similarly, Nilsson (1998) also described AI as the field of study dedicated to creating machines that are capable of performing duties that needs intelligence when perdone by humans. Artificial intelligence seeks to replicate or simulate human cognitive processes through computational systems and algorithms. Unlike biological intelligence, which arises from neural structures, AI operates through data, algorithms, and symbolic or sub-symbolic representations of knowledge.

While the human brain processes information using biochemical and neural manners, artificial systems rely on mathematical models and pattern recognition (Goodfellow, Bengio, & Courville, 2016). Despite their differences, both have the same goal of using information and act upon it effectively, suggesting that intelligence may be viewed as a system property rather than an exclusively biological part of a being (Boden, 2016).

Comparing Natural and Artificial Intelligence

Even though both natural and artificial intelligence share the goal of problem-solving and adaptation, their working methods and limitations are quite different. Natural intelligence is characterized by creativity, emotion, and intuition qualities that comes from the results of biological evolution and conscious experience. In contrast Artificial intelligence operates through computational logic. While AI can process great amounts of data with an unmatched speed, it lacks subjective understanding, ethical reasoning, and contextual awareness (Floridi, 2014).

AI Human Collaborative Architecture

In this context Human–AI collaborative architecture describes a design model in which artificial intelligence functions not as a replacement for the architect but as an active partner in the creative process. Unlike conventional digital tools that are primarily supporting the representation and execution, AI systems take part in the design reasoning by generating more alternatives, analysing performance, and adapting solutions with using data-driven processes (Gelener, 2024). This collaboration reshapes architectural workflows by combining human aspects, culture, judgement, and ethical responsibility with the computational capabilities of AI. While AI is very good at exploring large solution spaces and optimising complex elements, the architect remains responsible for defining goals, using the outputs, and putting context into the design. Therefore Human–AI collaboration represents a shift towards a symbiotic design model, where creativity is enhanced rather than being automated. So , to clarify this interaction, we outline five key stages that structurize AI-supported design these stages describe how collaboration between human and artificial intelligence is operationalised in architectural workflows.

1.Specifying the Objective

The first step in AI-assisted design. At this stage, the architect defines the goals, constraints, and priorities of the project, such as spatial requirements, performance targets, environmental conditions, or user needs. Clear objectives help and guide how AI systems are used and ensuring that computational processes remain aligned with design context.

2.Compiling and Preparing Data

In this step the is gathered and organised in a clear and consistent way. The data is structured and refined so that it can be processed by the AI systems. The quality and relevance of this input directly influence the reliability and usefulness of AI-generated design results.

3.Choosing AI-Related Tools and Technologies

Knowing that there is an abundance of tools , it is a key part to choose systems that best support the defined design objectives and available data. Different AI tools serve different purposes, such as generating design options, analysing performance, or supporting visual exploration. The architect evaluates these tools based on their capabilities, limitations, and compatibility with the design workflow, making sure that technology supports the design process rather than supports the design process rather than directing it.

4.Using AI in the Design Process

After deciding the best set of AI tools it is now time to implement them in the process.Now here the spectrum of usage is large knowing that the design process includes many actions from different fields.So AI's role may change across stages, but it remains integrated with a human controlled workflow, where the architect directs how and when AI is applied.

5.Monitoring And Evaluation

For now , AI's work is not 100% perfect and always reliable. It is common that AI systems can produce errors, biased results, or unsuitable solutions. So it is crucial and necessary for architects to critically review the outcomes produced with the support of AI. This evaluation enables corrections and refinements, ensuring that design decisions remain reliable, responsible, and consistent with architectural intent.

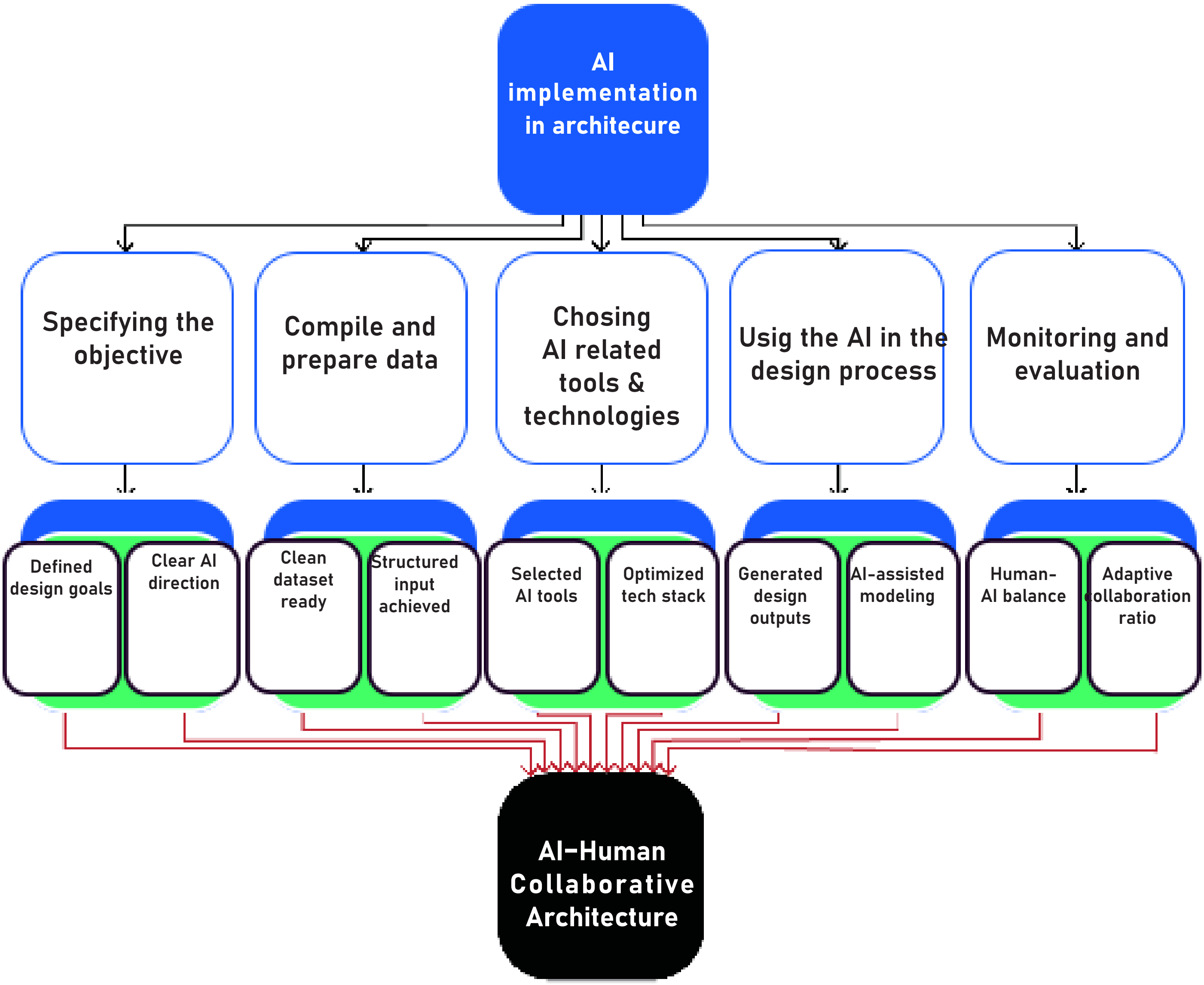


Figure 2. Created by the autor (2025). Diagram of AI-Human Collaborative Architecture

Key Advantes of Implementing AI in Architecture

The integration of AI into architectural practice has brouht in a set of advantages that affect design processes. Academic research consistently frames that AI is not as a replacement for architectural authorship, but as a system that enhances human capabilities by expanding design exploration, supporting analysis, and managing increasing levels of complexity (Gelener, 2024; Sabono, 2025) .

Human–AI collaboration and AI-driven design efficiency remarks that the benefits of AI in architecture is more than automation. AI helps with the creative exploration it improves visual communication, supports user centered design, enhances efficiency, enables adaptive responses to changing conditions, and allowing architects to extract structured insights from historical data (Gelener, 2024; Sabono, 2025) . These are supported by the professional analyses that highlight AI's growing role in improving efficiency and enabling architects to focus on more complex and demanding design challenges rather than keeping them occupied with the repetitive tasks that are a natural oat of the profession (Appinventiv, 2024; Chaos, 2024).

For this reason, seven key advantages are identified. These advantages are not set categories but recurring themes emerging across academic literature and professional practice. They represent the most relevant dimensions which AI visibly enhances architectural work at different scales and stages. The seven key advantages are innovation, visualisation, accessibility, space utilisation, adaptability, historical insights, and customisation. Together, they provide a structured framework for evaluating the contribution of AI to contemporary architectural practice and form the basis for the following sections.

1. Innovation

AI supports innovation in architectural design by widening the range of design possibilities. For example, generative design tools can produce varied building models in response to site conditions and performance goals, while image-based AI models can create visual concepts during early design stages. So this innovation emerges from the collaboration between human design and AI exploration.Therefor the innovation results from the interaction and communication between human aspect and computational elements.

2. Visualisation

AI enhances visualisation process in design by enabling faster and more realistic representations. AI-supported tools can generate high-quality images, and immersive visual results at early design stages, helping architects and stakeholders to better understand the expected results before construction phase. For example, AI-driven rendering and simulation tools can visualise lighting conditions, spatial atmospheres, or design variations in real time, improving communication and reducing misinterpretation during the design process (Chaos, 2024).

3. Accessibility

AI supports accessibility in architecture by helping architects identify and address the needs of users. AI tools can analyse layouts and user requirements to highlight potential restrictions and help with design adjustments that can improve this. AI can halp wit the evaluation of circulation paths, entrances, and dimensions to ensure that buildings are usable by people with different physical abilities. This allows accessibility to be integrated earlier and more consistently within the design process (Appinventiv, 2024).

4. Space Utilisation

AI can improve space utilisation by analysing how spaces are being organised and used, helping architects to design more efficient and functional plans. AI systems can process information related to user behaviour and their requirements to suggest improving of the conditions. AI-assisted tools can identify underused areas and propose alternatives that make better use of available spaces, particularly in complex or high density projects.

5. Adaptability

Artificial intelligence supports adaptability in architectural design by allowing buildings and spaces to respond more effectively to changing conditions. AI systems enable architects to simulate different environmental and functional scenarios and evaluate how the design performs under each condition. For example, AI-assisted tools can help assess how a building adapts to seasonal climate changes, evolving user needs, or alternative spatial configurations. This supports the development of flexible and resilient designs that remain functional and relevant throughout their lifecycle.

6. Historical Insights

AI systems can process large collections of previous projects, materials, and performance data to identify patterns and recurring strategies. For example, AI-assisted analysis can help architects to adapt learn and implement earlier building typologies or climate-responsive solutions, allowing historical knowledge to inform contemporary design decisions in a structured and efficient way..

7. Customisation

AI enables a higher level of customisation in architectural design by allowing solutions to be tailored to specific users, contexts, and project requirements. AI systems can process diverse inputs such as client preferences, site conditions, and performance targets to support personalised design outcomes. For example, AI-assisted tools can help adjust layouts, materials, or environmental strategies to better match individual needs while maintaining overall design coherence and efficiency.

Key Advantes of Implementing AI in Architecture

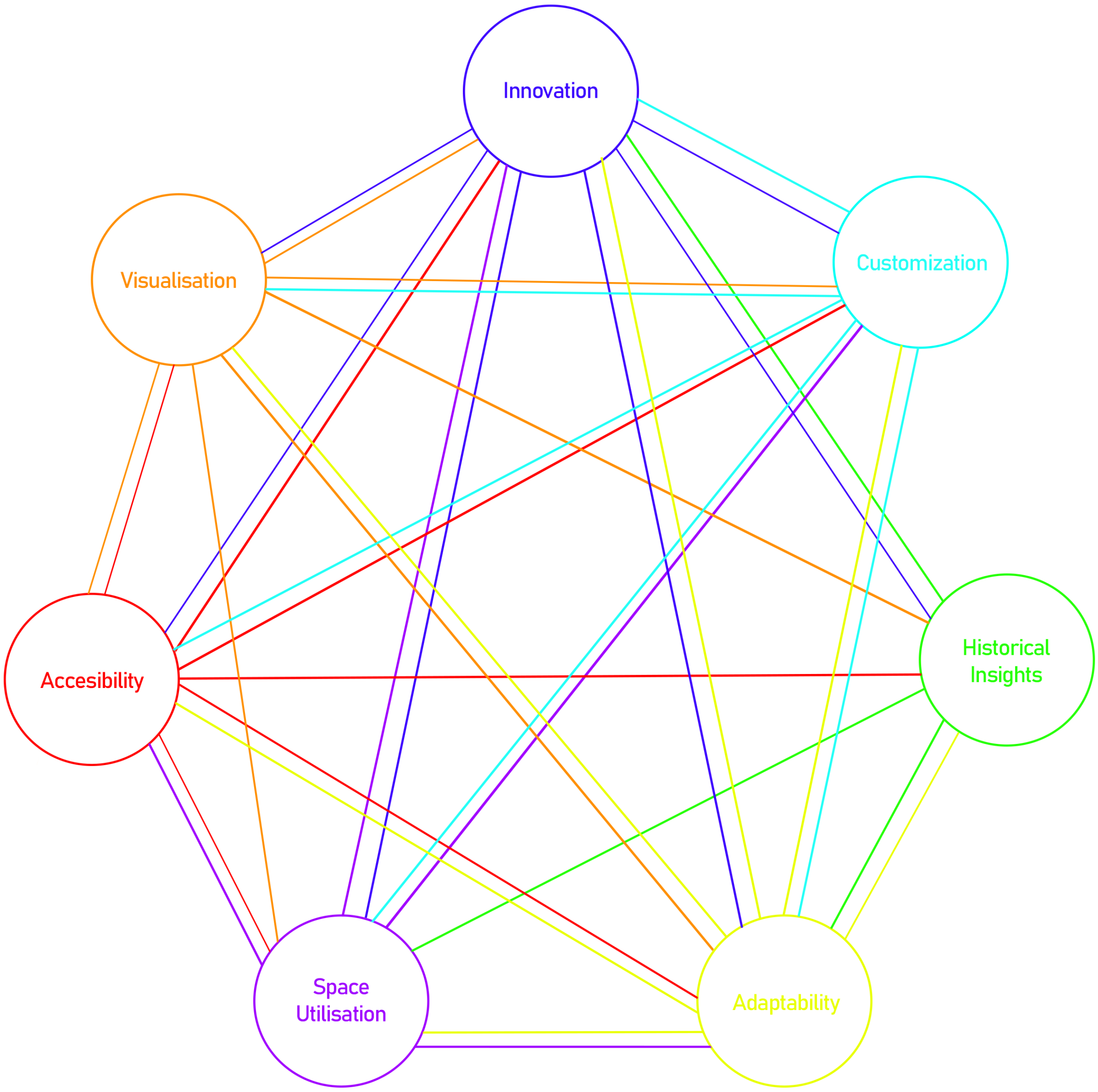


Figure 3. Created by the autor (2025). Key Advantes of Implementing AI in Architecture

1.2 Historical Development of Artificial Intelligence

The development of Artificial Intelligence is rooted in a rich intellectual ara that is before the modern computing. To understand this history is important for recognizing how contemporary AI emerged from decades of scientific, philosophical, and technological evolution. Each phase of AI's development helped with foundational concepts that directly effects the present-day computational design and human–machine collaboration in architecture. The historical move of AI not only shows the discipline's changing patterns but also shows how architecture is gradually becaming an ideal place for AI experimentations thanks to its complex demands.

Cybernetics and the Origins of Artificial Intelligence (1940s–1950s)

The foundations of artificial intelligence emerged in the mid 20th century with the efforts to model the intelligence as a computational process. Early research in mathematics and computing reframed human reasoning as something that can potentially be replicated by machines, creating the conceptual basis for AI as a scientific field replicated by machines. This period laid the conceptual foundations for AI by pushing intelligence from a philosophical concept to a technical and scientific element (Haenlein & Kaplan, 2019)

Alan Turing played a key role in this era he proposed that machine intelligence could be evaluated by observable behaviour rather than just consciousness. His work linked computation directly to intelligent actions and remains foundational to AI theory. During the same time period Norbert Wiener developed cybernetics, introducing concepts of feedback, control, and communication that shaped the early ideas about learning and adaptive systems. Claude Shannon similarly established thee information theory, providing a mathematical framework for processing and transmition of the information, which later became essential for AI systems (Haenlein & Kaplan, 2019).

Symbolic AI and Rule-Based Systems (1950s–1970s)

After the early theoretical foundations, artificial intelligence entered a phase represented by symbolic reasoning and rule based approaches. During this period, intelligence was represented as the manipulation of symbols with well defined rules, showing the idea that human reasoning could be formalised in logical structures. This way of approach cahnegd much of early AI research and led to development of programs designed to solve problems with using predefined knowledge (Haenlein & Kaplan, 2019) A central figure in this phase was John McCarthy, who formally named the term artificial intelligence and demonstrated symbolic logic as the central working mechanism of intelligence. Researchers like Marvin Minsky, symbolic AI systems were developed to perform tasks like problem-solving, understanding languages, and logical reasoning. Early programs, including rule-based expert systems and problem solvers, demonstrated promising results in controlled environments (Hiremath & Kenchakkanavar, 2025)

Challenges and AI Winter (1970s–1990s)
During the 1970s and 1980s, artificial intelligence entered periods commonly referred to as AI winters, characterised by reduced funding, slowed research progress, and growing scepticism. Early optimism surrounding symbolic AI and expert systems had led to expectations that surprassed the available computational power and methodological capabilities. As a result, many AI systems failed to perform effectively outside controlled environments, particularly when dealing with uncertainty, learning, or real-world complexity (Haenlein & Kaplan, 2019) A major challenge of this period was the reliance on manually encoded rules, which made AI systems difficult to scale and maintain. These limitations became evident as expert systems proved costly to develop and inflexible in practice. Critical evaluations by governments and research institutions questioned the

research institutions questioned the practical value of AI research, leading to significant cuts in public funding and institutional support (Hiremath & Kenchakkanavar, 2025)

Data-Driven AI and Machine Learning (1990s–2010s)
In 1990s, artificial intelligence experienced an important changefrom the rule based working towards data-driven approaches. Advances in statistical methods, increased amount of digital data, and enhanced computational power allowed AI systems to learn patterns directly from. This transition marked the rise of machine learning as a powerful model within the AI research. During this period, AI applications became more effective. Learning-based systems showed evidence of greater adaptability than early symbolic approaches, allowing AI to be used and applied across the wider range of fields. The growing success of machine learning brought back the confidence in AI research and led to renewed academic and industrial investment. This phase laid the groundwork for the rapid developments in deep learning and large-scale AI systems that emerged in the following decade (Haenlein & Kaplan, 2019; Hiremath & Kenchakkanavar, 2025) .

Deep Learning and Contemporary AI (2010s–Present)

From the 2010s onward, artificial intelligence started a phase defined by deep learning and large-scale data processing. Advances in neural network systems, combined with immense computational power and access to the large datasets, allowed AI systems to improve rapidly in many fields. These developments marked an important expansion of AI from experimental research into widespread real-world use (Haenlein & Kaplan, 2019) Deep learning systems are different from the earlier machine learning approaches by automatically extracting features from raw data, reducing the need for manual work. This capability has significantly increased the accuracy of AI systems, leading to their integration across multiple sectors . This period represents both the most advanced and the most critically examined stage in the historical development of artificial intelligence (Haenlein & Kaplan, 2019; Hiremath & Kenchakkanavar, 2025)

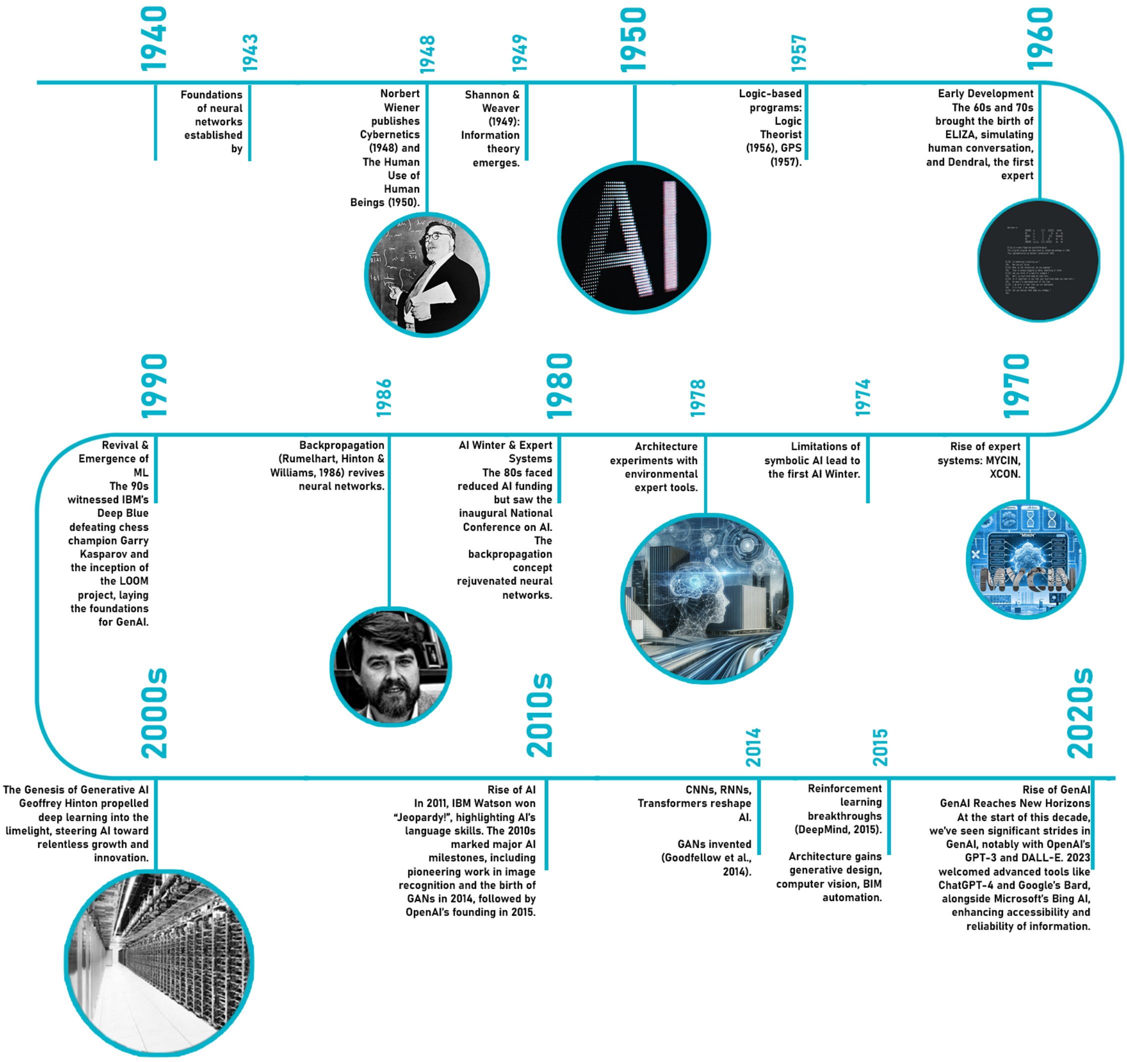
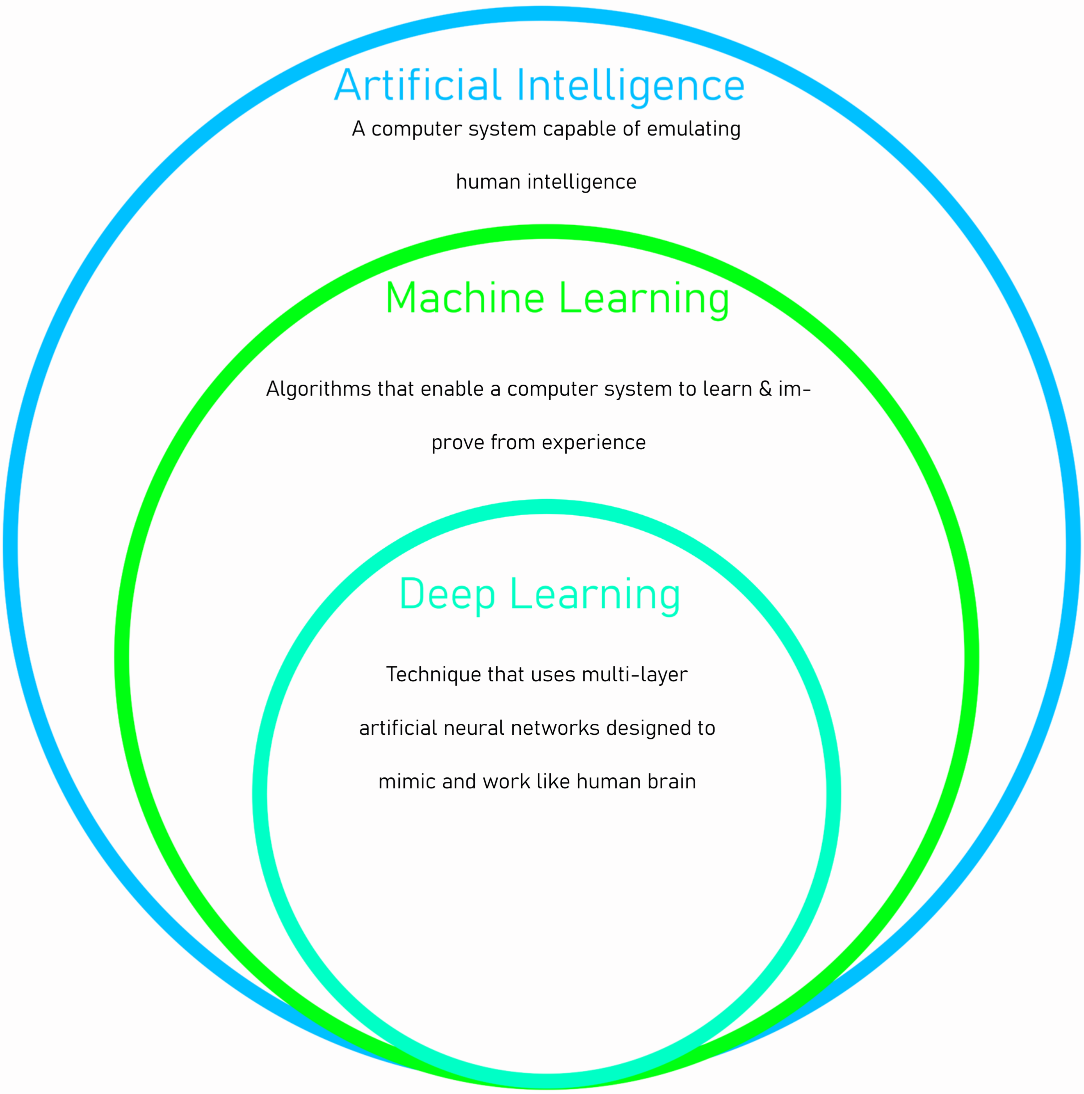


Figure 4. Created by the author (2025).Historical Timeline of the AI

1.3 Subfields of Artificial Intelligence Technologies

Artificial intelligence (AI) include a wide set of computational methods that seek to replicate aspects of human cognition. Over the decades, AI research has diversified into several subfields, each addressing different dimensions of intelligent behavior such as learning, reasoning, optimization, and adaptation.

The most prominent subfields—machine learning, deep learning, expert systems, and evolutionary algorithms—form the technological foundation of contemporary AI applications across disciplines, including architecture and design.



Machine Learning

Machine Learning is a subfield of artificial intelligence related to the development of computational systems that improve the performance with experience. Rather than relying just on the programmed rules, machine learning systems identify patterns inside the data and use these to make predictions and decisions. A widely accepted definition describes machine learning as a process that a computer program learns from experience within the frame of a class of tasks and improves its performance over time (Mitchell, 1997) So, machine learning operates by training algorithms on datasets so that models can create a froms of examples to new situations. This learning process usually involves constant adjustment of elements in response to feedback comes from the data. Machine learning systems are very effective in areas where strict rules formulation is difficult due to its complexity.Machine learning also shows a change in how intelligence works in digital systems. Instead of just the coding knowledge with using symbols, learning-based systems store knowledge in data-driven models. This shift matches Floridi's view of modern information technologies as part of a larger change where computation influences how we understand, process, and respond to reality (Floridi, 2014).

In real world settings, machine learning helps with tasks like classification, prediction, optimization, and pattern recognition. These abilities make it a key technology for many AI applications, including the ones that are used in design analysis.

There are three major categories of machine learning algorithms:

Supervised Learning

Supervised learning is a type of machine learning that models are trained with labelled data. Each input is paired with a defined output. The goal is to learn a function that connects the inputs to outputs, allowing for accurate predictions on new, unseen data. This method involves a learning process that follows specific feedback. Errors between predicted and correct outputs help improve model performance over time (Mitchell, 1997). In supervised learning, the training process typically has two phases: training and testing. During the training phase, the algorithm identifies patterns from a dataset that has features and corresponding labels. In the testing phase, the trained model is evaluated on new data to check its accuracy on the predictions. The success of supervised learning mainly relies on the quality and representation of the labelled training data (Nasteski, 2017)..

Supervised learning problems usually comes into two categories: classification and regression tasks. Classification aims to predict specific categories, while regression focuses on predicting continuous numerical values. Because of its structured nature and clear evaluation methods, supervised learning is one of the most widely used and successful approaches in machine learning.(Nasteski, 2017).

Unsupervised learning

Unsupervised learning uses data without defined labels or target outputs to train algorithms. The system is not directed by clear examples of adjusted behavior, unlike the supervised learning. It looks for patterns,or structures that are existing in the data itself. According to Mitchell, the main objective of unsupervised learning is to find relevant representations and relationships with input data rather than to predict the expected outputs (Mitchell, 1997). Here the algorithm works by analysing similarities, distances, or statistical corelations inside the data points. Common tasks include grouping data into clusters, reducing dimensions, and identifying features that summarise complex datasets. Since the no labelled guidance is provided, the learning is mainly exploratory, and the resulting structures require human interpretation to assess their relevance (Mitchell, 1997). A key advantage of unsupervised learning is the ability to work with high amount of unlabelled data, which is more relevant to real world scenarios. This makes unsupervised approaches very valuable for early-stage data analysis and situations where the structure of the problem is not yet well defined. Unsupervised learning forms the foundation for clustering, association analysis, fault detection, and representation learning techniques used across modern AI systems (Naeem et al., 2023)

Reinforcement Learning

Reinforcement learning is when an agent learns by interacting with an environment rather than learning from labelled data. The learning process is driven by feedback in the form of rewards or penalties, which evaluate the quality of actions taken by the agent. Instead of being told the correct action directly, the system must discover effective strategies on its own through experience (Mitchell, 1997) A defining characteristic of reinforcement learning is that feedback is usually delayed. Actions may not produce immediate rewards, requiring the agent to evaluate long-term results rather than short-term ones. This creates the challenge of credit assignment, where the

system must decide which past actions contributed to current success or failure. Mitchell identifies this delayed feedback as a key distinction between reinforcement learning and supervised learning models The goal is to find a way of acting that earns the most total reward by interacting with the environment many times. Learning usually means finding a balance between exploration, when the agent tries out new actions, and exploitation, when it uses strategies that are already known to give good results. This balance is essential for achieving stable and effective learning behaviour (Sutton & Barto, 2018). Since reinforcement learning does not require labelled datasets and can operate under dynamic conditions, it is mainly used to control, optimisation, and decision-making tasks. Its ability to adapt with experience makes it a foundational approach for systems that must respond to changing environments rather than static datasets.
”

Deep Learning

Deep learning is a part of machine learning that uses models made up of many layers of nonlinear processing units, which are usually called deep neural networks. Traditional machine learning methods mainly depend on manual data extraction, while deep learning systems can automatically learn layered representations straight from raw data.
This feature helps models find complex patterns and ideas that are hard to describe directly.(Goodfellow, Bengio, & Courville, 2016) One way to look at deep learning is as a process of finding the best way to represent data. Deep learning models are often trained with large datasets and use methods that improve the model step by step. More powerful computers and access to large amounts of data have played a major role in the recent success of deep learning methods.However, these models also bring problems like being hard to understand, needing a lot of data, and using more computer power, which sets them apart from simpler machine learning methods(Goodfellow et al., 2016).

Expert systems

Expert systems are designed to emulate the reasoning processes of human reasoning with well defined problems. According to Lucas and van der Gaag (1991), expert systems are characterised by their ability to present knowledge and to apply reasoning actions to generated conclusions. Unlike learning based systems, expert systems primarily rely on symbolic knowledge and logical inference rather than data-driven adaptation. A fundamental principle is the separation of knowledge and reasoning. The knowledge base has specific facts, rules, and relationships, while the inference engine provides the tools required to reason with this knowledge. This separation allows expert knowledge to be modified or extended without changing the reasoning process. The development of expert systems has a process known as knowledge engineering, which includes gathering knowledge and modelling it. This process is often one of the most challenging parts of expert systems, as expert knowledge is frequently implicit. Despite these limitations, expert systems remain valuable for decision support and reasoning, particularly in fields where interpretability and traceability of decisions are essential.

Expert systems represent an important point that built the foundation for many later developments in intelligent systems. Even tho they lack the autonomous learning capabilities of modern machine learning, their capability on structured reasoning continues to influence contemporary AI approaches (Lucas & van der Gaag, 1991).

Evolutionary Algorithms

Evolutionary algorithms are a set of optimisation and search methods inspired by principles of biological evolution. These algorithms keep a group of possible solutions and improve them over time. The main idea is that solutions with higher acceptance values are more likely to contribute to future generations, enabling the algorithm to explore and improve the solutions (Yang, 2018). Evolutionary algorithms rely on variation-selection mechanisms. Selection mechanisms guide the search toward individuals with higher fitness values, while variation elemets such as mutation and recombination bring diversity by creating new possible solutions. Evolutionary algorithms approximate optimal solutions by repeatedly applying this cycle over successive generations without the need for analytical models of information. (Bartz-Beielstein et al., 2014).

Evolutionary algorithms work especially well for problems with large, non-linear, or unclear solution spaces, and when gradient-based optimization methods do not work or cannot be used. Because they do not require analytic models of the problem, evolutionary approaches can operate under uncertain conditions. These methods use repeated steps and work with groups of solutions, they can find the best possible answers by adapting as they search. (Yang, 2018)

1.4 Current Application Areas of Artificial Intelligence in Architecture

Artificial intelligence is having a growing impact on architectural practice, not just as one disruptive technology but as a collection of skills used throughout architetural process. The RIBA AI Report 2024 states that AI is appearing at a time when architecture is under increasing pressure from climate change, urban complexity, stagnant productivity, and regulatory restrictions. In this setting, AI is seen less as a substitute for architectural practice and more as a tool that supports the architects. (Royal Institute of British Architects [RIBA], 2024).

AI in the Conceptual and Generative Design Process

Artificial intelligence is becoming more important in the early stages of architectural design, where ideas, forms, and strategies are explored. Leading architectural firms see AI mainly as a creative support tool that helps with the design exploration instead of replacing authorship (ArchDaily, 2024). During the early design phases, AI helps quickly generate multiple design options based on initial inputs like site constraints, program requirements, or aesthetic preferences. This generative process allows architects to investigate a greater range possibilities in less time. AI-driven tools are especially important for their ability to suggest unexpected configurations, helping designers to move beyond typical solutions while keeping control over interpretation. Architects still hold the responsibility for assessing the architectural quality and contextual relevance in the generated proposals. In this way, AI acts as a collaborator that speeds up ideation and visualization, while crucial design choices remain guided by human professional experience (ArchDaily, 2024).

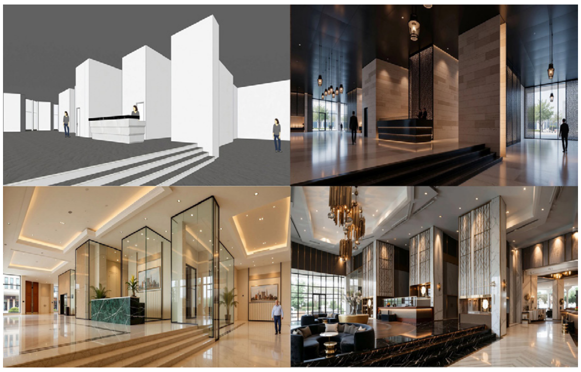


Figure 5. Workflows AI helps designers quickly explore interior style directions. Image Courtesy of AIRI Lab

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Simulation Optimization & Perfromance Prediction

AI is increasingly supporting the architectural assessment through advanced simulations, particularly during early and conceptual design stages.AI techniques enable architects to evaluate the performance elements of design decisions before producing detailed models or technical documentations. This creates a shift from traditional assessment process towards a more dynamic and design integrated evaluation. AI-based simulation tools allow designers to predict environmental and functional performance metrics by learning from existing data and simulations. Instead of just relying on computational simulations, machine learning tools can predict performance results rapidly, enabling designers to test multiple alternatives and compare scenarios in real time.This capability supports faster iteration and more precise decision-making during the conceptual design phase (Castro Peña et al., 2021). AI supported performance prediction also enables the early integration of sustainability considerations. By using predictive feedback directly into conceptual design, architects can assess the long-term impacts of design choices at a stage when modifications are still flexible. This early feedback loop powers.(Castro Peña et al., 2021).

AI in Construction Technologies and Fabrication

Artificial intelligence is being integrated to the construction technologies and fabrication processes.AI is nabling higher levels of automation and precision across the building process. Recent research frames AI not as a single construction technology, but as an enabling partne that integrates robotics, data-driven decision-making, and digital fabrication systems into construction works (Chen & Ying, 2022).

Figure 6. An example of BOD implementation of robot for Shanghai masonry from Robotization: Design for fabrication, assembly, disassembly, and the circular built environment with robot-oriented design, by Ng et al., 2022.

One of the most important fields is the robotics in construction industry. AI-supported robotic systems are incbeing used in the processes like prefabrication, on-site assembly, and disassembly, allowing construction processes to be guided with AI models rather than just using the manual methods. Robotic based fabrication approaches connect architectural input directly to fabrication, enabling buildings to be made with construction automation.In this framework, AI supports the coordination between design, fabrication, and robotics(Ng et al., 2022). AI is important for improving construction processes and controlling operations. Machine learning and optimization algorithms helps with many aspects of the planning, so systems can quickly adjust in the changing site conditions.

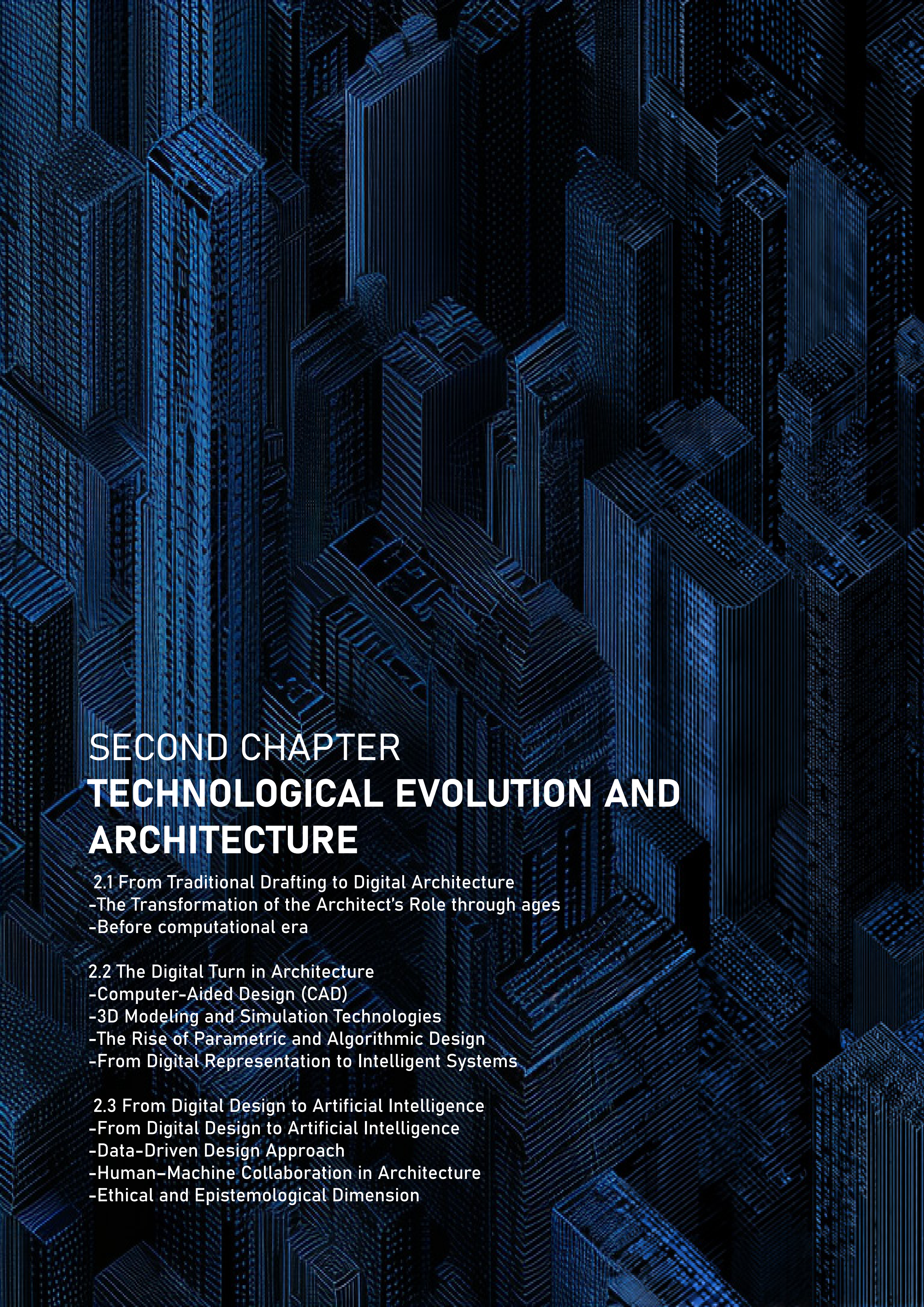
AI has an important role in construction. Machine learning and optimisation algorithms are being used in onstruction works, allowing systems to adapt dynamically to changing site conditions. These AI-driven processes improve productivity and safety in complex construction fields. In fabrication, AI enhances the integration of digital design models with automated manufacturing systems. AI supported robotic fabrication creates a rapid workflow and mass customisation without a great increase in cost and labour. Despite these advancements AI powered construction systems requires a careful coordination between design and human expertise. AI systems remain dependent on accurate data, well-defined borders, and human oversight.So AI in construction technologies is best understood as a collaborative system where architects, engineers, and machines operate within an integrated environment (Chen & Ying, 2022; Ng et al., 2022) .

Integrating AI across the Architectural Lifecycle

The application areas of artificial intelligence discussed in this chapter shows the start of a great transformation in architecture. Instead of just being limited to specific tasks, AI increasingly works as a funtional bridge that connects conceptual design, performance evaluation, construction, and fabrication to an ongoing process of information exchange (Carpo, 2017). AI is involved to the creative process and technical evaluation as well ,in early design stages, generative AI and technical aspects help architects to explore complex design possibilities while assessing performance at the same time. The same data helps to create models that can connect downstream processes like construction, fabrication, and optimisation decreasing the separation between design process and material creation.So , AI across architectural assessment do not bring the automation of architectural decision making and designing.Instead, it redefines and enhances the professional role of architects as coordinators and overseers of the complex systems. While AI supports responsive workflow, and analytical capacity, human expertise remains as the core for setting goals, measuring the outcomes, and highlighting the ethical, ethical, cultural, and contextual dimenaspects (Floridi, 2014; Carpo, 2017).

It is also important for us to remark that this integration is inevitable. Architecture by its complex nature has innovation as one of its foundational elements.And this integration already has some solid examples in the industry.
It is already operational and one of the great examples of that is the One Taikoo Place in Hong Kong. It was developed by Swire Properties with Arup as a its engineering partner. Arup's role has started during the start of the construction period in 2009.In the operation Arup has integrated Neuron an AI based platform being used as the brain of the building that analyses large datasets to optimise building systems, detect faults, and support the maintenance. (Arup, n.d.; Swire Properties, 2020). Neuron also shows how this integration depends on a data based foundation. it uses BIM to visualise and manage complex building data through a centralised console, and (in Arup’s own technical description) integrates 3D BIM with real-time data from building management and HVAC systems via open protocols such as BACnet and Modbus, effectively forming a practical digital-twin workflow for lifecycle asset management (Arup, n.d.; Arup, n.d.). The most important aspect here is that the efect of the AI integrati-

on has mesaurable outcome. Arup states that Neuron’s cooling-load predictions were within 5% of actual use and supported a 15% reduction in energy use for One Taikoo Place (Arup, n.d.).We will dicover more of this specific example and wider use of AI in leading architectural firms in Chapter 4,Industry Adaptation AI : Evidence from Leadin Firms.



SECOND CHAPTER

TECHNOLOGICAL EVOLUTION AND ARCHITECTURE

2.1 From Traditional Drafting to Digital Architecture
-The Transformation of the Architect's Role through ages
-Before computational era

2.2 The Digital Turn in Architecture
-Computer-Aided Design (CAD)
-3D Modeling and Simulation Technologies
-The Rise of Parametric and Algorithmic Design
-From Digital Representation to Intelligent Systems

2.3 From Digital Design to Artificial Intelligence
-From Digital Design to Artificial Intelligence
-Data-Driven Design Approach
-Human–Machine Collaboration in Architecture
-Ethical and Epistemological Dimension

02

2.1 From Traditional Drafting to Digital Architecture

The Transformation of the Architect's Role through the Ages

Throughout the history, architecture has always adapted technological changes, with each era showing changes in societal needs, materials, and means of production. The introduction of steel and glass during the industrial age transformed construction methods and building possibilities, while the emergence of digital tools in the late 20th century fundamentally changed processes of representation and design. In each case, technological innovation did not just added new tools, it redefined architectural practice and the professional roles. In the contemporary context, architectural representation has become increasingly diverse. Rather than just being shaped by a single strong way, current architectural production is mainly driven by the use of wide range of digital tools and computational design process enabling a great range of results that is functional for many cases. This condition actually shows a deeper transformation in the relationship between design and production. As Kolarevic explains, the introduction of digital and computational technologies has shifted architectural practice from representational drawing to a generative processes, setting a closer link with the design and fabrication (Kolarevic, 2003). This transformation brings an essential role for understanding the change from the digital design methods to AI-driven architectural systems. The digital revolution has had an important and a lasting impact on architecture. The introduction of tools like computer-aided design (CAD) and building information modeling (BIM) reshaped how architects create, develop, and communicate with he design. These technologies created new design approaches, including parametric and algorithmic methods, which enlarged the formal and technical possibilities of architecture. It has Increased precision, flexibility, and control over complex projects.At the same time, the common adoption of digital tools contributed to a fragmentation of architectural design style, making it really difficult to identify a single, dominant characteristic of the contemporary architectural era.

Before Computational Era

Before computers, architectural practice was mainly based on the act of notation. creating detailed drawings and blueprints that serve as a base for builders. Using manual tools and representational methods, architects took the role of visionaries and coordinators, while the physical act of construction was carried out by craftsmen and builders. With time this relationship began to change with the industrialization in the 19th century. The introduction of new materials like iron and glass in the construction industry has changed the building techniques and expanded architectural possibilities. A defining example of this transformation is Joseph Paxton's Crystal Palace (1851), which demonstrated how industrial materials and prefabricated elements could be used and combined into large scale architectural structures that still keeps the functional aspects of it.

Figure 7. The Crystal Palace at Sydenham Hill, London ,by Sir Joseph Paxton BBC Hulton Picture Library

This period also marked an important change in society, as architecture started to show the technological progress of the era. Industrialization sped up construction and brought innovative building methods, like prefabrication and modularity, to cover the needs of rapid urbanization. Standardizing and mass production came out as defining characteristics of the industrial era, driven by large economies. In architecture, this shift led to a move away from the handcrafted elements towards a standardized and repeatable construction systems. While standard forms met the general needs more effectively, customization became less possible and required more source This period set the foundations of Modernism, a movement that efficiency and standardization became central architecture. In response to rapid social and technological changes, Modernist architects moved away from ornamental traditions and adopted the principle of "form follows function." As we arrive to 20th century, Modernism became highly influential to shaping architectural theory and practice. Architects including Walter Gropius and Le Corbusier promoted the clarity, functionality, and the systematic use of industrial materials, viewing design and technology as instruments for social transformation which was taking place.

Figure 8. Walter Gropius and Le Corbusier at Les Deux Magots in 1930. The café in Saint-Germain-des-Prés area of Paris

During the mid 20th century, the work of Pier Luigi Nervi represents an important transition moment with traditional architectural practice and computational approaches after. Working firmly in the pre-computer era, Nervi explored the structural and expressive potential of reinforced concrete and intense experimentations with prefabrication, geometry, and structure. Projects such as the aircraft hangars in Orvieto, Italy, and the Palazzo del Lavoro in Turin (1959–1961) demonstrate how structural systems could serve functional efficiency and architectural expression at teh same time (Pier Luigi Nervi Project, n.d.). Nervi's design methodology wad relying on a deep understanding of structural behaviour, shaped by mathematical reasoning and hands-on experimentation rather than computational calculations. His use of repetitive modular elements, optimized the geometries, and prefabricated components created principles that would later become central to parametric and algorithmic design.Even with the absence of the digital tools, Nervi's works reveals an early form of design rationalisation, where geometry, material efficiency, and construction logic were tightly bound together. This approach foreshadowed later digital practices by demonstrating that architectural form could emerge from systematic rules and structural optimisation rather than stylistic ideas alone. Nevertheless, architectural production during this period remained fundamentally restricted by the manual drawing, hand calculations, and human labour of the time. Architects were required to master both representation and construction logic while knowing the limits of analog tools that are creating a long standing separation between design and execution that would only be fully challenged with the rise and advancements of the computational technologies.

Figure 9. Pier Luigi Nervi under the Viaduct of Corso Francia, Rome, ca. 1960, photo Oscar Savio

Figure 10. Pier Luigi Nervi. Aircraft hangar, Orvieto, Italy, 1935. Photo © Mario Carrieri

Figure 11. The Palazzo del Lavoro, Torino, 1959-1961 , Nervi & Bartoli and Antonio Badoni

2.2 The Digital Turn In Architecture

The rise of digital technologies in the late 20th century has marked a turning point in the evolution of architecture. Despite the initial hopes and efforts to utilize the digital potentials, their early technical obstacles limited a lot of the use in architectural practice. Even with the significant theoretical and technological advancements like Alan Turing's development of the theory of computation in 1936 and the creation of ENIAC in 1946, the first electronic general purpose computer and the real-world effects of these innovations came over time. As a result, the advancement of digitalisation was slow and heavy as computational technology mostly stayed separate from architecture in their initial phase. The first computer prototypes that arecapable of handling complex computational tasks started to emerge in the late 1950s, marking an important point in the development of digital technologies. And shortly after, the concept of artificial intelligence was formally created. In 1955, John McCarthy defined AI as "the science and engineering of making intelligent machines," cerating a foundational framework for future research. But , despite this early conceptual move, progress in AI soon slowed, leading to the first AI winter, because of the severe limitations in the computional power and the lack of data availability. The introduction of the IBM System/360 in 1964 represented an importnat milestone by standardizing the computer architecture across multiple models. This innovation improved compatibility, scalability, and the accessibility , enabling computational technologies to be used more broadly across different industries and disciplines and laying the foundation for the solid digital integration.

Figure 12. 1966, John McCarthy Image credit: Chuck Painter.

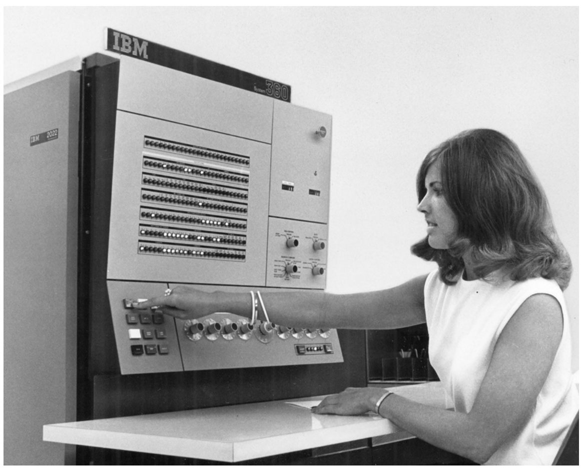


Figure 13. IBM System/360 Model 22. Photo from IBM.

The first application of computer aided design (CAD) was mostly attributed to Ivan Sutherland's development of the Sketchpad system in 1963, a pioneering interactive graphical system that enabled users to create and manipulate geometric elements directly on the computer screen (Sutherland, 1963). Sketchpad introduced important concepts like graphical interaction, geometric constraints, and digital modeling, that would later became bases of the working principles of CAD systems. At the time, these capabilities were mainly used of the engineering applications rather than architecture. Early CAD systems were developed to support the design and manufacturing of mechanical parts, where precision, and standardization was essential. So as a result ,these technologies were rapidly integrated to the mechanical and aerospace engineering, particularly in industries that use machinery and vehicle production, rather than by architects or designers (Sutherland, 1963). There were several reasons for the delay of adaptating the new technologies. Architecture was seen as a profession with low added value, however it was dealing with multilayered problems, data heavy drawings and imagesat the same time. The challenge of handling large data files was a major problem sixty years ago, and even now it's still occasionally an issue today.

Figure 14. Sutherland, I. E. (1963). Sketchpad: A Man-Machine Graphical Communication System.

As Sutherland explains, the systems enabled humans and computers to "communicate rapidly by using line drawings," replacing indirect text based commands with an immediate graphical interaction (Sutherland, 1963, pp. 8–9). By inegrating the logic, constraints, and structure to the representation, Sketchpad presented the design process as a process of managing information and rather than just producing drawings. In this sense, early computational drawing systems obtained a wider more complete understanding of design as a well structured problem-solving activity. An activity that drawing, communication, and reasoning are integrated with a single operational workflow.

Computer-Aided Design (CAD)

The 1980s marked the first impactful wave of the digital transformation in architecture. In this era, the increasing availability and affordability of personal computers brought technologies to the ecosystems of the architectural studios As digital tools became more accessible, the topic of computers not being available gradually lost its relevance. With the release of AutoCAD in 1982 architecture found itself on the brink of a major change. In this digital era the computers became tools for drawing rather than just being tools for conceptual reasoning and problem solving. Even though designing remained largely manual and labor intensive, CAD software improved significantly the precision, speed, and consistency in architectural work results . For many users, CAD was a direct digital extension of traditional drafting tools, putting hand drawn blueprints into the digital formats without really changing the design logic. However, for some CAD technologies opened new paths for architectural exploration. A new door, where the impossible became possible by enabling the creation of objects and complex shapes that manual methods wasn't able to achieve. The increased precision and control brought in by the-CAD , enabled new forms of geometric experimentation in architecture, leading tot he birth of the concepts llike splines and folding. The concept “fold” came from an interest in the ongoing transition between convex and concave geometries, mostly evident in S-shaped curves, which has allowed architects to generate fluid ,dynamic and controlled forms with a level of accuracy so precise that It's almost impossible to achieve with manual drafting methods. CAD has pushed the boundaries beyond the previous limitations of manual tools. These concepts have rapidly spread around and became representative of the initial stage of digitalization in architectural practice. As Mario Carpo (2011) argues, CAD “digitized” architectural representation but did not computationalized it. The computer was treated as a tool for precision rather than an agent of reasoning. Nevertheless, CAD laid the groundwork for a data-oriented design culture that would later become parametric and AI-assisted systems. An important moment in this transformation was the design of the Guggenheim Museum in Bilbao by Frank Gehry, one of the most complex architectural projects of its time. The project relied on the use of CATIA software which was originally developed for the aerospace engineering. This approach demonstarted that computational tools can be used not just for the representation , but as an active agent in the generation and control of architectural design. Gehry's work marked a turning point, illustrating how digital technologies could support experimental design while maintaining constructability. Most importantly hese projects demonstrated that digital tools could connect architectural ideas with physical implementation. Despite their complex forms, digital generated geometries could be translated into precise constructions, enabling a closer integration between design processes and fabrication methods. This development reinforced the role of computation as an assitant to the human design and generation process

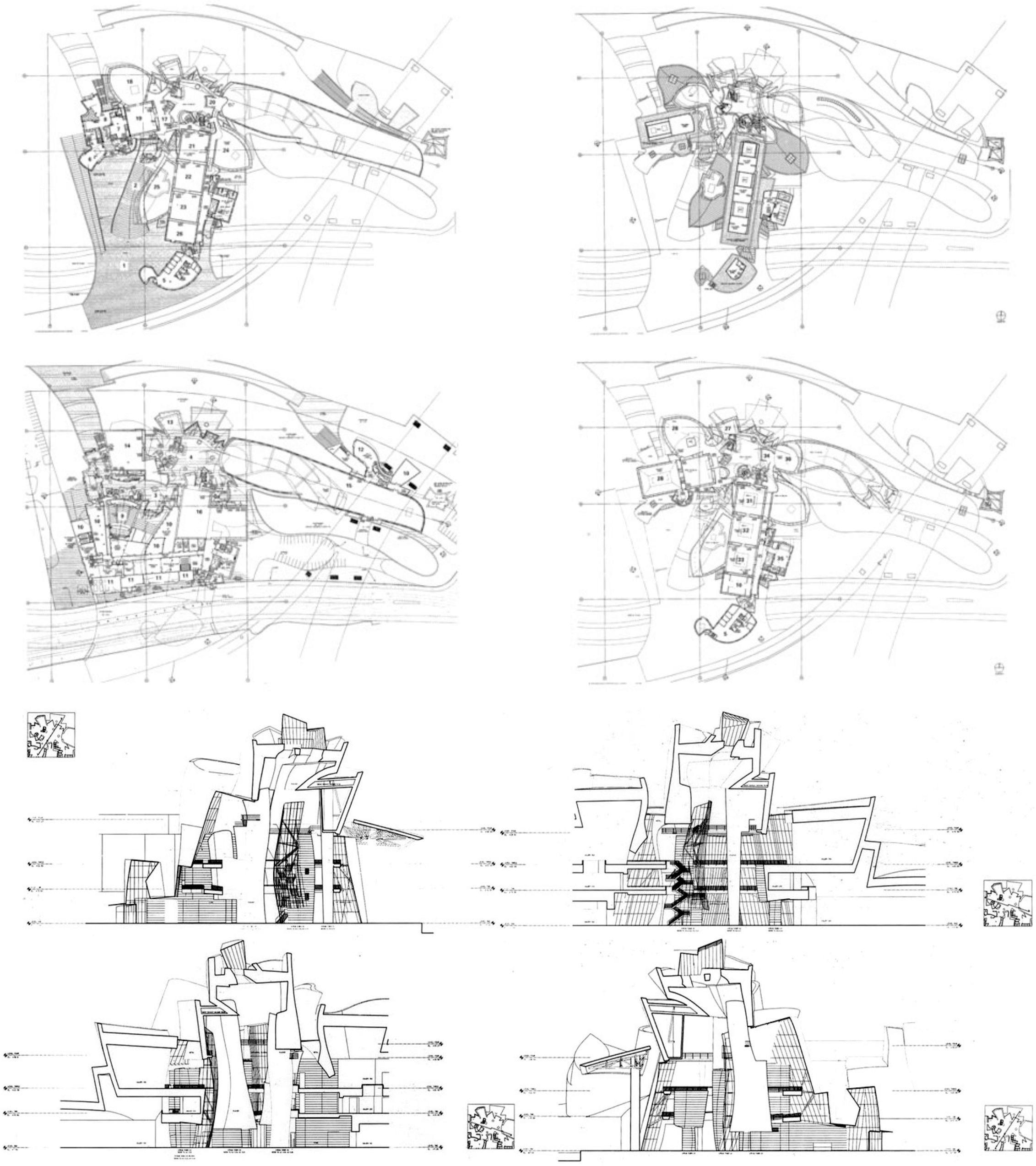


Figure 15. Floor Plans & Elevations by © Frank Gehry Architects.
Completed with use of CATIA 3D modeling software

3D Modeling and Simulation Technologies

In the early 2000s there was a great change in digital architecture, moving from a form driven approach to a process based design. While the early digital era brought architects great opportunities for experimentation by using of the new tools, attention gradually shifted it course to the use of digital technologies to optimize the design process. Rather than just focusing on the formal expression, architects have used digital methods in their workflows to evaluate design alternatives, and respond more effectively to context and performance related criterias. Digital tools evolved beyond their initial role as instruments for drawing. They have began to work as an active participant in the design process. The early 2000s also marked a critical period in the development of the accessible 3D modeling softwares like Form·Z, Rhino, and SketchUp. These applications enabled architects to turn conceptual ideas into the three-dimensional digital models which are supporting the visualization, evaluation, and decision-making during the design process. By facilitating intuitive modeling workflows, these tools expanded the capacity to explore complex geometries and spatial relationships with greater speed and flexibility.

3D modeling enables the creation of mathematical representations of three-dimensional objects, allowing architectural forms to be formed and manipulated inside a digital environment (Beknazarova et al., 2016). One of the main benefits of 3D modeling is its capacity to support more information based decision making during the design process. By working with digital models and noy just abstract projections, architects can evaluate more effectively the elemnts like proportions, geometries, and spatials reducing ambiguity and the risk of misinterpretation. Three-dimensional models also bring a rapid iteration phase allowing architects to modify and test alternatives more efficiently without having the need to redraw the entire sets of drawings (Beknazarova et al., 2016). 3D modeling contributed to a more close relationship between the design and production. Digital models could be directly translated into the construction, reducing the traditional gap between architectural conception and material realization. This continuity between the digital design and manufacturing stands as a defining characteristic of digital architecture and supporting the role of computation as a mediator between the creator and the technical execution (Kolarevic, 2003).

3D adavancements also took the simulation technologies to a further extent by introducing performance based designs. Environmental and structural analysis tools allowed architects to test many important aspects.Dynamic simulation tools enabled architects to measure how the variables like building orientation, massing and construction influence the energy performance and environmental impacts (Morbitzer et al., 2001). This integration reduced the division between different disciplines and allowed performance considerations to be addressed as part of the architectural design process rather than just being as external technical informations (Morbitzer et al., 2001).

So the increasing accessibility and the integration of the 3D & simulation technologies reinforced the architcets role as a creator. Even tho the need for external expertise is almost always required, the architect's role to handle these tasks got stronger thanks to these technologies. By integrating the information within the digital models, architects are now able to anticipate technical constraints and opportunities rather than responding to them retrospectively.Thus becoming more adaptive in their creative process.

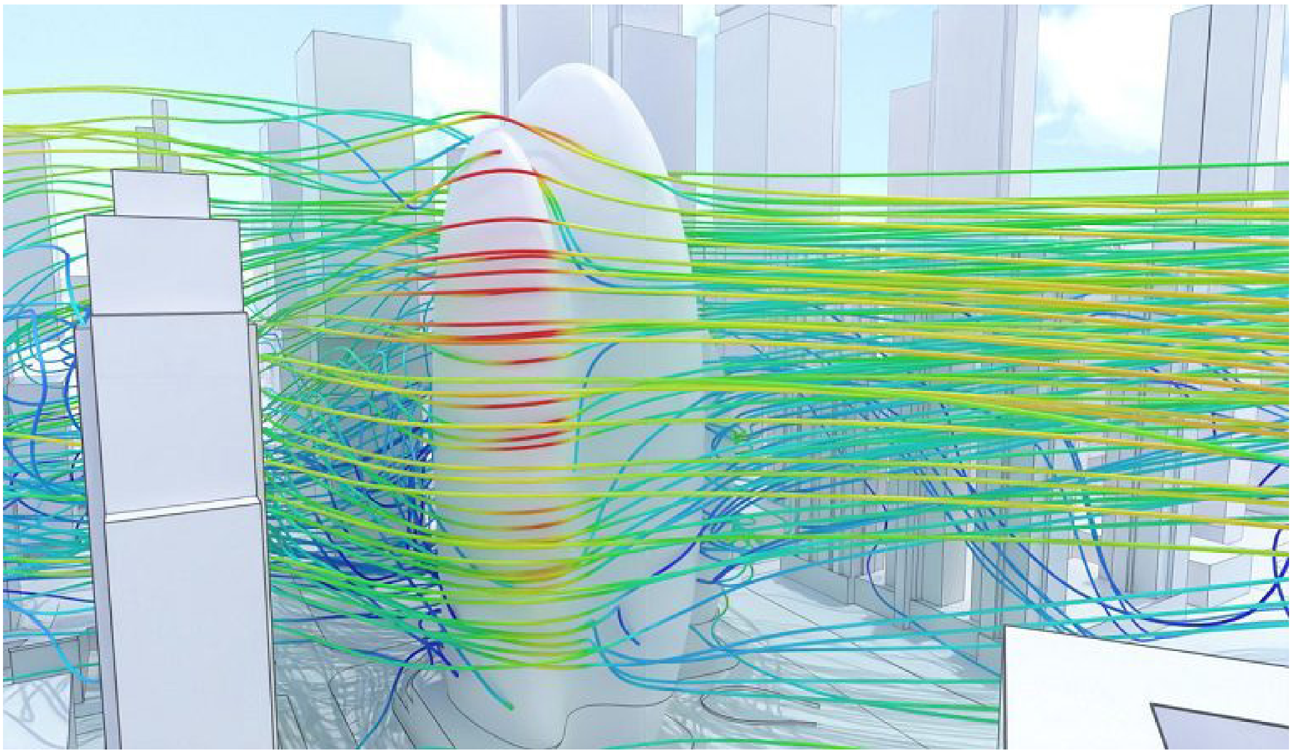


Figure 16. An external simulation of the OPPO HQ by Zaha Hadid Architects to evaluate airflow around the building.

The Rise of Parametric & Algorithmic Design

Unlike earlier CAD systems that used the static geometry, parametric and algorithmic design shows the relationship with the parameters and variables that are controlling the form. This allows architects to also cotrol complex geometries dynamically and to explore design variations by using a rulebased logic (Terzidis, 2006). In 2004 Autodesk released the Revit , a design and documentation platform that supports the design, drawings, and schedules required for building information modeling (BIM). BIM delivers information about project design, and phases it when you need it. In the Revit model, every drawing sheet has 2D and 3D view, and a presentation of information from the same digital building models. As you work on the building model, Revit gahers the information about the building project and coordinates these information across all other representations of the project. The Revit parametric change engine automatically controls the changes made anywhere in the model (Autodesk, 2024). Now , in theory this has fully revolutionized the design process by shifting architectural production from a collection of disconnected drawings to a single model of coherent, information rich project. By integrating the geometric, spatial, and quantitative information inside one parametric system, BIM fundamentally cahnged how architectural decisions are being made. Real-time collaboration and the fast exchange of information has sharpened the accuracy of the project management. BIM in architecture also helped with the reduction of the construction errors. These advancements did not happened immedietly but developed step by step through the progressive integration of digital modeling and information management technologies that has advanced over time.

Figure 17. Image Source: Yenra (2022). Generative Design in Architecture

Another important milestone in this field was the release of the Grasshopper as a plug in for Rhino in 2007. By providing a visual programming environment, Grasshopper enabled architects to use algorithmic logic and its working method to a more accessible and controllable way, allowing design intent to be expressed by using the relationships, rules, and parameters. Grasshopper played a key role in speeding up a new wave of parametric design. It made the algorithmic methods accessible to more than just specialized experts. With digital mass customization, architects are now able to handle complex designs while keeping consistency and control over design variations that are being generated. Instead of just creating one optimized solution, parametric workflows allowed architects to generate groups of solutions, creating more acceptable possibilities which can be useful for the architectural design process and exploration

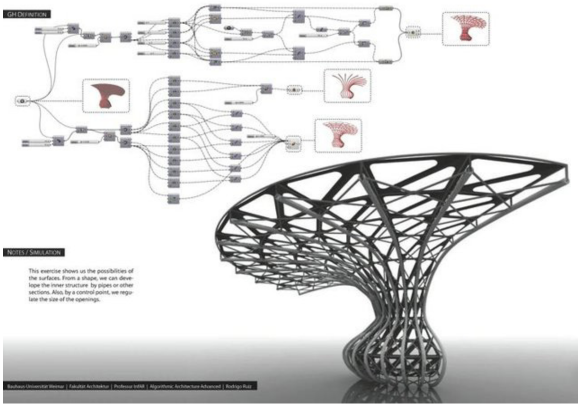


Figure 18. A typical exploration of architectural forms with Grasshopper. Image courtesy of Rodrigo Ruiz.

By combining parametric modeling with the performance simulations, these systems improve the bridge between design and performance without having the need of unnecessary details. Because of this, parametric design environments like Grasshopper serve as platforms for informed architectural thinking and not just as tools for forming experiments. They connect creative intention with performance awareness in the initial stages of the architectural design (Jabi, 2014).

While parametric and algorithmic design are mostly metioned in the same context in modern architecture, Terzidis (2006) highlights an important difference between those two. Parametric design manipulates and it sets the parameters with an already known framework, letting architects to explore different variations of a similar solutions. In this context ,the parametric systems focuses on control, predictability, and optimization, as the possible result are being limited by pre-defined relationships. On the other hand, algorithmic design does not adjust these parameters, it focuses on the logical steps that create the form iself. Here, the architect designs the algorithm by writing down the rules & conditions and then processes that can lead to unexpected results (Terzidis, 2006). This allows architecture to develop from with computational reasoning. Algorithmic design aslo challenges the traditional views on authorship and intuition, viewing the architect as a designer of the systems rather than designer of objects, and providing a crucial foundation for future advancements in AI-assisted architectural design (Terzidis, 2006).

From Digital Tools to Computational Intelligence

As an inevitable result of the ongoing digitalization in architecture, the practice has significantly changed how design is created. What started as the digitization of visual representations with using CAD slowly turned into a model-based, data-rich environment that combine the geometry, information, and performance. Three-dimensional modeling shifted architectural thinking and approach from a simple projection to a whole spatial collective simulation. AT the same time, performance analysis integrated an evaluative feedback inside the design process. Architecture increasingly shifted from linear workflows to a collection of multi layered complex methods. Parametric and algorithmic design brought in another shift by viewing architecture as an algorithmic system of relationships, rules, and procedures. Computational tools allowed architects to handle complexities and explore a wide ranging design options, assigning some aspects of form creation and evaluation to a digital system. Consequently, architects took on the role of designers of processes and systems, managing the interactions between the components of these complex structures. All these changes have turned the digital tools from passive insturments of representation to active parts of architecture. By normalizing the rule based logic, simulation-driven evaluation, and automated changes, digital architecture laid the technical and conceptual foundations that needed for the artificial intelligence to emerge.But AI here does not represent a sudden break from digital design, it serves as a logical and expected next step , bringing learning and adaptation to already existing computational design processes. This continuity shapes the basis of exploring how architectural practice evolves from digital design to artificial intelligence.

2.3 From Digital Design to Artificial Intelligence

As we have seen each digital breakthrough in architecture has pushed architects beyond their comfort zones. Each digital era has redefined the architectural process and expression. It has also reshaped the architect's role. At first, computers were tools for understanding complex calculations. Then, they became machines for drawing. Later, with BIM, they turned into tools for simulating and coordinating complex processes. Now, with the rise of AI, we are on the brink of a new era that computers as machines that can think and create. This new condition shows a significant change in our understanding of intelligence. Artificial intelligence represents a channge for the new systems that can learn, adjust, adapt and make decisions based on the data. Unlike earlier digital tools, which enhanced human abilities a lot but still needed essential and direct control, AI offers a kind of computational independence that works on its own. In architectural practice, this change clashes against the traditional lines between human intent and machine function. It brings up issues about authorship, responsibility, and creativity. Instead of just speeding up current workflows, AI can actively be involved in the design process. This brings a new role for the architect ,not just as a creator of shapes or processes, but as a manager and an overseer of intelligent systems. (Tegmark, 2017).

Figure 19. Ankrom Moisan used Midjourney to design a multifamily housing project that evokes the iconic Sea Ranch seaside.

However, even with the introduction of logic and automation these systems still rely heavily on clear human instruction and direction. Design processes follow a collection of set rules and relationships. This limits the indepedent computational agency to carry out expected results. The rise of artificial intelligence signals another major shift. It moves architectural computation from fixed frameworks to an adaptive ecosystem that can learn from the data, and create design knowledge beyond established limits. The shift from digital design to AI assisted architecture is an important change in how architects work. Computation is no longer just a tool, now , it is actively collaborating in design thinking process. Architects no longer just produce or control the forms. Instead, they work with systems that can process the data, spot patterns, and help in making decisions. This change enhances the ability of architects interaction with the technology. Now the design intent is coming from engaging with the computational intelligence rather than being determined solemnly by the architects. And this change challenges old views of creativity and control. It shifts the architect's role from a maker of forms to a coordinator of computational processes and smart systems. (Carpo, 2017).

Phase 1:Traditional Architectural Drafting

Representation

Hand-drawn plans, sections, and elevations

Physical media as primary interface

Knowledge Structure

Tacit, experiential, and embodied knowledge

Drawing as an interpretive act

Design Logic

Iterative through manual redrawing

Strong dependence on individual skill and craftsmanship

Assessment Mode

Qualitative judgment

Experience-based evaluation

Post-design verification

Phase 2: Digital Architectural Drafting

Representation

Vector-based digital drawings

Increased geometric precision and reproducibility

Knowledge Structure

Explicit, rule-based representation

Separation between drawing and material execution

Design Logic

Faster production and modification

Drawing as controlled representation rather than interpretation

Assessment Mode

Rule-based checks

Geometric and dimensional verification

Phase 3: AI Assisted Architectural Drafting

Representation

Parametric and information-ric h models

Geometry embedded with performance, material, and relational data

Knowledge Structure

Architecture as an informational system

Models function as databases rather than static drawings

Design Logic

Continuous modification through parameter manipulation

Integration of simulation and evaluation

Assessment Mode

Computational and data-driven evaluation

Performance-infor med decision-making

Figure 20. Created by the author (2025).Evolution of the Elements & Phases of Architectural Drafting

Data Driven Design Approach

With the emergence of artificial intelligence , architecture coincides with the global increase of the data of environmental, social, and material elements. Data has become a new form of design material, helping architects to make decisions grounded in real world information feedbacks rather than just assumptions. Based upon this shift the data-driven design changes architectural practice into a process of gaining knowledge from large datasets. Instead of mainly relying on the intuition or past examples, architects are now working with the data as a source of insight and design material. This approach can discover patterns, correlations, and constraints which most of the time ignored by the traditional design methods. Digitalization allows the integration of real time data and historical datasets to the architectural workflows. This integration helps with the architectural decisions responding to a dynamically changing environmental, and user related conditions. So data here does not replace the design intent but it informs and reshapes. This approach supports more adaptive, and evidence based , performance oriented architectural productions (Cantamessa et al., 2020).One of the most important effect of data driven design is that it can make architectural and construction processes more efficient, especially when it comes to time, resource and coordination. Traditional model driven workflows are often broken up into the parts that depend on making decisions and sharing information by hand. This can cause delays, inconsistencies, and rework. By contrast, data-driven and digitally integrated approaches enable earlier evaluation of design decisions, reducing uncertainty and minimizing downstream corrections. Studies indicate that the lack of data integration and coordination is a major contributor to productivity loss in the construction industry, resulting in wasted time, inefficient use of resources, and budget overruns (McKinsey Global Institute, 2017).

Now , data driven design approach and AI has a natural comapatabilty and a functioning framework that they can be integrated with each other. Data-driven design approaches set up many of the conditions needed for artificial intelligence to work in architectural workflows. Design information is organized relationally, not descriptively. It connects spatial parameters, environmental conditions, material properties, and performance criteria in clear data structures. These connections allow design states to be assessed not separately but as parts of interconnected systems. AI systems can use this relational data to understand design idea, create alternatives and aid in iterative exploration. This is possible because design information is structured, constrained, and readable by machines.It is important to mention that This alignment does not mean that authorship shifts from the architect to the machine. Instead, data-driven design places architects in the role of curators who manage datasets, constraints, and evaluation criteria that influence AI behavior. AI systems work within frameworks set by human intent, turning architectural knowledge into a computational format. In this setup, artificial intelligence builds on data-driven design by incorporating adaptability and

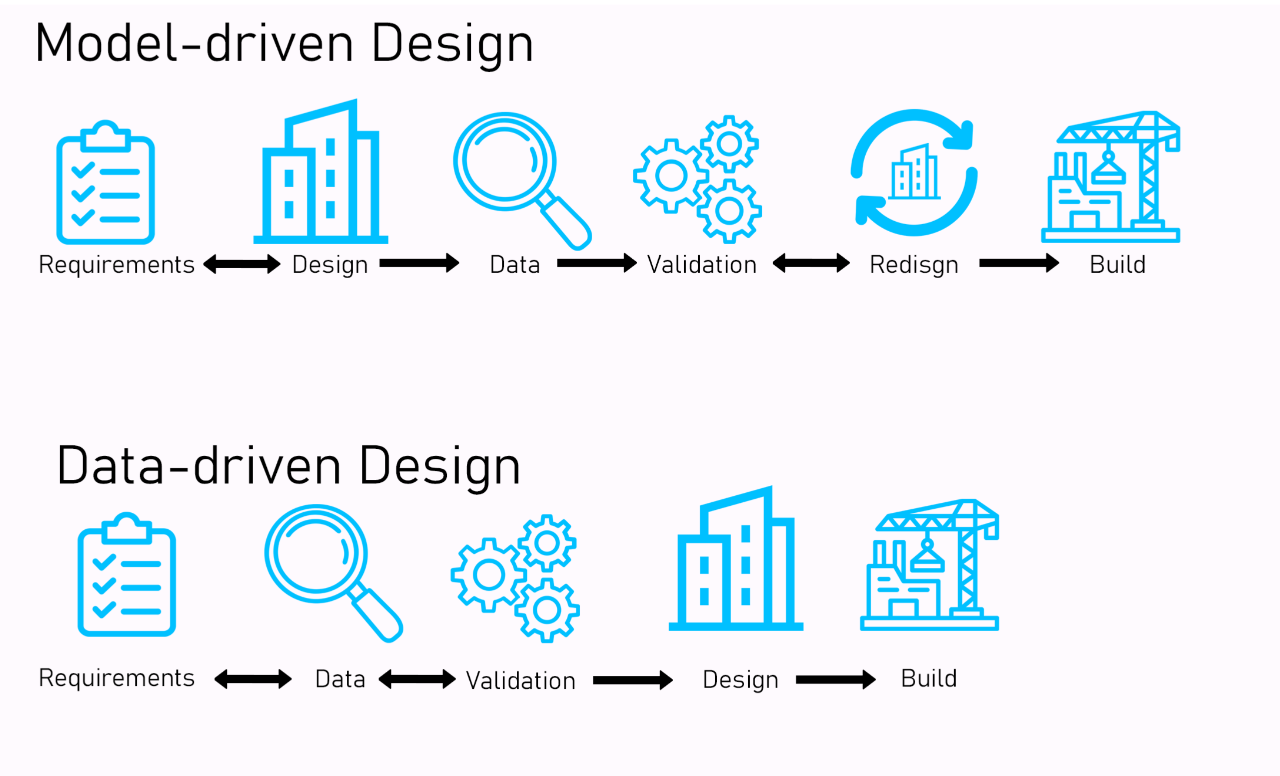


Figure 21. Schematic overview of model driven and data driven design logics
created by author

learning, rather than taking over human decision-making.So data-driven design builds on the ideas of computational design by making learning, prediction, and adaptation part of the design process. It signifies a cultural transformation in architecture, transitioning from intuition-based authorship to information-driven co-creation, wherein human creativity and algorithmic intelligence exist in a symbiotic relationship.

Human–Machine Collaboration in Architecture

The integration of AI into architecture does not show the replacement of the architect but rather the emergence of cooperation between humans and machines.

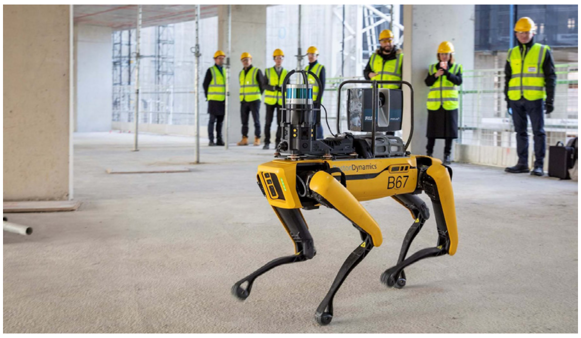


Figure 22. Boston Dynamics' robot dog, Spot, to help capture and monitor progress on construction sites Courtesy of Foster + Partners

This partnership is a point of going from control to co-creation, where both players contribute with a distinct form of reasoning. Contemporary architectural design increasingly emerges from an interaction between human and computational logic, where designers establish rules and relationships that are explored and materialized by using algorithmic processes. So, the increasing use of artificial intelligence in architecture is not just one way humans and machines interact but It shows a range of collaborative relationships influenced by various levels of control, and responsibility. AI should not be seen as an independent replacement for architectural intelligence. Instead,because it is a technological system that requires human interpretation and context to be meaningful and effective (Gerber, Mieskes, & Franck, 2024). Within this view, human and machine collaboration can be boild down to the base of how much machine systems are involved in design process and decision-making. The design outcomes happen through back-and-forth interaction, where human intuition and machine generated options work together to create the expected architectural solutions. Here the idea of autonomous systems raise an important question about the authorship and the responsibility, and the limits of how much letting machines can take over architectural tasks. And this results in three main ctagories of the AI changes architectural work without taking the role of a technology that controls everything. Assistance, Co-Creation, and Autonomy are the key categories how AI should and can be implemented in architecture. (Gerber et al., 2025).

Assistance

Assistance is the most basic level of AI contrubiton in architecture. In this role, artificial intelligence acts as a tool that improves efficiency, visualization, and workflow without engaging in architectural reasoning and defining a context. Design, interpretation, and responsibility stays completely in the hands of the architects, while AI works inside a well defined and supervised environment (Agkathidis et al., 2024; ArchDaily, 2023). In assistance based use, AI tools are mostly used to speed up tasks like early design explorations, and improving workflows by taking on the repetitive tasks. The study by Agkathidis shows that how AI image-generation systems help in architectural practice by quickly creating visual prompts that inspire ideas. These results are neither architectural solutions nor the end produtcs, they serve as abstract references that architects can reinterpret.Here the AI supports the design process without affecting architectural judgment or authorship (Agkathidis et al., 2024). Recent research on AI supported design automation shows that the best uses of artificial intelligence in architecture is when AI acts as a support system instead of a standalone designer. Studies reveal that AI greatly improves efficiency by taking on the repetitive and tasks. This includes generating initial options, updating the documents, organizing design data, and providing early visuals. These tasks lower the workload and speed up decision making without replacing architectural judgment. However, the same research points out that AI generated results most of the time need human control. This is because of the issues like the data quality, instability of algorithms, and lack of context. Because of this, AI-assisted automation funtions in the best way in a hybrid workflow where architect keeps the total control over the goals and assessments. This confirms the role of AI's as a helpful tool, not as a creative leader (Akdağ & Künyeli, 2025). AI generated results do not learn during the project or assess architectural performance. They also do not make independent decisions. Instead, architects keep the full control of how they define problems, choose outputs, and develop designs. Both academic and professional insights show that AI generated content often contains inconsistencies or elements that are not suitable for the context. This emphasizes the need for human interpretation and critical judgment at every stage of this collab (Agkathidis et al., 2024; ArchDaily, 2023).Based on this research we can identify seven key aspects of assistating role of the artificial intelligence in architectural design process.

Key Elements of AI Assistance in Architectural Design

Human Control

The key aspect of AI assistance is that all decisions, interpretations, and evaluations are led by humans. AI outputs are clear, predictable, and do not change based on the project context. This reinforces the architect's role as the only author and decision-maker.

Task Acceleration

AI helps by speeding up time-consuming or repetitive tasks like image generation, data sorting, precedent search, and documentation support. This lets architects concentrate more on conceptual thinking and critical design instead of manual work.

Information Management

AI helps organize, filter, and retrieve a lot of project-related data, including drawings, images, regulations, and precedents. This makes workflows clearer and lowers mental effort without affecting design intent.

Error Reduction and Consistency

In supporting roles, AI helps find inconsistencies, omissions, or conflicts in drawings and models. This function improves accuracy and coordination while leaving decisions about judgment and resolution to the architect.

Visual and Representational Support

AI systems provide quick visual outputs, such as concept images, massing variations, or stylistic references. These visuals serve as inspiration or communication aids. They do not represent architectural solutions but act as prompts that designers interpret and transform.

Early-Stage Exploration Support

AI allows for quick creation of several options at a high level, which helps architects explore directions effectively. Importantly, these options stay exploratory and the system does not evaluate or choose them on its own.

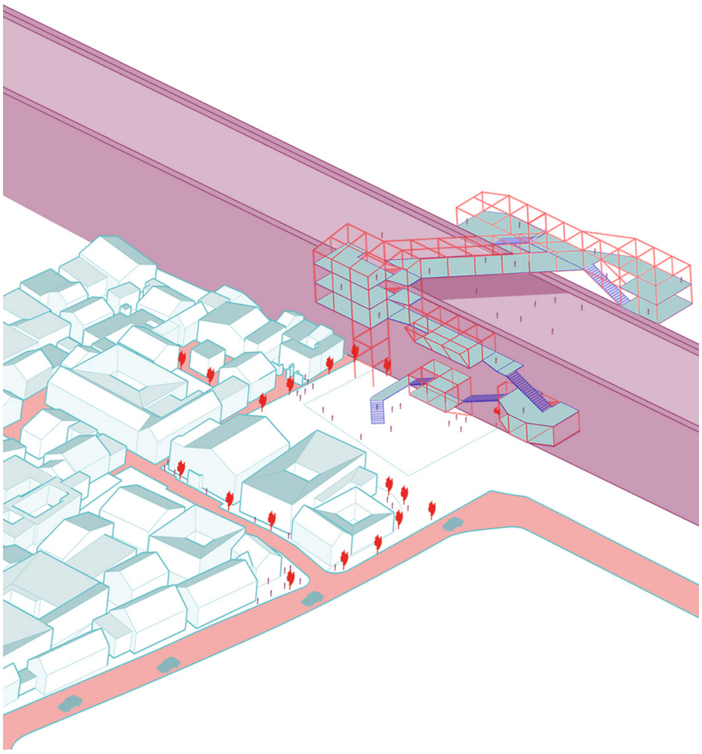
Limited Learning & Adaptive Behavior

In assistance mode, AI systems do not fully learn from the feedback from a project or change their behavior on their own. Their role is limited to execution and support; they do not engage in reasoning or creative tasks.

Co-Creation

Co-creation refers to a way where usable architectural design results are generated in an ongoing interaction between architect and the artificial intelligence. Unlike assistance-based applications, where AI mainly helps with certain tasks, co-creative systems take on an active role in the creation and modification of design options. In this pace ,the design practice is shared with human judgment and AI generated products. Architectural results , options and ideas emerge from ongoing discussions and interaction between humans and AI (Li et al., 2024). So Generative AI systems here has a co-creative role throughout various stages of the architectural design process.They contribute in many aspects of it. Instead of creating finalized and usable architectural solutions, these systems produce variations and proposals of the expected outcomes. Architects then evaluate, adjust, measure and incorporate them into their overall design work. Generative AI models respond to prompts and constraints provided by architects ,while they refine their goals and parameters based on the system's response. This communicational process enables the exploration of complex design options with a rapid pace than using regular manual methods ,at the same time preserving & strengthening the architect's role in the contextualizing design outcomes to the aimed results (Li et al., 2024).

Figure 24. Two images generated by MidJourney as a reference for an early stage expolarion period of a residential villa project with the inspiraiton and the architectural style of Zaha Hadid. not as final product workflow results



This is an axonometric view of a "belvedere" concept for the architecture and structural forms atelier (ACC AY. 2021-2022). Located in the Nanjing Hehua Tang city & the wall. This model was first created with Rhino and SketchUp late the axonometric view was rendered using Adobe Photoshop and Illustrator. The goal was to produce a schematical representation of how the design was placed on the wall creating a view point for the people and circulation path outside of the normal horizontal pathways. Different colors were assigned to each each element to recognize them.

Here is the same view but this time represented in a realistic render style.This was created with GPT image generator by providing the the image above and typing the ptompt to get exactly what shoud be the end result.This simply demonstartes that AI tools can help us visualize what we woud like to achieve and taking the future steps adjusted to that goal. Now this image can not be used in a final projec or product simply because there are major errors such as the buildings on the ground level and the on the structure iself.

Autonomy

Autonomy refers to the ability of computational systems to work more independently throughout the design process. Recent advances in artificial intelligence and robotics have changed traditional views of the autonomy. These systems can learn from data, change their behavior over time, and produce results that are not entirely set by humans thus having their own input in the process. This shift in architectural workflows reframes autonomy as more than just technical automation. It redistributes power among the human designers and computational tools which architecture is made and used. As machine learning progresses, systems can operate beyond well defined rule based logic. And this brings up important questions about the concept of authorship and control making autonomy a key issue that changes the relationship between architecture, its production processes, and its technological tools (Wit et al., 2018). So the definition and the distcintion here should be made in a really careful way. The full autonomy of the architectural practice is almost impossible. Living spaces can be created with a fully autonomus process but these would be nothing more than "tools to live and use".These creations may satisfy the basic standards of living but they would be lacking the human aspect that essentially creates the sense fullfilment. Architecture is not just concerned with shelter or utility, it is a form It is a way for us to express our values, culture, identities and shared memories. So The limitations of autonomous AI systems in architectural design can be understood through broader ideas about human intelligence. Gardner's theory of multiple intelligences highlights that human thinking is not just one computational ability but a mix of different and connected types of intelligence, such as spatial, interpersonal, and intrapersonal skills (Gardner, 1983). Architectural design heavily depends on these skills because it involves cultural interpretation, ethical judgment, and awareness of context, which go beyond simple problem-solving. While AI systems can perform well in specific computational tasks, they lack the embodied, social, and reflective intelligence that is essential for architectural reasoning. Therefore, having AI autonomy does not mean it has architectural intelligence, which emphasizes the need for ongoing human oversight and responsibility in design processes (Gardner, 1983).

Ethical and Epistemological Dimensions

While AI has great potential for improving architecture, it also brings up important questions about ethics and authorship. Automating design and construction raises issues a great amount of issues corelated to accountability. This is highlighted in frameworks that stress the need to avoid harm from biased datasets and to ensure clarity and accountability. (Floridi et al., 2018). For example, if an AI generated design leads to material waste or social exclusion, figuring out who is responsible gets quite complicated. This highlights the need to tackle the issue of control. We must ensure that advanced AI should able to match human values before it goes beyond our ability to manage it otherwise the operation would generate nothing more than a bland and hollow result that will probably bring negative biproducts (Bostrom, 2014). AI systems mainly learn from past data. This learning can bring the aleady existing unresolved issues and may repeat it without having the notion and the concept of what is good and what is bad as decision making sometimes need the "the human aspect" . Architects must think critically about AI, viewing it not just as a technology but an agent capable of inflicting cultural and ethical influence. This notion is similar to the warning about choosing control over the reckless , unsupervised progress (Bostrom, 2014). This awareness highlights the importance of “ethical execution of architecture.” So in this context, AI should be used to support sustainability, inclusivity, and human-centered design through approaches that promote well-being and respect for autonomy.We will be covering these topics in a more extensive way int the next chapter where we inspect the changing role of the architect with the artificial intelligence.

03

3.1 The Changing Role of the Architect in the Digital Transformation

The Technology Recap

The role of the architects have been changing significantly since the late 20th. This change was influenced by the ongoing technological advancements that have transformed the tools, workflows, and the evolution of the profession. The shift from manual drafting to computer-aided design (CAD), then from CAD to Building Information Modeling (BIM), and finally from BIM to computational and data-driven automated processes has changed how the architects work. It has also shifted how architectural problems are defined and understood. This section of the chapter outlines this evolution to clarify the basic conditions that allowed the emergence and the practical use of artificial intelligence in architecture and the scale of its importnace. The purpose of this review as we continue exploring more of how the role is being effected is to show current events in relation to their historical predecessors. By summarizing the situations and connections that influence the current state of architecture, we can better speculate about future architectural trends and expect changes in building technology and AI. Early CAD systems changed manual drawing methods into computer based methods. They improved precision and efficiency but mainly kept the manual principles. Architects were still the main creators, using computers as drafting tools instead of thinkers. However, even in this early stage, architects like Nicholas Negroponte predicted a deeper , more effectivechange. In The Architecture Machine, Negroponte envisioned computer systems that can talk with architects, learn from their preferences, and actively take a role in decision making (Negroponte, 1970). As digital technologies developed, the introduction of Building Information Modeling (BIM) marked a significant change. Unlike CAD, which was about geometry, BIM redefined architecture as an information system. This system embedded almost all the required data inside a single model. This has changed the architect's role from drafter to coordinator and the information manager. Architects now had to maintain consistency across complex datasets. The 2024 aı report of the Royal Institute of British Architects show how BIM changed architectural workflows by emphasizing this collaboration (RIBA, 2024). Marking that architectural project became less about a collection of drawings and more about a dynamic database. This has required new forms of skills.

The rise of computational and parametric design further changed architecture. Instead of creating fixed forms, architects were now able to define and create systems of constraints, and parameters that could produce various desired and funtional outcomes. This approach has changed the role of architects from designers of objects to designers of processes that are able to use and functionalize the inserted data. It was a new mathematical and a form of computational understanding in architecture. In this context, form manifests from the ongoing interaction between human input and computational responsive logic (Burry & Burry, 2010). So the architect’s role is not vanishing , rather it becomes to the creator of algorithmic structures that need strategic control instead of manual control. The shift from computational design to artificial intelligence is the latest and most significant part of this evolution. Unlike parametric systems, which work with well structured rules, AI systems, especially the ones that are using the machine learning, learns patterns and make decisions based up on that specific information. This change is crucial for architecture because now It is moving from predictable processes created by architects to a more flexible type of systems that can make inferences and predictions. Bernstein describes this change as a shift from “automation of tasks” to “automation of judgment.” In this new form, machines starting to affect not just how designs are produced, but also how those decisions are made (Bernstein, 2025). So, architects increasingly focus on managing data, overseeing outcomes, and evaluating the machine generated results during the design process.And currently the professional assessments support this idea Recent RIBA report highlight that while AI improves efficiency and increases capacity of exploration, it also increases the need for architectural oversight and ethical accountability. (RIBA, 2025). Architects are now more than just users of tools; they act as a controller between algorithmic processes and human values. This matches with Neal Leach’s description of AI being an “alien intelligence.” It with a using non human logic, so it needs careful translation and management with architectural practice (Leach, 2023). As we can see , the digital transformation of architecture shows a clear path of moving from representation to information, from information to systems, and from systems to learning machines. Throughout all these ages and stages, the architect's role is being changed. Architects have shifted from drafters to coordinators, from form-makers to process designers, and now increasingly to supervisors of intelligent systems. As of today artificial intelligence is not a replacement for architectural practice it is the latest step in a long happening evolution towards a controlled, data-driven, and collaborative forms of design methods. This historical continuiation builds the foundational groundwork for understanding the current role of the architect in this age of artificial intelligence. Artificial intelligence is the latest step in a history of mediated design practice. It expands from just staying in the computational involvement role to the areas of inference and judgment. This shows that AI doesn’t exist outside architectural practice it is involved from the inside of it. With this in mind, today’s architects collaborates with intelligent systems that can impact the design results. However , this situation raises important questions about agency, authorship, and professional responsibility. These factors provide a foundation for exploring the architect's role in the era of artificial intelligence.

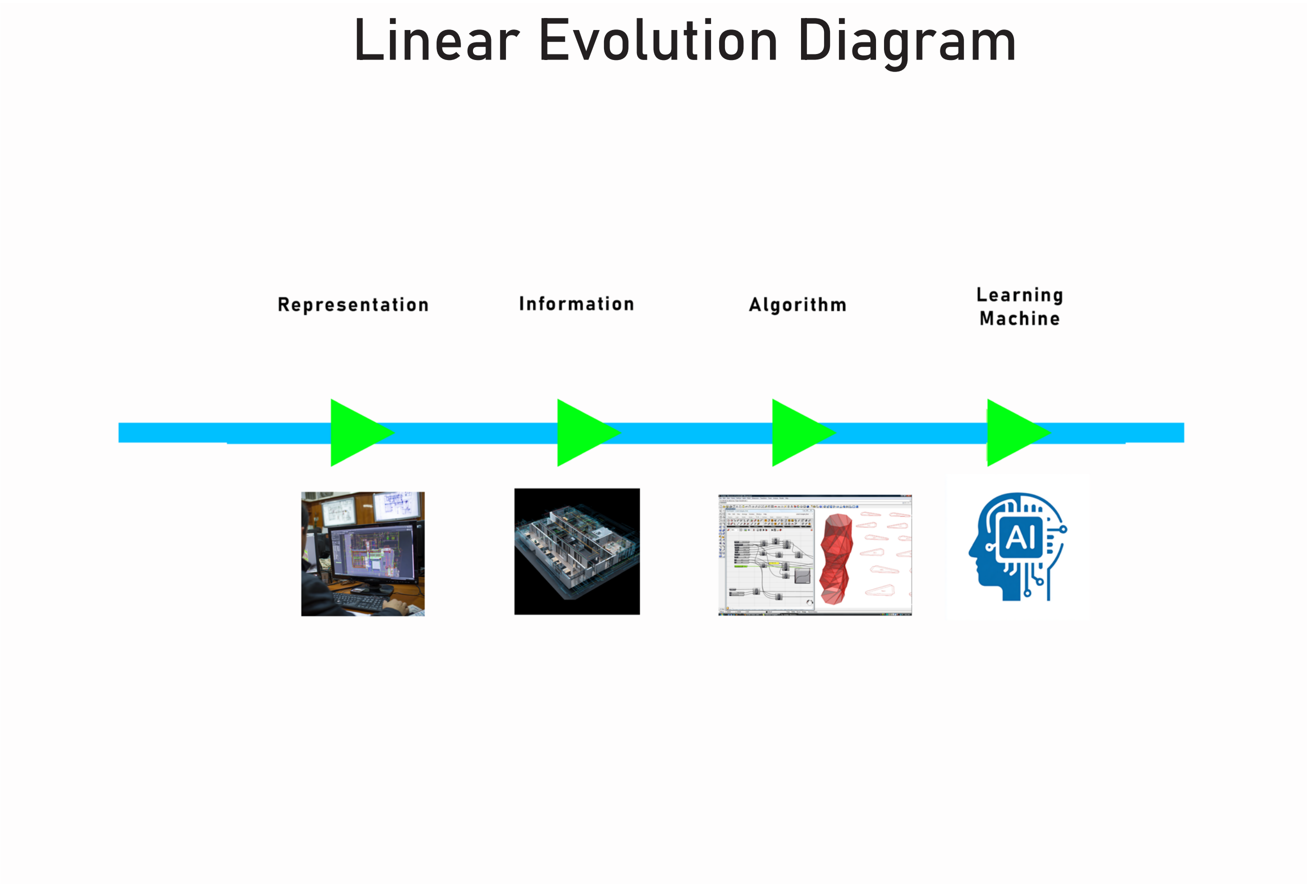


Figure 25. Created by the author (2025).This diagram illustrates the progressive transformation of architectural computation from representational drawing tools to data-driven, learning-based systems, highlighting how each stage expands the architect's mode of reasoning rather than replacing the previous one.

3.2 The Architect in the Age of Artificial Intelligence

The AI integration to architectue marks a major change in how architects think and create. Instead of being a distant or theoretical technology, AI is already effecting the professional processes on daily basis. This includes everyt-hing from early concept development to project coordination. AI is expected to improve architectural practice by increasing efficiency and bringing the analytical capacity leading the changing the professional roles. However, core responsibilities stay firmly in human hands (Royal Institute of British Arc-hitects [RIBA], 2024). Architect's role is changing from a direct producer to a one that is orchestrating a great complex process. As AI systems taking over the routine and data heavy tasks, architects must engage more critical-ly with elemnts of intent and context. They need to reassure that computa-tional results must support ans align with the social, cultural, and environ-mental goals. In this way, AI increases responsibility of the architect instead of actually reducing it. So in this context architects need new skills in managing intelligent systems and checking the-ir results within the larger concept of professional practice (RIBA, 2024). This current situation serves as the basis for exploring how the architect's role is being redefined in the age of artifi-cial intelligence. Human creativity and generative AI processes both take place in similar activities .This suggests that creativity in both humans and AI is about remixing and reimagining familiar inputs to create something new. Tradi-tionally, architects have been seen as a creative professional, responsible for shaping ideas. And that mainly came from the human inspiration. However, as generative AI mimics these men-tal processes and it starts producing outputs with a rapid pace. While archi-tects have historically been the central 'creative beings' in the design process, the rise of AI raises concerns about whether our creativity is at risk since machines now able to generate ideas in seconds. So, is our creativity in dan-ger ? Human creativity is often limited by what we know and the tools we have to bring that creativity to material world. Creativity has typically seen as a human trait acentral one that is shaped shaped by our cultural context, know-ledge, experiences and collective me-mory. However, these new technologies work beyond human limits that humans have. With access to vast and diverse databases,and being able to store them in their memory, AI can generate and explore possibilities that might exceed our resources and current imagination.

As Clark explains, the cognitive processes are often "supersized" and enhanced by technologies which becomes a key part of how humans think, and create (Clark, 2008). From this point of view, tools do not just support creativity , they have an impact of actively shaping it. Artificial intelligence is an extension of the long standing bridge between human thinking and external systems. It works at a scale and speed that surpasses individual human abilities. By analyzing the large datasets and finding patterns that are not immediately obvious for human understanding.By doing this AI is opening up new possibilities for design outcomes instead of replacing human creativity. Therefore, creativity arises not as a solo, human centered act but as an active exchange between designers and the intelligent systems they use. Understanding this shared nature of creativity offers an important way of seeing AI not as a threat to but as a partner that can enhance creative exploration beyond the human limits (Clark, 2008).

Defining Human-in-the-Loop in Architectural Practice

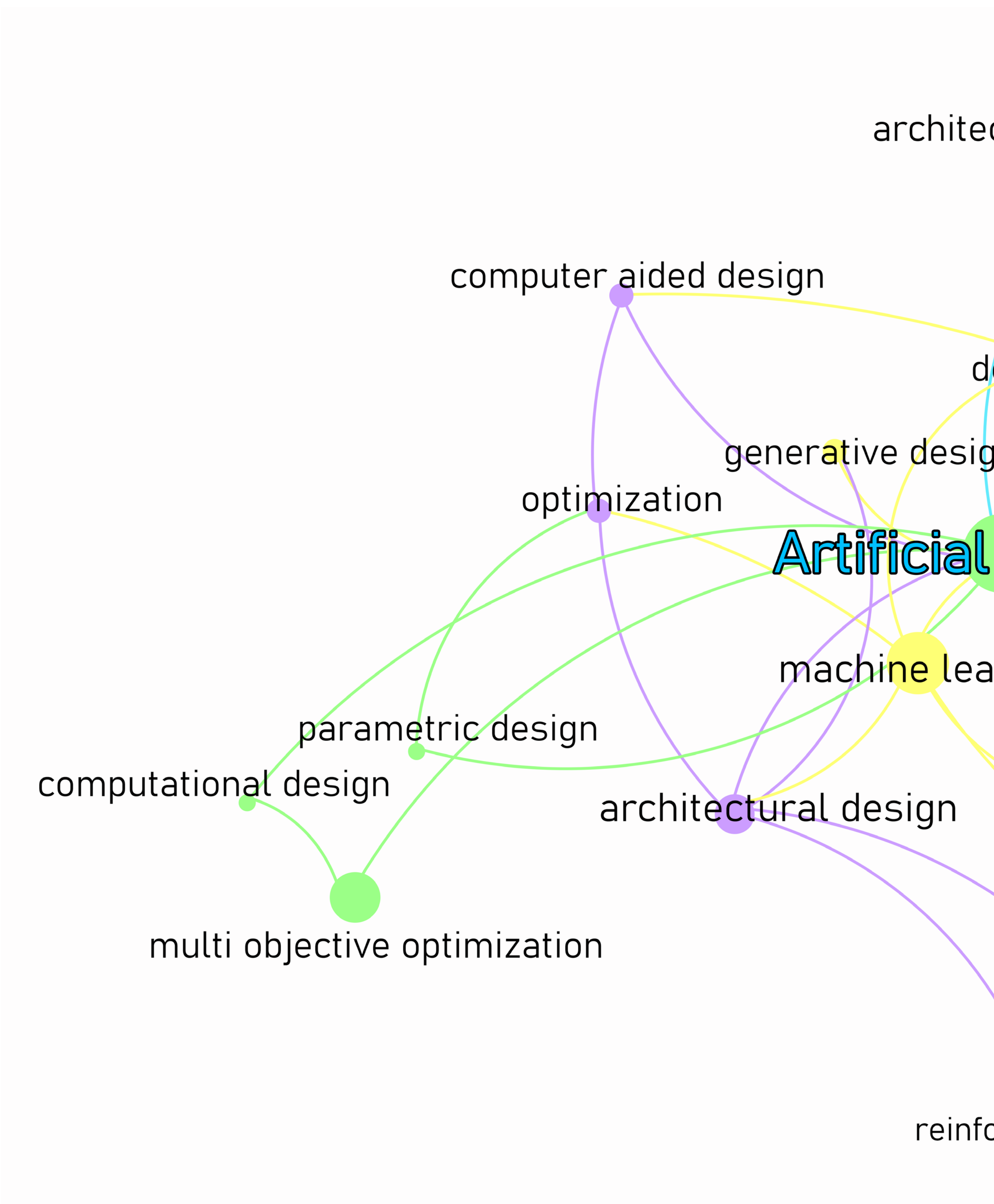
The idea of human-in-the-loop comes from artificial intelligence and automation. It refers to systems where humans are involved in decision-making instead of being completely replaced by automation, where tasks are done without any human involvement, or with autonomous systems that set their own goals and act on them, human-in-the-loop models intentionally keep human oversight and judgment at the central points in processes. This is particularly important in architecture because the design decisions including the ethical, cultural, social, and contextual factors cannot be simplified to just computational logic of AI(Petrovic et al., 2021). Architecture does resists the full automation not because of technical limitations alone, but because of its nature, it operates within complex real world conditions that demand direct intervention and accountability. As discussions in the field have highlighted, architectural design goes beyond solving problems. It is a process shaped by human intent. While artificial intelligence systems can generate optimizations , refining parameters, and analyzing the large datasets, they do not grasp the meaning, context, or consequences that can accur like humans do. This is why modern AI tools in architecture mainly serve as supportive systems instead of independent designers. They emphasize the need for architects to remain actively involved (ArchDaily, 2021). Inside the human-in-the-loop architectural workflow, the architect is responsible for defining project goals, setting constraints, and evaluating outcomes. AI systems act as generators, analyzers and recommenders by producing alternatives, assessing the performance, showing the patterns, however, they can not make final decisions. This clear division of roles shows a separation between computational ability and professional responsibility. Architects choose which generated solutions are the most suitable, making sure that responsibility for the built environment stays with the people (Autodesk, 2020). By creating this clear separation between computer support and human responsibility, human-in-the-loop models gives a basic understanding of how architects collaborate with AI today. Artificial intelligence speeds up processes and create a large variety of design options. However, architects are still the key decision-makers, interpreters, and ethical agents in the process. This framework forms the basis of modern practice and prepares the way for a closer look at ethical and professional issues in the following sections.

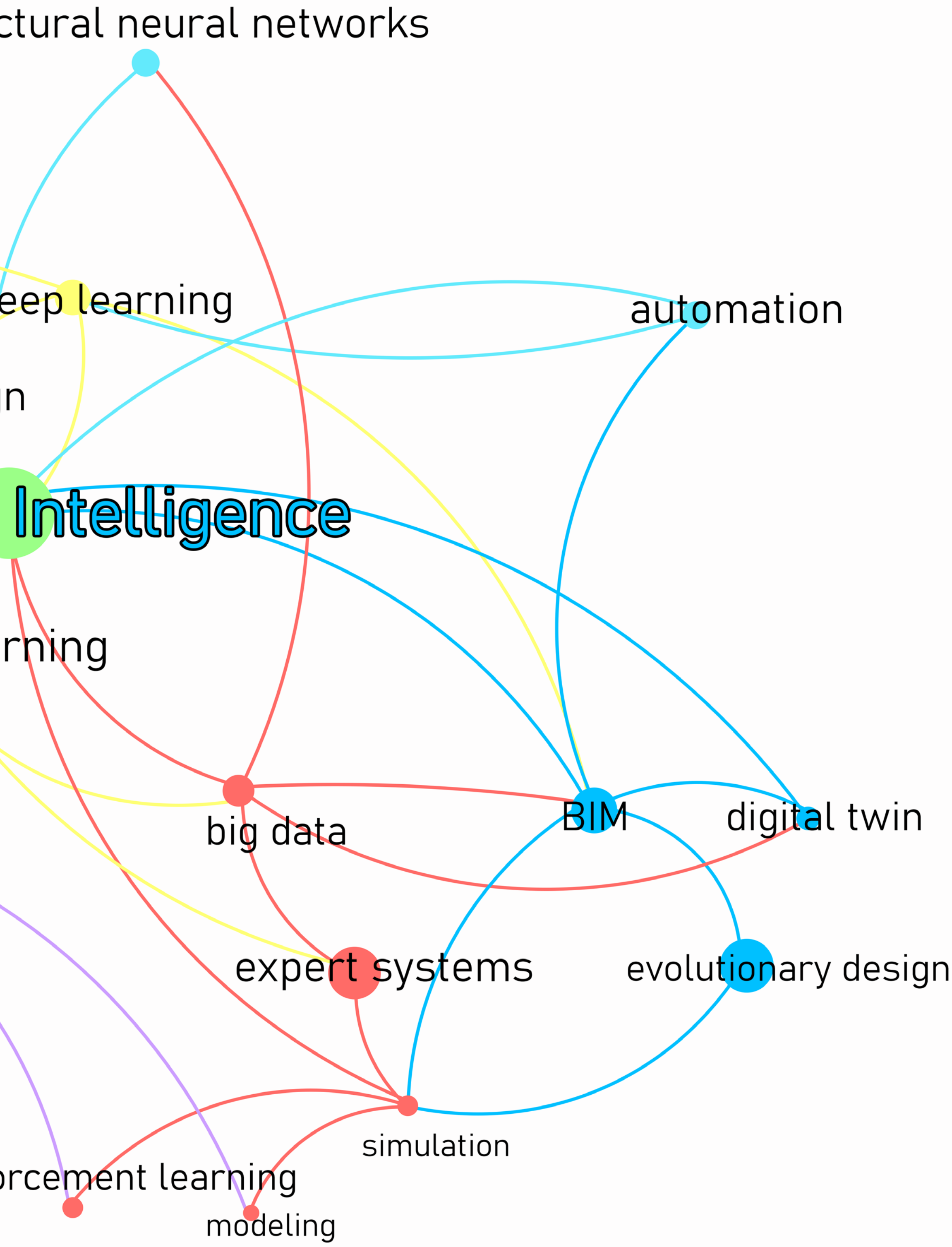
Redefining Architectural Creativity in the Presence of Generative Systems

The growing presence of AI in architecture is changing where professional value is being created. Instead of focusing on the manual production of drawings, and renderings, or repetitive documentation, the field is shifting towards a more skills related supervision in the automated settings. Professional practice surveys show that AI is being tested and used, but its regular use of funtioning agent is still limited. This way of adoption usually manifests during the early stages of skill transitions, where experimentation happens before the standard integration of AI into the institutions (American Institute of Architects [AIA], 2024). As AI becomes a part of design process, data becomes the main design material. Architects are expected to understand what types of data inform AI outputs, how inputs shape the results, and what are limitations or distortions can appear from an incomplete or poorly structured dataset. This does not mean every architect needs to become a software engineer, but they should have the basic understanding of data quality, origin, and how to work with them. Research shows that organizations now see data and AI literacy as essential skills rather than just specialized knowledge acquired by specialists, especially as the AI tools are becoming more common in the everyday work situations (DataCamp, 2024). In European professional and institutional agendas, digitalization and AI are increasingly viewed as areas of skill that need careful attention. This shows that the addition of these skills

is not just technological it also has an educational and organizational aspe-ct to it (Architects' Council of Europe [ACE], 2025). A key requirement of AI-assisted practice is that the archite-cts must be skilled enough to evaluate the outputs. This means critical evalua-tion skilss is a technical and professio-nal essential not just a "soft skill." Mo-dern risk and governance frameworks view AI as a socio-technical phenome-non. Performance, harms, and reliability depend not only on models but also on how these systems are put in to the use. Regulatory frameworks are estab-lishing the expectation that humans can monitor, and override AI outputs whi-le avoiding the crucial danger of over reliance. This idea is clearly stated in the EU's requirements for human over-sight in high risk AI systems (European Commission, n.d.). For architects, this reinforces an important point, AI can generate, but architectural practice still requires justification and accountability for the possible consequences. These changes suggest a new way of thinking about architecture and It shifts from creating outputs to selecting inputs and interpreting results. The architect now plays a cenral role in deciding what data and constraints should be given and put in the use for the practice. They decide how to filter the AI generated options and which outputs match the project's goals, user needs, and con-text. This is why the tool literacy, or knowing what systems should be used for the which specific goal of challenge matters the most in the AI supported workflows. In practical guidance, AI is increasingly seen as something archi-tects should not only use but also guide it. They should direct its use towards a design goal while keeping human cre-ativity and professional responsibility.
In summary, the change in AI assisted architecture involves a tarnsition from a completely manual work to important skills like data literacy, critical evalua-tion, systems thinking, and interpretive responsibility. These abilities neither diminish nor harm the architect's role instead, they move architectural exper-tise to a new stage where goals are set, evidence is interpreted, and outcomes are evaluated and all done by the arc-hitect. Shaping the creativity in a form where new fields are being integrated to the practice.We will explore some of the tools that allow architects and the fied of architecture to be more integra-ted with the rapidly evolving context of artificial intelligence.

Network analysis of the studies on artificial intelligence and architecture

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To better understand how creativity is being reshaped in architectural practice, it is necessary to examine the AI tools currently entering design workflows. While many of these systems improve specific stages of work, a persistent gap remains between visually driven AI outputs and data-rich architectural modeling. Diffusion-based tools can generate compelling images rapidly, supporting ideation and communication, but they do not carry embedded spatial, material, or performance information. By contrast, data-driven AI tools can support optimization and structured outputs, yet often operate within tighter constraints and provide less flexibility for open-ended exploration. This division reveals not only a technical difference in data formats, but also a broader separation between aesthetic exploration and functional modeling within current AI tool ecosystems. In everyday practice, this disconnect mirrors a broader workflow tension between early conceptual sketching and the structured logic of BIM environments. Moving from loosely defined visual ideas to coordinated models remains a demanding transition, and iterative changes often require rework across representations. Rather than eliminating this issue, the introduction of AI tools has made it more visible: image-based systems accelerate concept generation and client feedback cycles, while model- and data-oriented tools improve evaluation and coordination, but the connection between the two remains limited. A more integrated pipeline would require formats and workflows capable of translating conceptual intent into structured design information more directly—something that current tools only partially support. For this reason, AI tools should be understood as complementary rather than complete solutions. They can meaningfully speed up particular stages,especially ideation, visualization, and certain forms of analysis,but still rely on architects to interpret outputs, ensure technical validity, and maintain coherence across the design process. The following overview categorizes representative tools currently used in practice, providing a concrete basis for discussing how AI is being applied across different phases of architectural work and what kinds of competencies these tools demand.

So this has produced a diverse ecosystem of tools, but a relatively small group has become especially visible and widely adopted in day-to-day workflows. The tools presented in Table X represent some of the most commonly used and frequently referenced systems in current architectural practice, spanning early ideation, spatial planning, visualization, and regulatory or documentation support. This overview is not intended to be exhaustive; rather, it captures representative platforms that practitioners repeatedly rely on because they are accessible, practical, and aligned with recurring needs in design projects. To better understand this concept, these tools were organized by their main function in the architectural workflow. The first category, Generative Design and Concept Exploration, includes systems that generate quick visual ideas and support early creative development. The second category, AI-Assisted Design Optimization and Space Planning, groups tools that work with constraints and performance goals to create or refine layouts and massing options. The third category, AI-Augmented Visualization and Design Development, consists of tools that speed up rendering and iterative visual refinement, often by building on existing models or views. Lastly, Code Compliance, Analysis, and Documentation includes tools designed to help with regulatory checks, cut down on repetitive documentation tasks, and improve consistency in deliverables. Organizing the tools this way makes it clear how AI is currently positioned in practice: not as a single unified system, but as a set of specialized supports integrated into different stages of design and project delivery.And we will further explore how each of these tools change, help assist , increase or decrease the creativity ,quality & the work flow of architects.

AI Tools Used Across Architectural Workflows

Tool	AI type	Workflow fit	Best for
ChatGPT	LLM (language model)	Multi-stage	brief writing, concept framing, option reasoning, prompts, code support
DALL·E	Diffusion (text-to-image)	Concept	fast concept imagery, mood exploration
Midjourney	Diffusion (text-to-image)	Concept	strong style, atmosphere, visual ideation
Stable Diffusion	Diffusion (customizable)	Concept	flexible pipelines, controllable generation
ComfyUI	Diffusion workflow interface	Concept / Visualization	advanced control, repeatable pipelines, batch iteration
Adobe Firefly	Diffusion (creative suite)	Concept / Comms	quick visuals for presentation + content
Spacely AI	GenAI visualization	Concept / Interiors	rapid interior visualization
Architectures-AI	GenAI concept tool	Concept / Early design	concept imagery + early scheme outputs
Autodesk Forma	Data-driven / AI-assisted analysis	Feasibility / Site	site + massing studies, early performance
Autodesk Project Refinery	Generative design / optimization	Optioning / Optimization	multi-objective design exploration
Finch 3D	AI-assisted space planning	Schematic	rapid layout generation
A Space AI	Space planning automation	Schematic	automated space-planning options
Giraffe (Giraffe Technology)	Generative layout / massing	Schematic / Massing	fast massing + layout generation
EvolveLAB Veras	GenAI visualization in BIM	Design development	rendering from BIM context
Trimble SketchUp Diffusion	GenAI visualization	Concept / Dev	model-to-image iteration
ArchiGAN	GAN-based generation	Research / Concept	experimental form/image generation
UpCodes	Code intelligence / compliance	Compliance	code support + regulatory checks
Swapp AI	Documentation automation	Documentation	automated documentation & sheets

Typical inputs	Typical outputs	Integration level	Key limitation / risk
text + context	text, structured outputs	Standalone / API	must be verified; can be inaccurate or overly confident
text prompts (+ optional images)	2D images	Standalone	no embedded building data / scale logic
text prompts	2D images	Standalone	not data-rich; hard to translate to BIM
prompts, images, control inputs	2D images	Standalone / local	consistency depends on workflow and tuning
nodes, prompts, models, control nets	2D images (and sometimes meshes depending on workflow)	Local / technical	complex setup; requires technical skill
text prompts, images	2D images	Integrated (Adobe)	limited technical design linkage
images, prompts	2D images	Platform	primarily visual; limited technical data
prompts / constraints	images / schemes	Platform	depth varies; may be rigid
site data, constraints	analytics + studies	Platform	early-stage; depends on input quality
goals, constraints, parameters	ranked options	Autodesk ecosystem	needs clean objectives + good input data
program + constraints	layouts	Platform / export	rule-based limits; not full BIM authoring
program + constraints	layouts	Platform	struggles with complex bespoke needs
constraints / parameters	scheme options	Platform	constrained by predefined typologies
BIM views + prompts	images / renders	Plug-in	visual output ≠ validated technical solution
SketchUp scenes + prompts	2D images	Plug-in	still image-based; no BIM data
datasets / prompts	generated images/forms	Research-level	not stable for production workflows
project info / code context	compliance outputs	Platform	doesn't design; requires interpretation
project inputs	drawing/document sets	Platform	requires validation; risk of over-trust

Toolsheets

In the folllowing part we will see an analysis and a documentation of some of these tools ordered in the forms of "tool sheets".These tools have been chosen based on their relevance and usage in the field. The sheet structure refines the necesary information for us to understand how these tools work and how they their place in the practice. Sheet follows this structure:
Name of the tool , the category that it is in , the company that owns it and the rlease/starting year. Then we have an overview describing the genral outlines of. Typical outputs describe the the moust common and usual resluts the tools generate. How it works explains the working method and principles behind it.Workflow placement shows how these tools are being applied and used in the practice. Beneifts list the main and the most substential positive aspects they bring, risks & limitation in contrary presents the most impactful negative outcomes and effects.Then we have the human oversight , explaining how the architects should be controlling the tools , their functions and the outcomes. Notes are the personal reflections derived from the research that has been carried out for the tools and using some of them personally to better see and test how they work.

Analysis of these AI tools showed a certain pattern that repeats itsel throughout the usage and the research. Even tho these technologies can streamline specific stages and tasks, a great gap remains unchanged between 2D image generation and 3D data-rich modeling. This gap actually reflects the limitations of these AI tools. Diffusion tools are able to produce visually compelling images without integrating any data, but the data-driven AI tools generate functional outputs but lack creative input and amount of options. This division shows that this is not just a data format issue but it is also a the leaning for AI tools to be optimized for either aesthetics or the function. It was stated that in architectural workflows , the transition from CAD to BIM represented an important point of transition fromsketches to structured, data-intensive models. Frequent modifications almost alway required redrawing designs, and the prevailing processes remain linear, which can impact design innovation. The integration of AI tools has not resolved this problem infact it has made the limitations more apparent. Both diffusion tools and data-driven tools are quite effective by their own but they require new data formats that could enable a smooth integration between conceptual and operational phases. But despite this overarching gap, AI tools still accelerate certain aspects of the workflow, mainly in the concept generation and client feedbacks. For example, diffusion tools enable fast generation of concept images and adapt the results of the prompt responses to feedback, reducing some of the manual effort. However, transition from these tools to data driven platforms is still quite complex, as matching the aesthetic results with technical data brings some significant challenges. Client feedback loops using data-driven tools are also constrained by feasibility requirements. Depending on project objectives, rapid design options may be achieved using either feasibility-focused or aesthetics-foused tools. For now, the impact of these tools on architectural workflows are more on the positive side of the spectrum, but primarily in isolation. Furthermore, effective use of AI tools requires an ongoing collaboration with architects. AI should be regarded as a supportive instrument that enhances the creative process, ensuring that human oversight and expertise must remain at the center of architectural design.

Disclaimer

The following pages present a set of "tool sheets" serving as a identification of the AI assisted tools used in architecture. To stream line the workflow in this chapter manually aquired and gathered information has been inserted to the Chat GPT with the defined constraints of

Overview
Typical Outputs
How it works
Workplace placement
Benefits for Practice
Risks & Limitations
Human Oversight

these restraints with their well defined descriptions has generated the outcome of categorization of the informations, later all of them have been reviewed and refined.

Chat GPT ™

Category : Large Language Model

Owner : OpenAI

Starting year : 2022

Overview

ChatGPT is a large language model (LLM) that generates and transforms text based on prompts, context, and examples. In architectural practice, it serves mainly as a support tool. It helps architects think through problems, organize information, and communicate ideas more clearly. Unlike design software that creates geometry or BIM elements directly, ChatGPT works through language and supports the conceptual and management aspects of design work.

Typical outputs

ChatGPT generates text-based outputs that usually include:
- summaries of complex material, such as briefs, reports, regulations, and meeting notes
- structured documents like project narratives, design rationales, and scope descriptions
- ideation support with concept directions, alternatives, and pros/cons
- checklists and workflows for task sequencing, QA steps, and deliverable plans
- prompt drafting for image-generation tools and visualization workflows

How it works

ChatGPT generates responses by predicting the most likely continuation of text based on patterns it learned from extensive training data. It does not "understand" architecture like a human professional does. It also does not verify facts on its own unless the user provides reliable references or steps for validation. Its apparent intelligence results from its ability to create coherent language, infer intent, and keep context in a conversation. Therefore, its outputs should be seen as temporary and must be checked against project realities, regulations, and professional judgment.

Workflow placement

Pre-design / briefing: turn client needs into requirements; prep discovery questions; draft program summaries.
Concept / early design: build concept narratives; explore options; develop naming/story frameworks; draft visual-ideation prompts.
Schematic design: compare options; write decision memos; summarize consultant input; manage feedback loops.
Design development: support specs; create coordination checklists; clarify trade-offs/constraints.
Practice management: draft proposals/scope/fees; meeting agendas; internal templates.

Benefits for practice

Best for text-heavy work: repeated explanations and scattered info.
Faster output: emails, reports, narratives, structured notes.
Quick rewrites: tailor the same content for clients vs. technical teams.
Coordination: turns notes/comments into clear summaries + action items.
Consistency: standard templates, QA checklists, documentation language.
Clearer design intent: improves decisions and client alignment.
Better prompts: translates architectural intent into usable image-tool prompts.

Risks & limitations

Factual errors: can sound right but be wrong (tech/regulatory info).
False confidence: fluent wording can overstate certainty.
Missing context: won't "see" site or constraints unless you provide them.
Bias: may reflect generic norms or narrow cultural assumptions.
Oversimplification: can flatten complex trade-offs (safety, access, procurement).
Text-only limits: still needs humans to turn outputs into drawings/models.

Human oversight

Verify technical claims: materials, structure, performance, regs, feasibility—check reliable sources.
Confirm project fit: site + brief + client needs + stakeholder constraints.
Check consistency: contradictions, invented details, and "filled gaps."
Keep responsibility human: use as drafts; decisions/sign-off stay with the architect.
Review ethics & culture: tone, assumptions, accessibility, equity impacts.
Protect confidentiality: don't share proprietary data without an approved workflow.

Notes

Used with the proper safeguards, ChatGPT can be seen not as a designer, but as a tool that improves clarity, speeds up iteration, and strengthens coordination, while keeping architectural knowledge, responsibility, and authorship firmly with the architect.

DALL-E ™

Category : Generative AI

Owner : OpenAI

Starting year : 2021

Overview

DALL·E is a text-to-image generative AI tool that creates images from written prompts and, in some workflows, from reference images. In architecture, it is mainly used for conceptual visualization, helping architects quickly turn abstract ideas, atmospheres, or stylistic directions into visual form. Unlike CAD or BIM tools, DALL·E does not produce geometry or detailed models; it creates images that aid in idea generation and communication.

Typical outputs

-2D concept images, including massing impressions, façade moods, interiors, and lighting atmospheres.
-Style variations, which offer multiple interpretations of the same idea.
-Visual references for storytelling and presentations.

Image edits or variations based on available interface features.

How it works

DALL·E uses a diffusion-based method to create images. It learns patterns from training data and then produces a visual result that matches the prompt and constraints. It does not understand architecture in a structural, technical, or coding sense. Instead, it generates images that appear plausible based on visual patterns it has learned. As a result, the images might include appealing but unrealistic details or spatial inconsistencies.

Workflow placement

DALL·E is most useful in the early and communication-heavy stages of projects.
Pre-design / briefing: exploring stylistic directions that match a client's mood or brand identity.
Concept design: quickly generating ideas for atmosphere, massing impressions, and material moods.
Client communication: presenting several "visual directions" swiftly for discussion.
Internal design exploration: trying out different themes before moving on to modeling.
Presentation support: creating illustrative images for narratives and concept boards.

Benefits for practice

Speed: produces visual directions in minutes, reducing time spent on manual mood boards or early renders
Iteration: enables rapid exploration of alternatives (style, material mood, lighting, setting)
Client feedback loops: helps respond quickly to "show me another option" requests
Communication clarity: supports early alignment when stakeholders struggle to read plans or abstract diagrams
Design stimulus: can suggest unexpected combinations that spark new design routes

Risks & limitations

No embedded architectural data: outputs are images without BIM intelligence, dimensions, or constructability logic
False realism: images may look convincing while being technically impossible or contextually wrong
Scale and spatial errors: doors/windows/stairs can be inconsistent; circulation may be nonsensical
Over-trust risk: clients may mistake concept images for "the design," creating expectation problems
Bias in visual norms: results may reproduce common aesthetic stereotypes or cultural defaults
Interoperability gap: translating images into 3D/BIM typically requires manual remodeling
IP / authorship ambiguity: images raise questions about originality and acceptable use in professional deliverables

Human oversight

To use DALL·E responsibly, architects should:
Label outputs clearly as "AI-generated concept imagery" to avoid misleading stakeholders
Validate feasibility: treat images as inspiration, not evidence of constructability
Control expectations: explain that images are directional and will change through modeling and coordination
Check context: ensure results reflect site, culture, climate, and program (not generic visuals)
Translate carefully: when moving toward BIM, extract only the intent (mood, proportion cues, material language), not literal details

Notes

DALL·E is a powerful tool for concept communication and idea generation. It helps expand visual exploration. The architect is still responsible for turning intent into clear, technical, and accountable design outcomes.

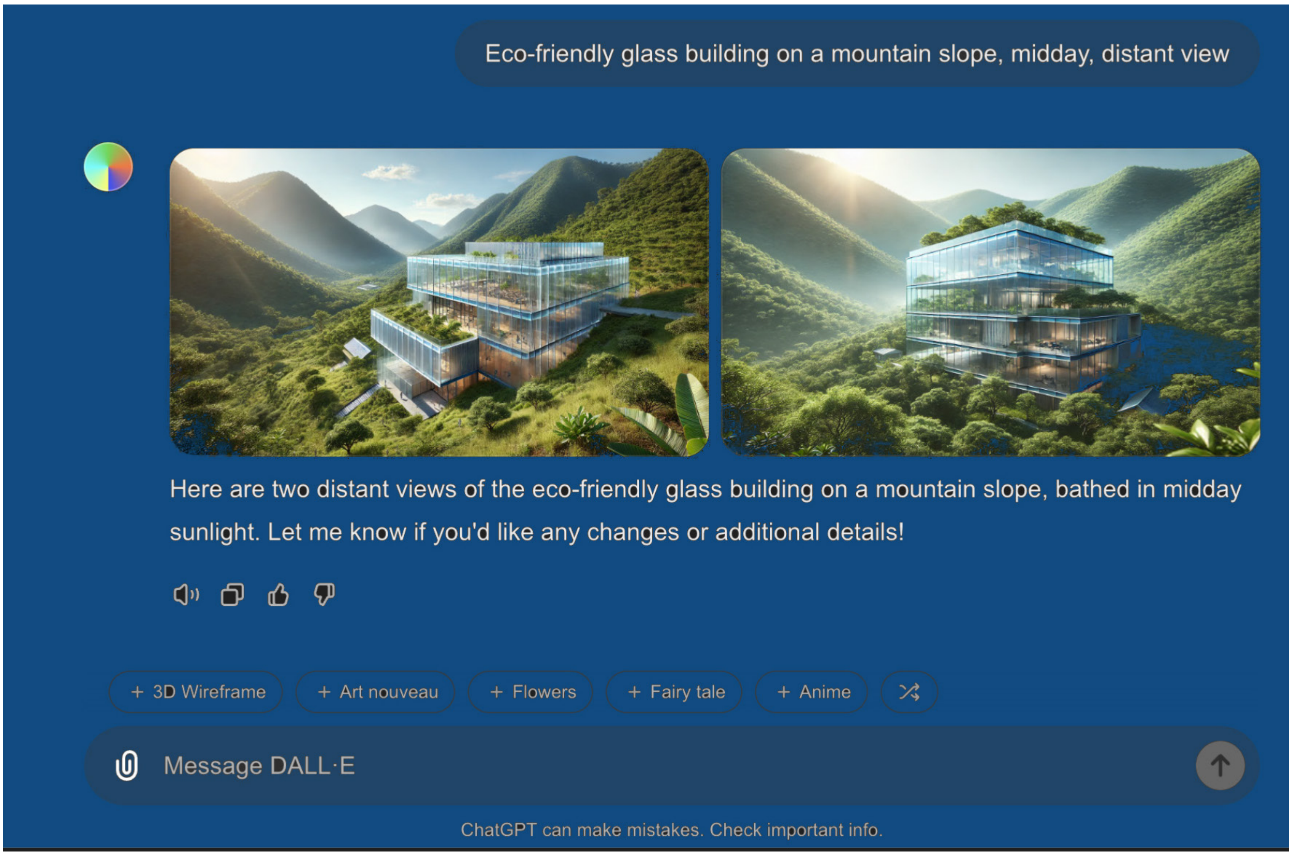
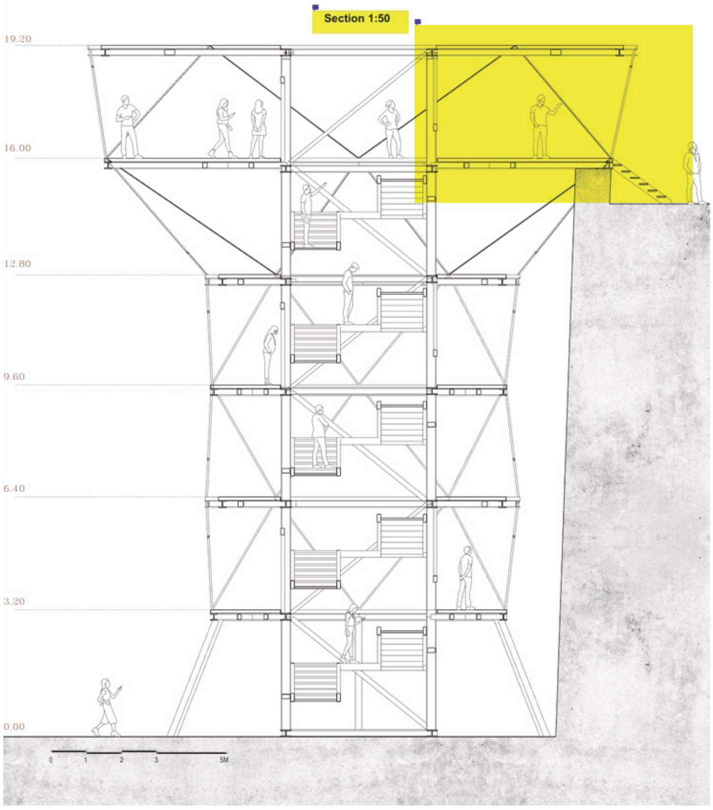


Figure 26. How prompts are transating to image results by DALL-E
Image Credits: How to Create High-Quality Architectural Visuals with DALL-E
https://parametric-architecture.com/

Figure 27. Prompt: Minimalist concrete house in a lush forest, early morning light, ground-level view.
image results by DALL-E
Image Credits: How to Create High-Quality Architectural Visuals with DALL-E
https://parametric-architecture.com/

Figure 28. Prompt: Ultra-modern white villa on a hill, ocean view, bright midday, aerial shot.
image results by DALL-E
Image Credits: How to Create High-Quality Architectural Visuals with DALL-E
https://parametric-architecture.com/



Input:A section of the Belvedere concept for the architecture and structural forms atelier (ACC AY. 2021-2022). Located in the Nanjing Hehua Tang city & the wall.

Prompt: Create a Realisitc Architcectural render of this section of a tower.Reflect the pattern and visuals of materials such as steel , concrete , glass and stone. make sure to keep the human figues as well. Focus on the structural elements and discard the texts and higlights while creating the render.

Output:Structural and visual incocnsistencies.Overall acceptable performance on renderring the structural materials,still far from being used in any sort of final product. Can e used as a great reference for what type of a section render can be done.

Midjourney ™

Category : Generative AI

Owner : Midjourney,Inc.

Starting year : 2021

Overview

Midjourney is a text-to-image AI tool that many people use to create high-quality images from written prompts. In architecture, it mainly serves as a visual brainstorming tool that helps architects quickly explore atmosphere, composition, material mood, and style. Like other diffusion-based systems, it doesn't create BIM objects or coordinated 3D models; it generates striking images that aid early-stage design thinking and communication.

Typical outputs

Midjourney typically outputs:

-2D concept images for architecture and interiors
-multiple variations of a prompt to explore different directions
-stylized visual stories, cinematic mood, historic or futuristic styles, material choices
-iteration results through repeated adjustments of prompts
-image remixing and generating variations where possible

How it works

Midjourney creates images using a diffusion-based method. It starts with noise and gradually builds an image that reflects patterns related to the prompt. The system focuses on visual harmony and aesthetic appeal instead of architectural accuracy. Consequently, it might produce images that look realistic but have inconsistencies in structure, scale, circulation, or feasibility.

Workflow placement

Concept exploration: Generating several style options for massing, façade design, or interior feel.
Narrative and storytelling: Building a clear visual world for a project vision.
Client alignment: Showing different ideas helps clarify preferences early.
Competition and presentation imagery: Quick production of engaging concept visuals.
Material and lighting exploration: Testing mood in different environments or at various times of day.

Benefits for practice

Strong visual quality: produces polished images quickly and often works well for early presentations.

Fast iteration: supports quick exploration of alternatives without the need to rebuild models.

Improved communication: helps non-specialist stakeholders grasp a design direction early.

Creative expansion: generates unexpected combinations and stylistic ideas that may not come from traditional searches.

Presentation efficiency: cuts down the time spent finding mood boards and reference images.

Risks & limitations

Lack of technical accuracy: outputs may conflict with structural logic, regulations, accessibility, or environmental feasibility

Scale and geometry inconsistency: repeated elements like windows, stairs, and openings can be irregular or physically impossible.

Misleading realism: clients may interpret images as “final design,” creating expectation misalignment

Aesthetic bias: outputs may reinforce popular visual tropes, leading to homogenized or trend-driven results

Context loss: visuals can drift toward generic “architecture imagery” unless the prompt contains strict contextual constraints

Human oversight

Use as concept art, not solutions: mood/massing/material direction only.
Be transparent: label as “Midjourney AI concept image” in decks.
Keep outputs repeatable: save prompt + key settings/model version.
Don't treat details as real: verify structure, code, performance, buildability before advancing.
Translate deliberately: re-model in BIM/3D—don't copy “AI details.”
Mind ethics & confidentiality: avoid biased cues and don't upload sensitive/client data.
Maintain governance: avoid sensitive data in prompts and maintain an internal policy for use in client materials

Notes

Midjourney is best for high-speed tool for visual exploration and narrative alignment, enabling architects to test stylistic possibilities rapidly while keeping responsibility for technical correctness, contextual coherence, and final authorship firmly human.

Prompt

Minimalist architectural house with strong attention to material transitions, off-white and pale grey palette, recessed lighting along the façade, micro-textured surfaces, soft natural shadows enhancing details, subtle reflections on glass and water,

Output

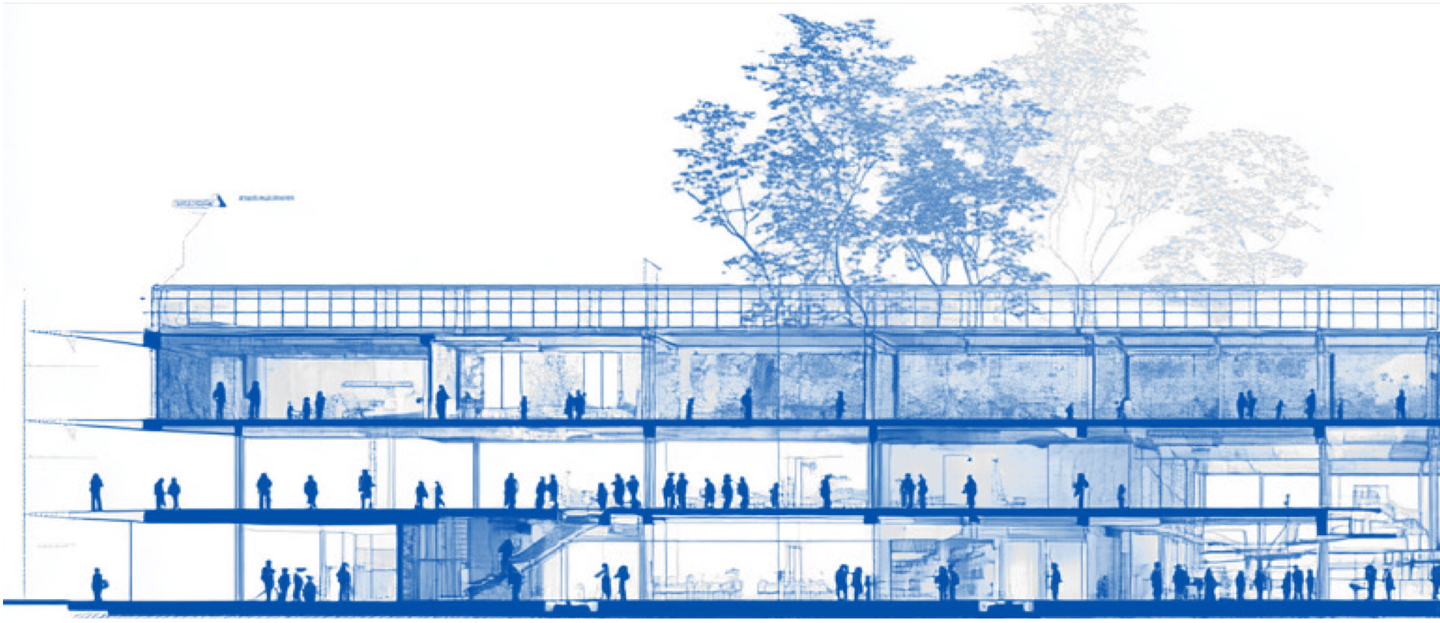
Prompt

A plan for an outdoor modern art museum with greenery features a flat layout design with equally sized square spaces for different areas, such as a seating area and exhibition walls. In front of each large space, there is a small rectangular area to display

Output

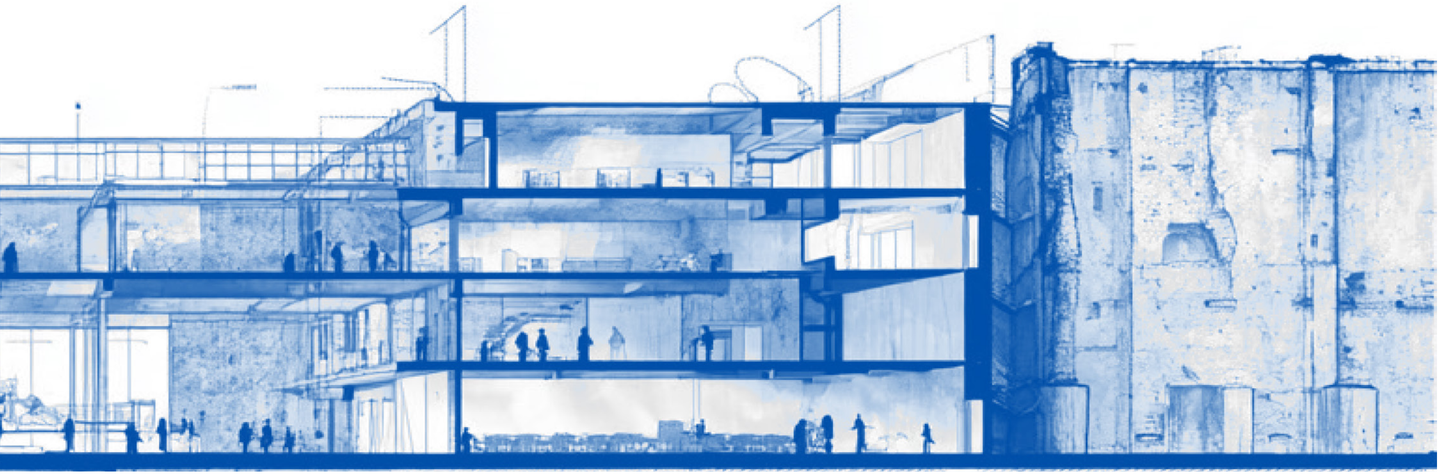
Prompt

a horizontal architectural section drawing of a long, abandoned industrial building, 2:1 aspect ratio, high-detail black and white drawing, fixed height, showing both ends of the structure, gradual transition from decayed and unused spaces on the left to revitalized interiors on the right, minimalistic technical linework, architectural illustration style.



Prompt

an elevation of a modern house with two floors, brick walls, and wooden louvers on the facade of one floor, greenery in front, a white fence around it, and trees behind the wall, in the architectural drawing style rendering.



Stable Diffusion ™

Category : Generative AI

Owner : Stability AI

Starting year : 2022

Overview

Stable Diffusion is an open and highly customizable text-to-image generative AI system. It creates images from written prompts or reference images. In architectural practice, it is often used as a flexible alternative to closed platforms. It can run locally, be customized with plugins, and be adjusted to produce more consistent results across a project. Like other diffusion models, it generates 2D images instead of detailed 3D models. Its main purpose is to support conceptual exploration, communication, and quick visual iteration.

Typical outputs

Stable Diffusion typically outputs:
-2D concept images (architecture, interiors, atmosphere, material mood)
-image-to-image variations (refining an existing sketch or concept render)
-style consistency workflows (repeatable visual language across images)
-controlled generation (when combined with control methods such as pose/edge/depth guidance)
-batch iteration for exploring multiple options quickly

How it works

Stable Diffusion uses a diffusion-based approach. It learns the statistical connections between text and image prompts and visual patterns. Then it creates new images by gradually changing noise into a clear result. What sets it apart in practice is its ability to adapt. Since it is often used in open workflows, it can be set up to follow stricter rules and keep style consistency better than purely closed interfaces. However, it still does not grasp architecture as a technical field. Visual plausibility does not ensure that a design is spatially or structurally sound..

Workflow placement

Stable Diffusion is most often used in early to mid design communication phases, and in iterative visual development:
Concept exploration: quickly generating massing impressions, façade language, and spatial atmosphere.
Sketch enhancement: transforming rough sketches into clearer visual concepts.
Design narrative and style control: developing a consistent visual identity for a project.
Client feedback cycles: rapidly producing alternatives based on preferences.
Internal testing: exploring various directions before dedicating time to 3D/BIM modeling.

Benefits for practice

Flexibility and control: adaptable workflows make it easier to constrain outputs and achieve consistent results
Repeatability: supports systematic iteration rather than one-off "lucky" images
Customization potential: workflows can be tuned toward specific aesthetics or office standards
Rapid optioning: accelerates early-stage exploration and decision-making
Local deployment (in some setups): can support more control over data privacy and internal workflows
Better integration with creative pipelines: can be combined with tools that guide output using drawings, depth cues, or edges

Risks & limitations

No embedded design intelligence: outputs remain 2D images without geometry, quantities, or BIM data
False realism and spatial inconsistency: images can contain impossible details, illogical circulation, or incorrect scale
Technical barrier: running and controlling workflows may require more expertise than closed platforms
Model and dataset bias: outputs depend heavily on the underlying model and training influences
Translation gap: converting an image into a buildable design still requires manual interpretation and modeling
Expectation risk: stakeholders may misread visuals as validated design proposals
Workflow complexity: customization can produce inconsistent results if the process is not standardized across a team

Human oversight

While using , architects should maintain clear oversight by
Framing outputs as conceptual imagery, not design documentation.
Validating feasibility before adopting any generated idea into BIM or construction planning.
Checking for misleading cues. Structure, accessibility, climate, and circulation are often visually suggested but not clearly resolved.
Maintaining consistency. Use office standards for prompts and workflows to avoid random outcomes.
Managing client communication. Clarify what AI images represent and what they do not.

Notes

Stable Diffusion can be highly effective for architectural practice when treated as a controlled visual exploration system,one that accelerates ideation and feedback cycles,while relying on architects to make visual intent into coherent, technically validated, and accountable design outcomes

Figure 30. Image courtesy of Heatherwick Studio, showing a 2D diagram used to generate design options based on their custom models/ with using stable diffusion AI

Comfy UI ™

Category : Node-based GUI/diffusion image generation

Owner : Comfy Org

Starting year : 2023

Overview

ComfyUI is an open, modular interface used to build and run Stable Diffusion (and related) image-generation workflows through a node-based graph system. Instead of typing prompts in a simple "one-box" interface, ComfyUI lets users assemble repeatable pipelines by connecting nodes for prompts, models, control inputs, image processing, upscaling, and export.

Typical outputs

ComfyUI enables architects to produce:

2D images (concepts, atmospheres, iterations)

consistent "series" outputs using saved workflows

controlled variations (e.g., consistent viewpoint/style using structured pipelines)

batch generations (multiple options per run)

How it works

ComfyUI works by letting the user design an image-generation process as a graph (a flowchart of connected operations). Each node represents a step (loading a model, setting prompts, applying conditioning, sampling, post-processing). The graph can be saved, reused, and adjusted, which makes experimentation more systematic and less dependent on "random luck."

Workflow placement

ComfyUI is mainly used in:
Concept design: controlled ideation pipelines (consistent mood, style, camera logic)

Visualization exploration: generating many variants quickly while preserving a coherent "project language"
Studio/team workflows: repeatable pipelines that multiple team members can run

Client optioning: producing controlled iterations when feedback requires fast change without rebuilding a 3D model

Benefits for practice

Repeatability: saved node-graphs allow consistent outputs across a project's visual direction

Control: supports more disciplined iteration (less trial-and-error)

Scalability: batch generation helps explore options rapidly

Workflow transparency: the "graph" makes it clear how an image was produced, helping internal coordination

Customization: open ecosystem enables specialized workflows (image processing, text processing, etc.).

Risks & limitations

Technical barrier: setup and workflow building require more expertise than plug-and-play tools

Still image-based: outputs remain non-BIM, non-parametric, and non-validated for structure/code

False realism risk: high-quality imagery can be misread as resolved design

Inconsistent results without standards: teams need shared workflow templates to avoid fragmentation

Interoperability gap: translation to 3D/BIM typically still requires manual modeling

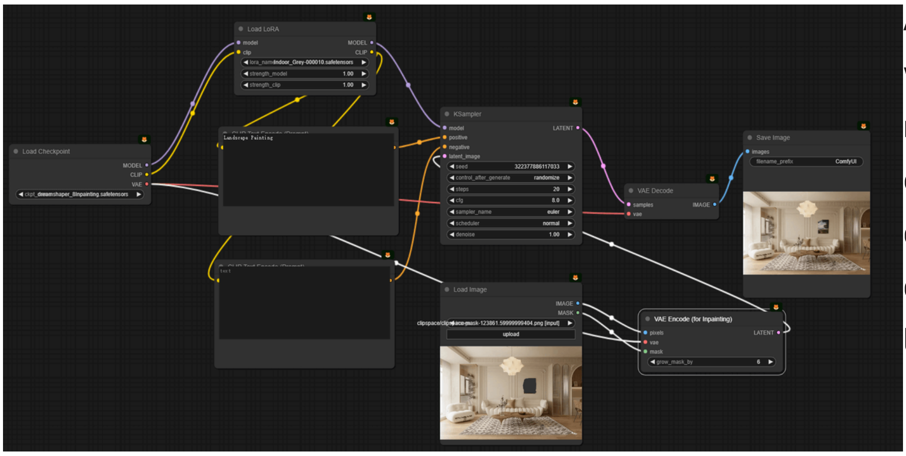
Human oversight

While using ,architects should:

treat outputs as conceptual imagery, not technical resolution
verify scale, circulation, structure, accessibility, and environmental plausibility
manage stakeholder expectations (label AI visuals clearly)
standardize internal workflows (approved node graphs, naming conventions, QA steps)
avoid embedding confidential project data unless a controlled policy exists
Controlling data use. Avoid embedding sensitive project information unless a secure workflow is in place.

Notes

ComfyUI is best understood as a visual pipeline editor: it lets architects "wire" prompts, references, control layers, upscalers, and model swaps into a repeatable graph that can be reused across a project. Its real advantage is process control (batching variations, isolating what changed, keeping a consistent visual language), but it still needs architectural judgment to prevent aesthetic outputs from being mistaken for resolved, feasible design decisions.



An interior design concept workfow with nodes generated by ComfyUI with each input loaded with a ceratin dataset to maintain consistency and achiveable image result.

The outputs of the generation process

ARCHITECTURES ™

Category : Cloud-based GenAI building design + feasibility platform

Owner : Architechtures, Inc.

Starting year : 2022

Overview

Architectures-AI (often branded as ARCHITEChTURES) is a generative, AI-assisted building design platform focused on rapidly producing early architectural solutions ,especially for residential developments, within feasibility, conceptual, and schematic phases. It positions itself as a system that can generate building proposals in minutes rather than months, supporting early decision-making when multiple options must be tested quickly .

Typical outputs

Architectures-AI is designed to generate:
early design schemes (typically massing + layout logic depending on configuration)
data and “blueprint”-style outputs suitable for feasibility/concept/schematic studies
option exploration using predefined typologies and configurable parameters/presets
site-informed positioning, including adjustment to topography imported from OSM or CAD in its workflow

How it works

At a high level, the platform operates through a combination of typology logic, parameter constraints, and AI-assisted generation. Users work within an editor where they select typologies and configure parameter presets that guide outputs. The tool then generates options aligned with the defined constraints, and can adapt building placement to site/topography inputs .

Workflow placement

Architectures-AI is mainly used in early-stage workflow moments such as:

Feasibility studies (quick option generation, early yield/area reasoning)

Concept and schematic design (rapid alternatives and iteration under constraints)

Developer/client option comparisons (testing scenarios before committing to full BIM)

Benefits for practice

Speed in optioning: accelerates early design iteration, allowing teams to compare multiple schemes quickly.

Constraint-driven exploration: encourages structured exploration by forcing clarity about goals, typologies, and parameters.

Earlier evidence-based discussions: helps architects communicate feasibility trade-offs with clients earlier, before heavy modeling effort is invested.

Workflow efficiency: reduces time spent generating “first-pass” schemes that can later be refined through conventional CAD/BIM work.

Risks & limitations

Typology limitation: outputs tend to follow what the platform is optimized for .

Over-trust risk: fast “blueprint-like” outputs can appear more resolved than they truly are; feasibility output is not the same as validated technical design.

Assumption sensitivity: results depend strongly on inputs (constraints, site data, presets); weak inputs can generate misleadingly “good-looking” solutions.

Interoperability friction: even when export is possible, translating early AI schemes into full BIM still often requires remodeling and coordination work.

Human oversight

Architects should treat Architectures-AI as an option-generation system that supports early reasoning, while maintaining control over:

goal definition: ensure objectives and constraints reflect the real brief and context

verification: validate areas, circulation logic, accessibility, code implications, and structural feasibility before adoption

context fit: check cultural, urban, environmental, and stakeholder appropriateness (not just optimization outcomes)

Notes

ARCHITEChTURES is strongest as an early-stage feasibility and option-generation engine: it turns constraints (program, metrics, and rulesets) into fast, comparable schemes with structured outputs you can push into a conventional workflow. The risk is metric-driven overconfidence—it can make “optimized” options feel resolved—so architects still need to validate local code interpretations, context, and spatial quality, and then redesign/refine beyond what the platform can standardize.

Figure 31. Manual project modeling integrated with AI

The user models in 2D and 3D the volume of the above-ground and below-ground buildings and parkings on which the automated design process is performed. The resulting designs can be easily adapted manually to suit user's requirements.

source https://architechtures.com/en

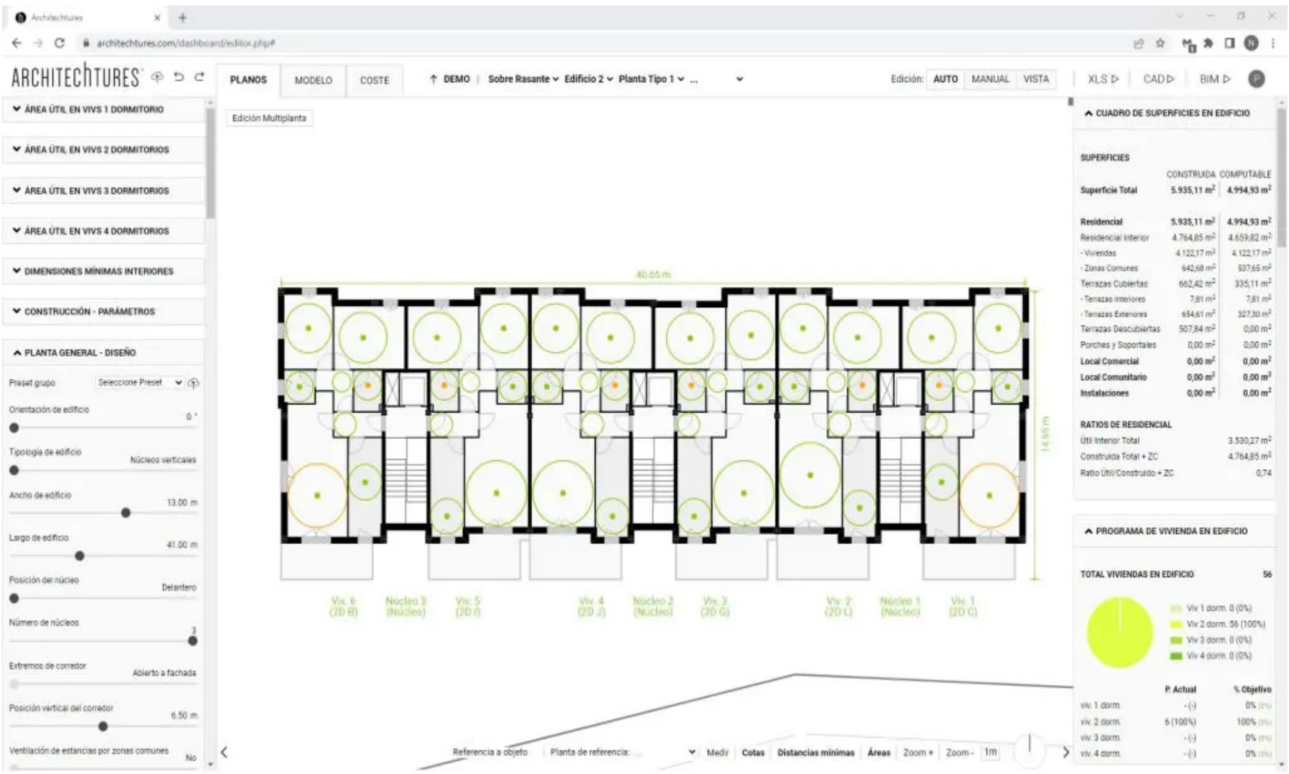


Figure 32. Design optimized to meet users needs

The best solution is the one that best suits the user's needs. The AI-aided process allows to iterate the design parameters offering in real-time the architectural solution that best suits the user's standards.

source https://architechtures.com/en

Figure 33.Real-Time BIM model navigable online

The system generates in real-time a BIM model with the geometry resulting from the AI-aided design process, all with a data structure that is completely navigable online to facilitate user review and design edition.

source https://architechtures.com/en

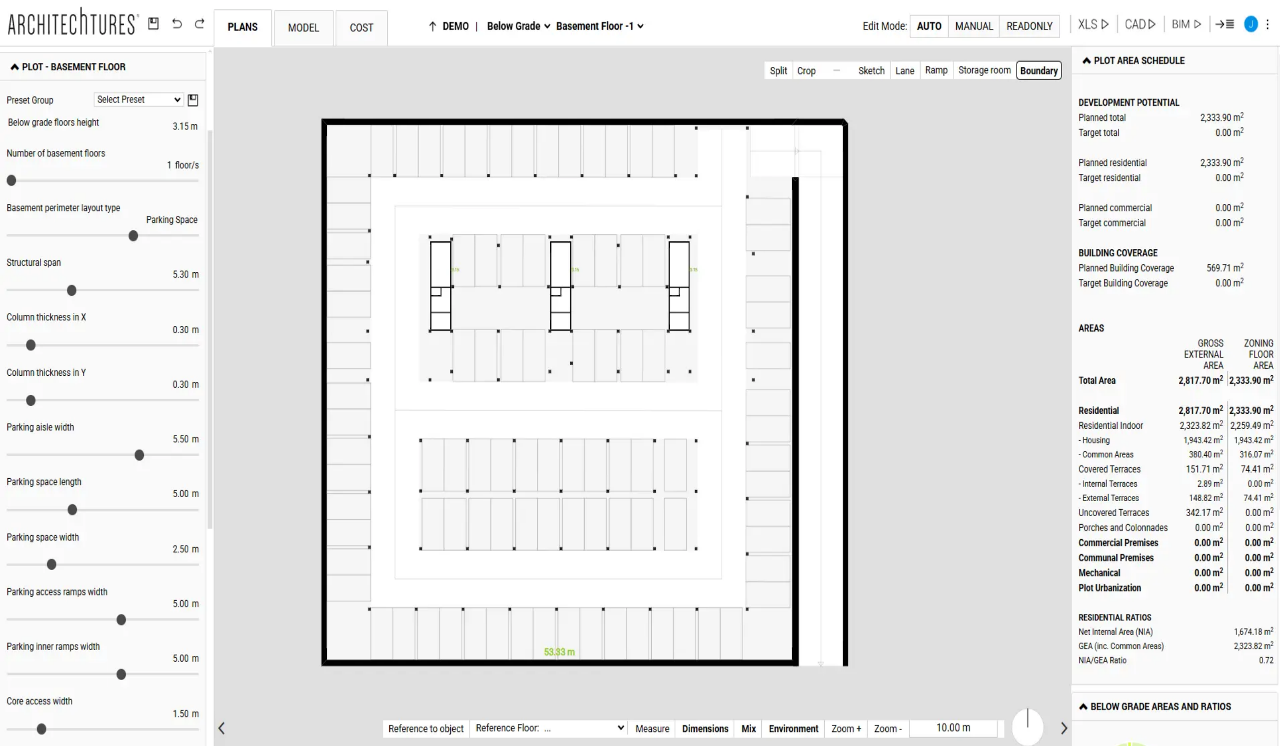


Figure 34.Assisted generation of Below Grade Parking

AI provides an instant layout of underground parking, considering design criteria and the user-defined contour. This process allows for exploring different solutions by iterating based on parameters and the positioning of elements such as access ramps, lanes, or storage areas.

source https://architechtures.com/en

AUTODESK Forma

Autodesk Forma ™

Owner : Autodesk

Category : Cloud-based AI Based Design Platform

Starting year : 2023

Overview

Autodesk Forma is a cloud-based platform intended for pre-design and schematic design, where architects need to explore early massing options and understand site-related constraints quickly. Autodesk presents Forma Site Design as an AI-supported environment for early-stage decision-making

Typical outputs

Forma supports early-stage work by enabling:
site setup and context modeling
rapid massing and option comparison
built-in early analyses such as daylight potential and wind analysis
Autodesk
Outputs are typically massing proposals plus analysis results (maps/indicators) used to compare and refine options before detailed BIM modeling begins.

How it works

Forma combines a cloud design environment with integrated analysis tools that provide fast feedback while the design is still flexible. Autodesk describes Forma's analysis features (e.g., daylight potential based on Vertical Sky Component, and wind analysis) as early-phase evaluation tools supporting option testing and redesign.

Workflow placement

Forma is primarily used before detailed BIM authoring:

early feasibility checks

massing and zoning exploration

early performance-aware optioning (daylight/wind)

early stakeholder alignment when major decisions are still open

Benefits for practice

Faster iteration: enables quick option testing with environmental feedback while changes are inexpensive

Earlier performance awareness: daylight and wind tools help surface constraints early rather than after heavy modeling

Improved early coordination: supports clearer discussions with clients/teams around trade-offs at concept stage

Risks & limitations

Early-stage reliability boundary: outputs are decision-support indicators, not compliance-grade verification (they must be validated later).

Over-trust risk: analysis visuals can look authoritative and be misread as final performance proof.

Handoff friction: early massing studies still require careful translation into detailed BIM workflows and consultant verification.

Human oversight

Architects must verify that inputs reflect real project conditions (site, constraints, assumptions) and treat outputs as directional guidance. Any conclusions that affect compliance, comfort, or performance should be confirmed with later-stage simulation and specialist coordination.

Notes

Forma works best as a front-end "sandbox" for urban and site moves: you can test massing, daylight/wind/noise type impacts, and program distribution early, before committing to heavy BIM effort. Its main value is speed + comparability (options you can review side-by-side with consistent metrics), but the architect still has to police the assumptions behind the analyses and make sure what looks "good" digitally translates into planning reality, stakeholder constraints, and a buildable scheme.

Figure 35. Area analysis
Understand relevant site area metrics and assess the impact of design decisions across the project. by Autodesk Forma

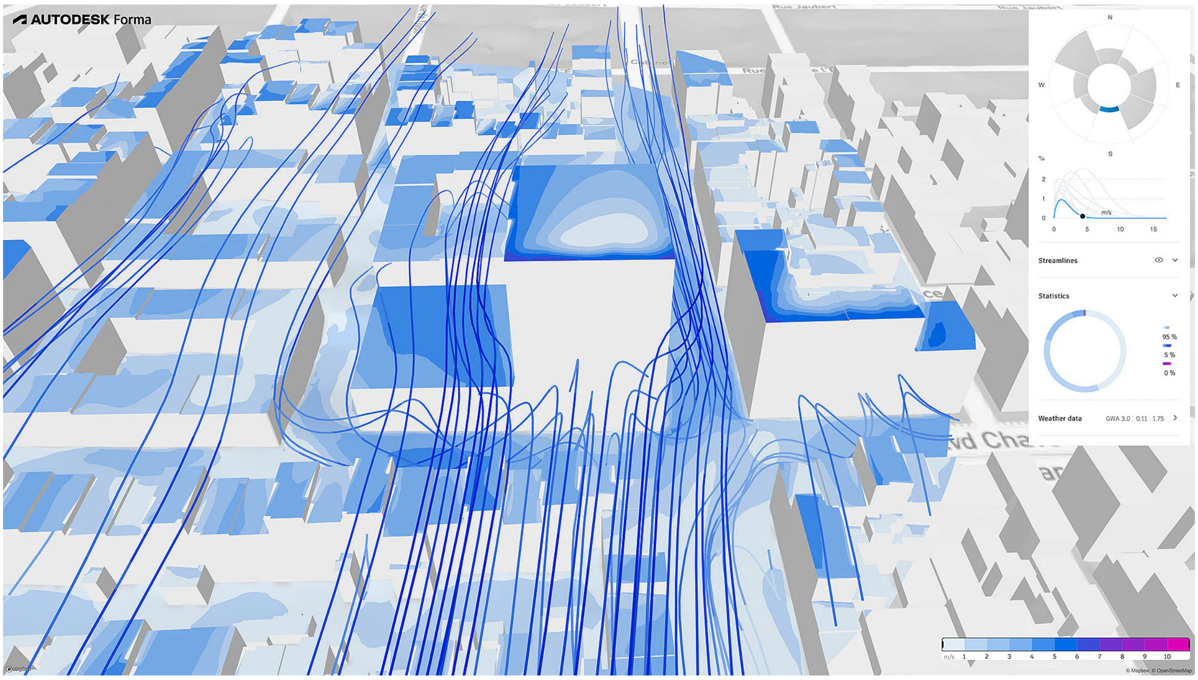


Figure 36. Wind analysis
Use detailed or rapid wind analysis to assess the impact of site wind exposure conditions on building mass. by Autodesk Forma

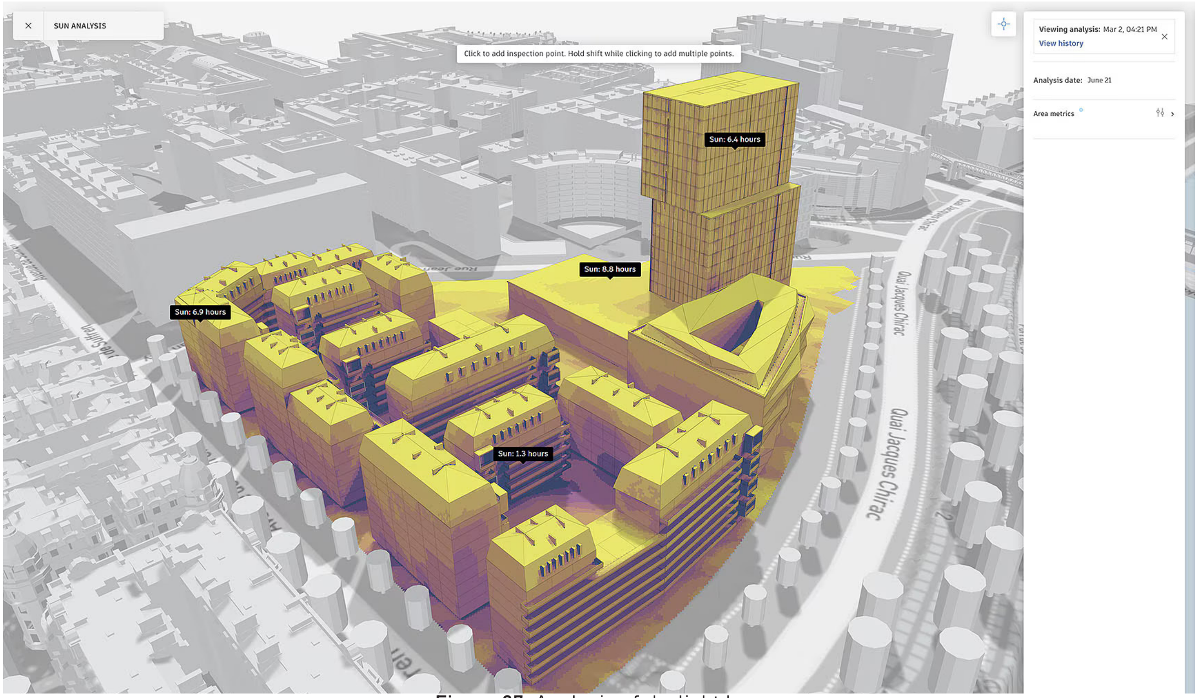


Figure 37. Analysis of daylight hours
Calculate the hours of exposure to sunlight at different points on the site or building facade at any time of the year. by Autodesk Forma

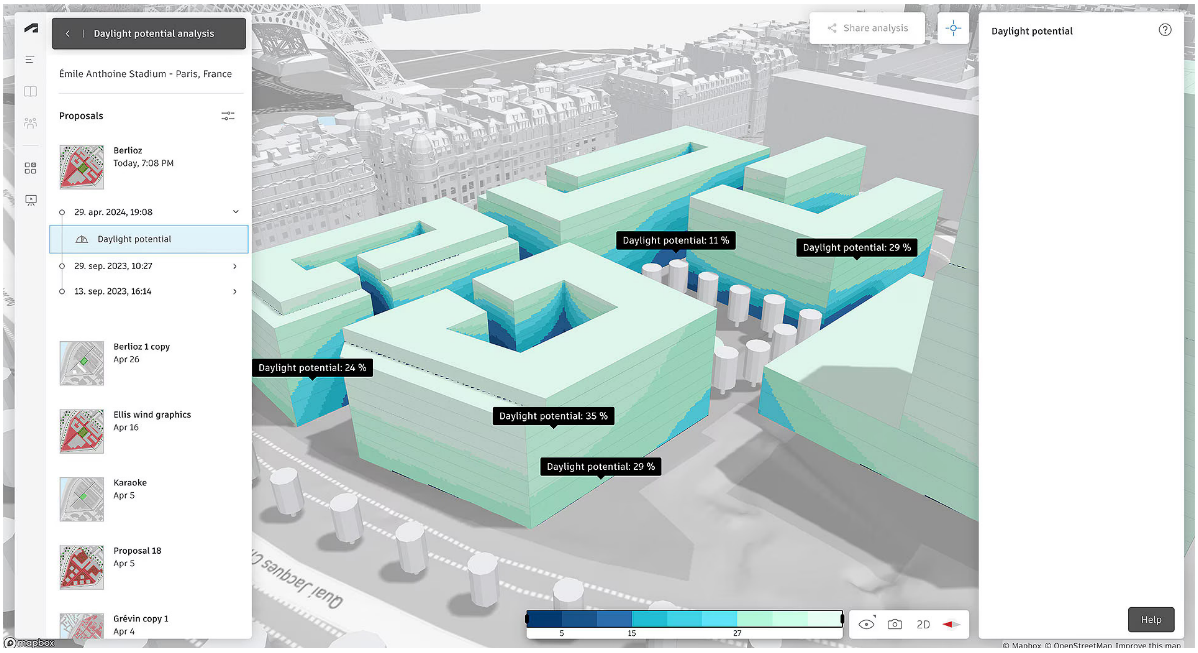


Figure 38. Analysis of daylight potential
Ensure your design meets daylighting requirements by identifying and redesigning areas with insufficient or excessive exposure. by Autodesk Forma

Autodesk Project Refinery ™

Category : Generative design

Owner : Autodesk

Starting year : 2018

Overview

Autodesk Project Refinery is a generative design and optimization tool (released as a beta for AEC) designed to explore and optimize parametric design spaces,especially through Dynamo-based workflows. Autodesk describes it as a way to quickly explore and optimize Dynamo designs for AEC.

Typical outputs

Refinery enables:
generating large sets of design options from a parametric definition
comparing outcomes using performance criteria
running "optimize" workflows where solutions improve over generations and population sets according to defined criteria
Outputs are typically a set of candidate solutions ranked or filtered by chosen metrics, supporting evidence-based option selection.

How it works

At a high level, Refinery runs inside (or alongside) Dynamo workflows, varying parameters across a defined search space and evaluating results using chosen metrics. Autodesk explains that in "optimize" mode it uses a multi-objective optimization approach refined over generations for a given population size.

Workflow placement

Refinery is used when a project can be expressed as a parametric model and evaluated through measurable criteria, commonly in:
early-stage optioning (layouts, massing logic, flows)
parametric studies and performance trade-off exploration
situations where teams want many alternatives, not just one "best guess"

Benefits for practice

Expands the solution space: produces many options quickly, enabling broader exploration than manual iteration

Makes trade-offs explicit: helps teams compare options against multiple criteria instead of relying on intuition alone

Supports structured decision-making: useful for documenting why certain options were selected (criteria-driven logic).

Risks & limitations

"Optimizing the wrong thing": results depend entirely on how objectives and metrics are defined—bad metrics produce misleading "best" solutions.

Beta / workflow complexity: Autodesk materials explicitly describe Refinery as beta in AEC contexts and tied to Dynamo workflows, which can limit accessibility for non-technical teams.

Constraint blindness: if important constraints are missing, outputs can look successful while failing real requirements.

Human oversight

Architects must define objectives carefully, verify that evaluation metrics reflect real project priorities, and review solutions for feasibility beyond what the optimization captures (e.g., usability, code logic, constructability, and stakeholder needs). Refinery should be treated as decision support, not as an authority for "the best design."

Notes

Project Refinery is most appropriate for data-driven option exploration, where a clearly defined parametric model can generate and rank alternatives against explicit metrics. It is effective for comparing trade-offs early; however, its results depend entirely on the quality of the input logic and metrics, and therefore require professional review before informing project decisions. (It later matured into Generative Design in Revit 2021.)

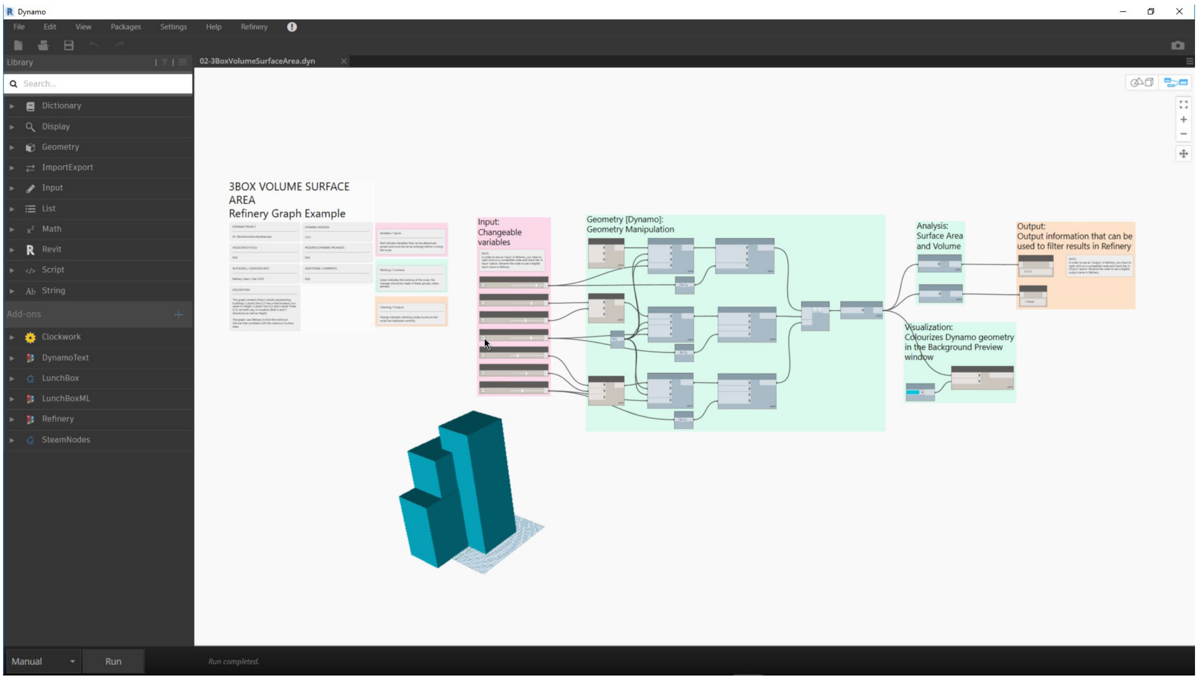


Figure 39. Graph was developed with a goal of discovering the maximum volume. www.autodesk.com

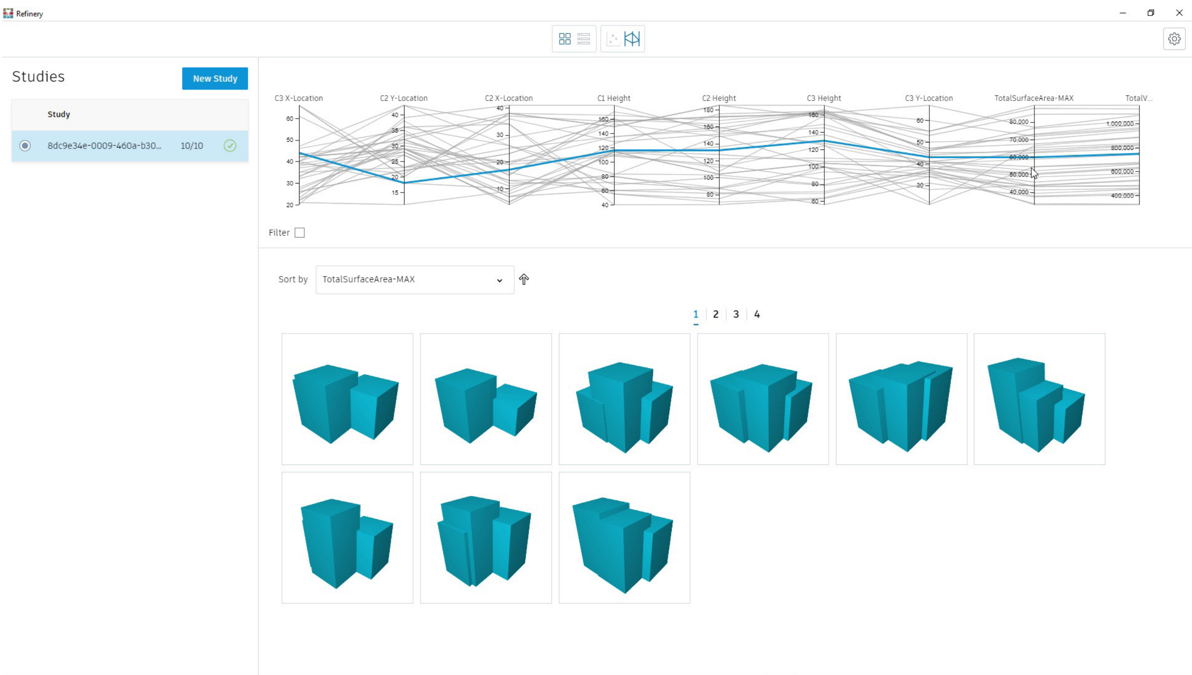


Figure 40. Project Refinery shows your design options resulting from random input values within the range. www.autodesk.com

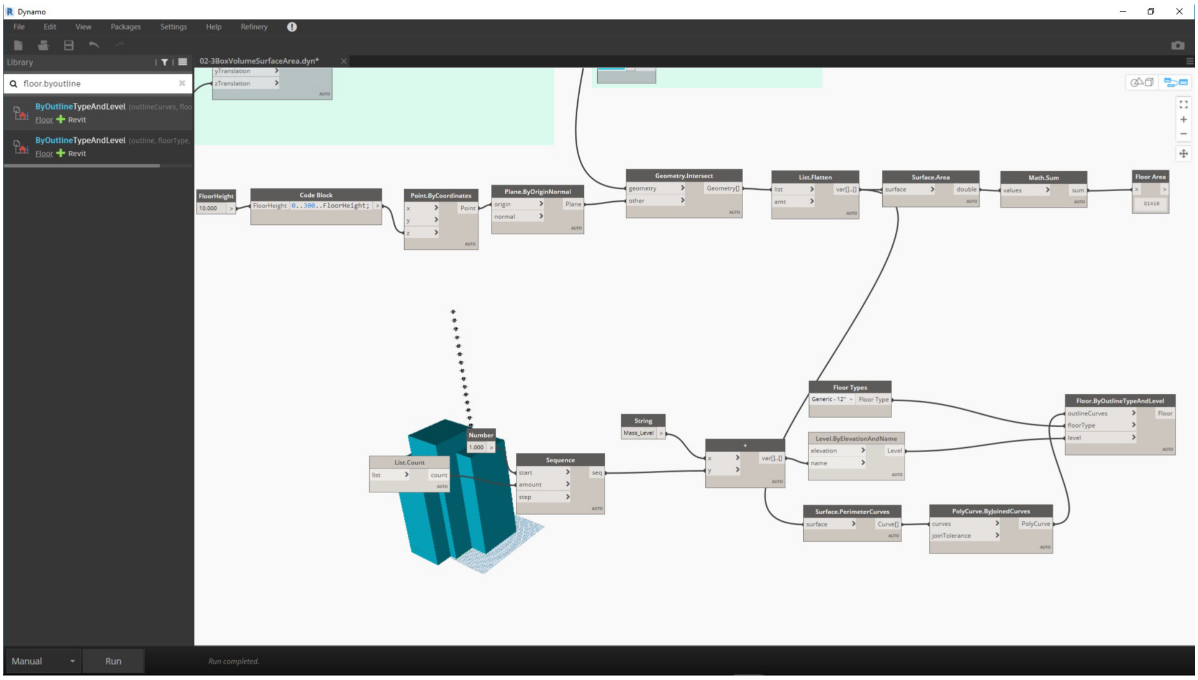


Figure 41. Graph is developed to create floors that correspond to the input from our ideal optimized solution.
www.autodesk.com

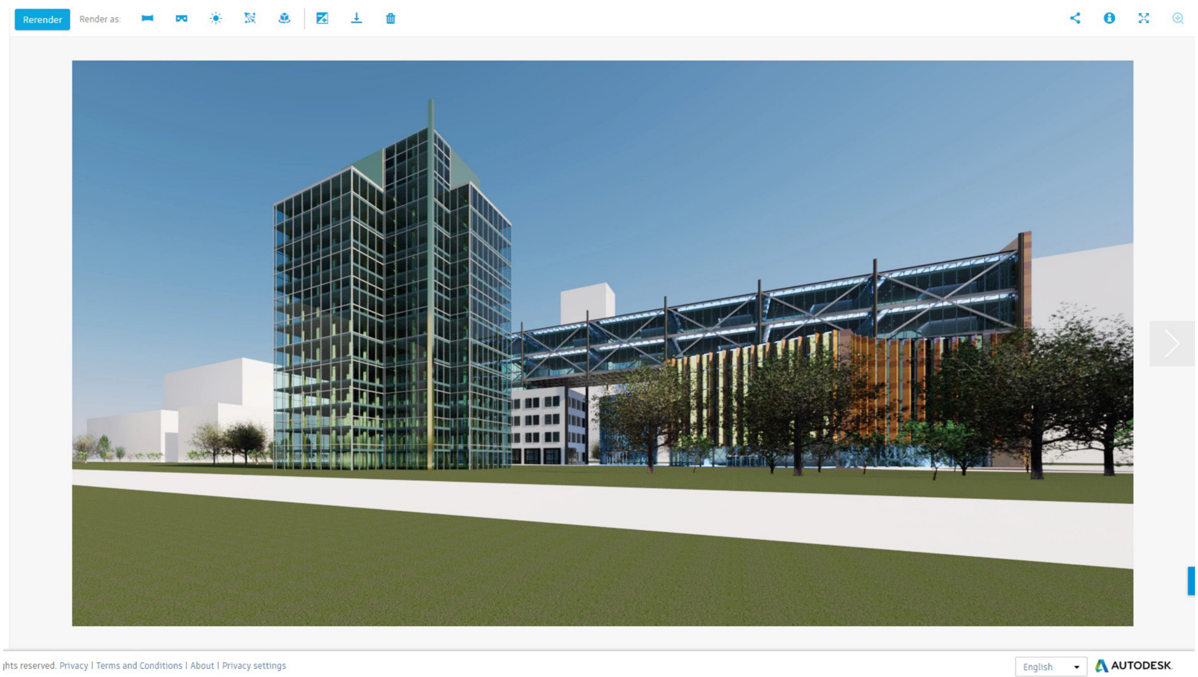


Figure 42. Project Refinery and Autodesk Cloud Rendering for early stage design.
www.autodesk.com

Finch 3D ™

Category : AI-assisted parametric building-planning software

Owner : ArchFinch AB

Starting year : 2019

Overview

Finch 3D is an AI-assisted, generative early-stage design tool focused on producing and adapting floor plans and unit layouts quickly under changing constraints. It is primarily used for rapid iteration in the feasibility, concept, and schematic phases, where architects need to test many alternatives before committing to detailed BIM development.

Typical outputs

Finch is mainly used to generate and adjust early planning outputs such as floor plates and unit plans, while giving the designer structured control through constraints and libraries. It also supports workflows where designers generate unit plans using their own plan library or Finch's AI suggestions.

Typical outputs include schematic-level plan variants and variants that can be taken forward for detailing in other environments (for example Rhino via Finch's plugin workflow).

How it works

Finch works by letting the architect define a planning problem through constraints, tags, and planning logic, then producing plan variants that adapt when dimensions, boundaries, or requirements change. Its documentation shows workflows that use constraints to control how spaces can grow or shrink, and includes rule-like mechanisms such as accessibility bounds and collision warnings when plan changes violate clearances.

Workflow placement

Finch is typically used in the early planning pipeline, especially when space planning must respond to program requirements and frequent iteration:
-early feasibility and schematic planning for housing and mixed-use typologies
-rapid option testing under changing unit mix, floor plate boundaries, and constraints
-handoff to downstream design work once a promising variant is selected, often through export workflows to Rhino (and related early-stage modeling environments)

Benefits for practice

Finch's core benefit is accelerating iteration when projects require many plan options and frequent revisions. Industry coverage describes it as a tool that automates floor plan generation and supports feedback and optimization, which helps compress early-stage optioning cycles.
Its documentation-based workflows also show how constraints and accessibility bounds can make iteration more controlled and less "manual redraw," helping architects respond faster to brief changes while preserving internal planning logic.

Risks & limitations

Finch outputs can appear "resolved" because they are structured, but they remain early-stage and must be validated for code, constructability, and project-specific logic. There is also an interoperability boundary: Finch supports specific CAD/BIM ecosystems (notably Rhino/Grasshopper and Revit versions listed by the company), which means workflow fit depends on office standards and downstream toolchains.

A further risk is over-trusting constraint-driven outputs: constraints encode priorities and assumptions, so if the constraint set is incomplete (or wrongly defined), a plan can look optimal while failing qualitative or contextual requirements.

Human oversight

Architects remain responsible for:
ensuring constraints reflect real project requirements (program, circulation logic, accessibility intent)
verifying results against local codes and project standards (Finch can support planning logic, but does not replace compliance responsibility)
checking qualitative aspects that tools cannot fully capture, such as spatial character, hierarchy, contextual response, and user experience
managing handoff quality when moving from Finch outputs into Rhino/Revit workflows, to avoid loss of intent or hidden planning assumptions

Notes

Finch 3D is particularly effective for rapidly generating and comparing multiple layout alternatives, especially for housing and other repetitive typologies, by applying defined rules and constraints and returning immediate quantitative feedback. It should be treated as an early-stage planning and decision-support tool rather than a compliance or design-authority system. Architects remain responsible for ensuring spatial quality, contextual appropriateness, and verifying any apparent "compliance" results against local regulations and project-specific requirements.

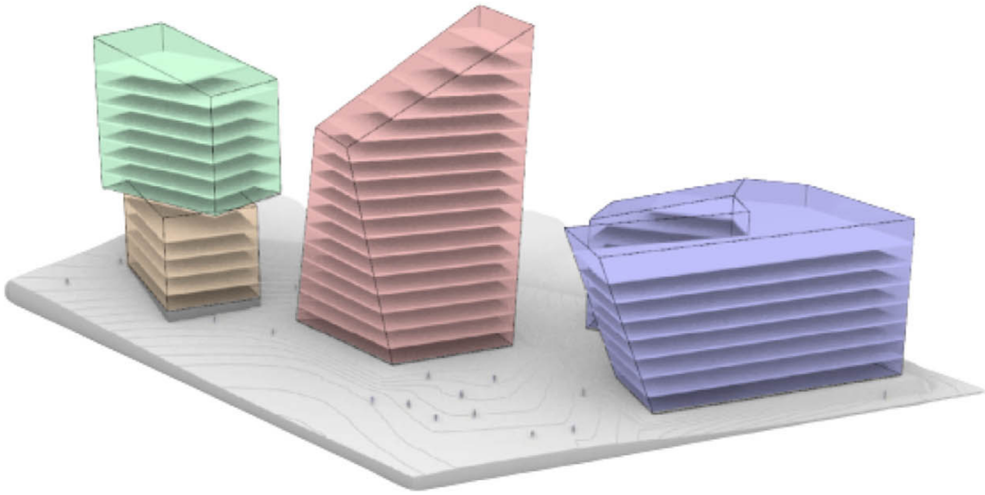


Figure 43. Massing in Finch
www.finch3d.com

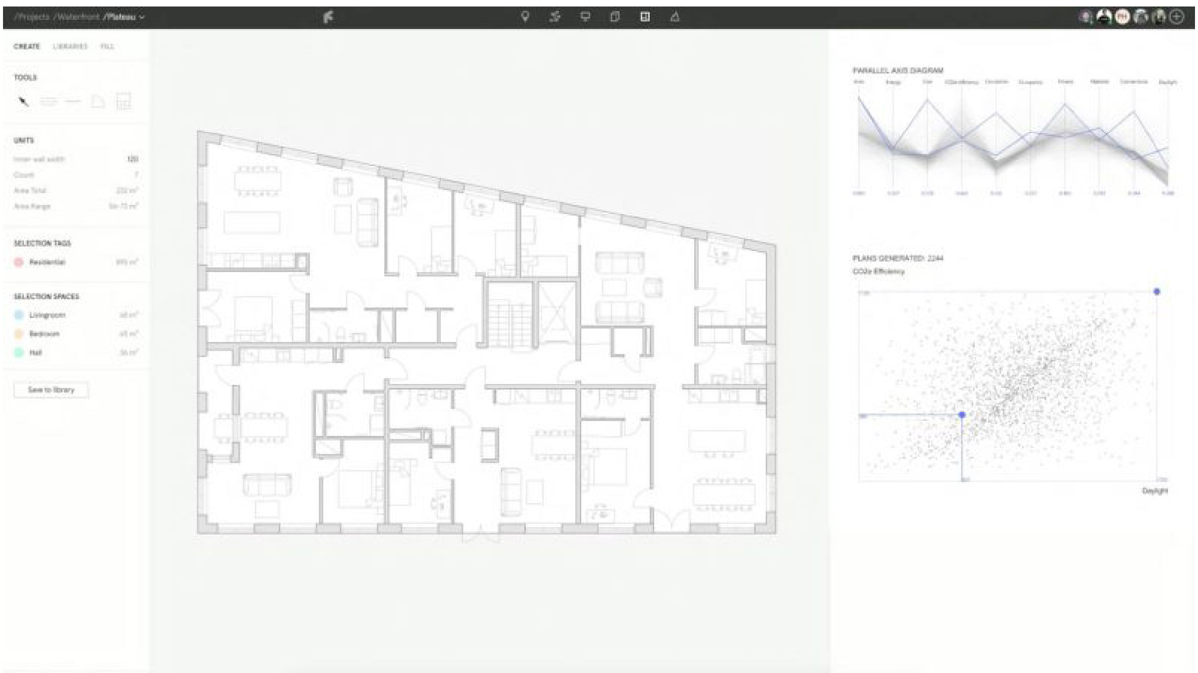


Figure 44. Automated Floor plan generation
www.finch3d.com

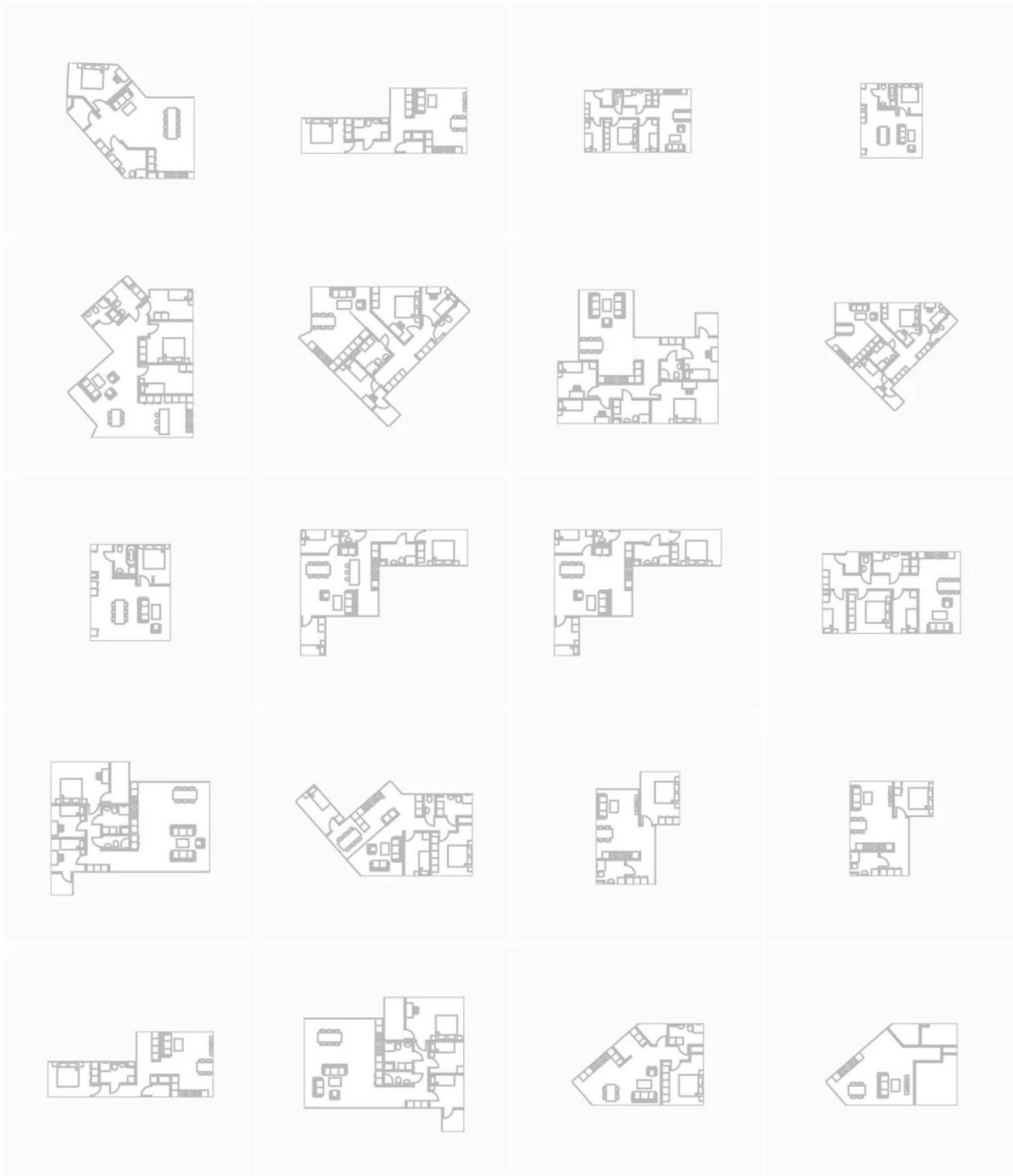


Figure 45. Iterative space plans
www.finch3d.com

Giraffe Technology ™

Category : Cloud-based site planning + feasibility platform

Owner : Giraffe Technology Pty Ltd

Starting year : 2018

Overview

Giraffe is an early-stage design and feasibility platform used for site planning, massing, and scenario testing in urban design and development workflows. It is positioned as a tool that combines sketch-based design with real-time context and analytics, supporting rapid exploration of alternatives during the feasibility and concept phases.

Typical outputs

Giraffe enables users to sketch and adjust early massing and site layouts while receiving up-to-date quantitative feedback, allowing alternatives to be compared using yields and other development metrics. Its outputs typically include early-stage massing/site schemes, scenario comparisons, and exported visuals and datasets for reports or downstream workflows.

How it works

At a high level, Giraffe works as a sketch-and-analyze environment where design actions and evaluation happen together. As users draw or modify massing and site elements, the platform updates metrics in real time so teams can immediately see how design changes affect feasibility indicators. This supports a workflow where iteration is guided by feedback loops rather than by a linear "draw first, calculate later" process.

Workflow placement

Giraffe is typically used before detailed CAD/BIM authoring, when key questions relate to feasibility, yield, site structure, and option comparison. It fits masterplanning, precinct-scale planning, and early-stage development studies where the priority is to test multiple alternatives quickly and communicate their implications to stakeholders.

Benefits for practice

The main benefit of Giraffe is speeding up early-stage iteration by linking design moves to immediate evaluation. This reduces dependence on disconnected workflows across CAD, GIS, and spreadsheets and can improve coordination in early decision-making because teams can compare alternatives using consistent metrics while the design is still flexible.

Risks & limitations

A major risk is over-trust in early metrics, since feasibility analytics depend on assumptions, simplified models, and the quality of input data. If the chosen metrics are incomplete or misaligned with real project priorities, the tool can encourage optimization toward what is measurable rather than what is architecturally meaningful. Interoperability is also a practical boundary: while Giraffe supports exporting to common formats for reuse outside the platform, translating early studies into detailed BIM and consultant-verified design still requires careful handoff and professional judgment.

Human oversight

Architects must confirm that assumptions behind feasibility indicators are valid for the specific context, that scenario comparisons are not mistaken for compliance-grade verification, and that qualitative issues such as spatial character, cultural fit, and lived experience are not reduced to numerical performance alone. Any decisions that influence planning commitments, compliance pathways, or performance claims should be validated through later-stage modeling, specialist input, and formal review processes.

Notes

Giraffe is useful for feasibility and site-planning phase, where rapid massing studies and yield metrics support option screening and stakeholder discussions. Its outputs should be used as indicative decision support, with the architect verifying planning assumptions, data accuracy, and translating the preferred scenario into a properly resolved design workflow.

Figure 46. 3d GIS modeling
www.giraffe.build

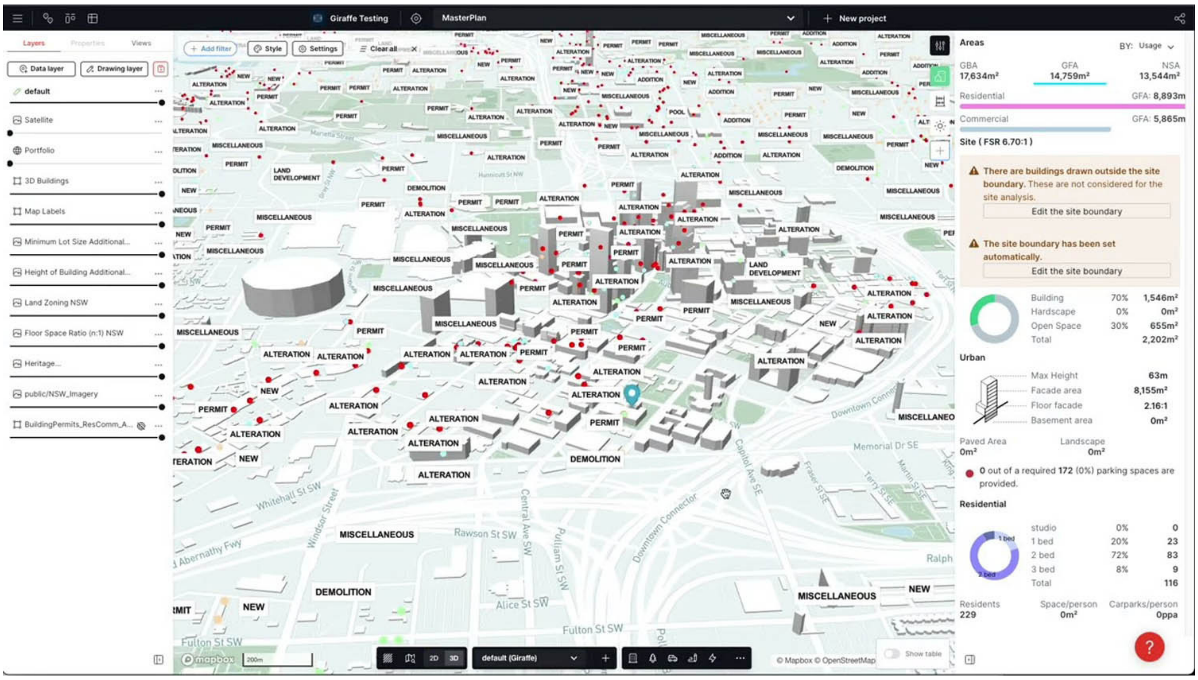


Figure 47. GIS Mapping information output
www.giraffe.build

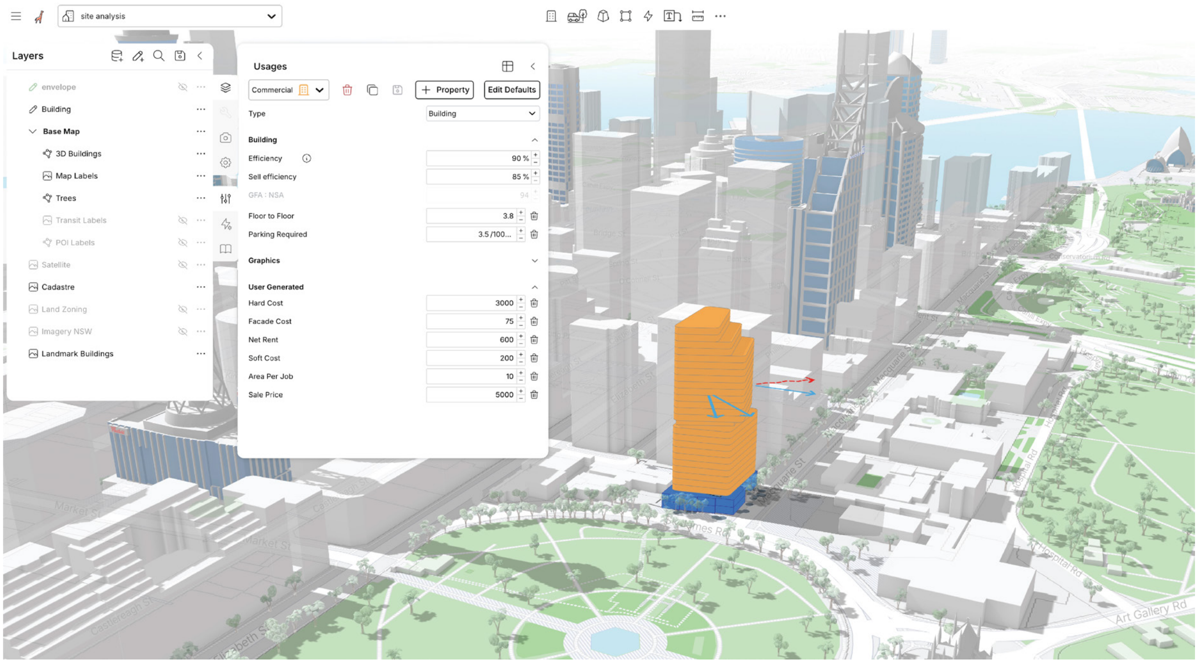


Figure 48. Building assesment
www.giraffe.build

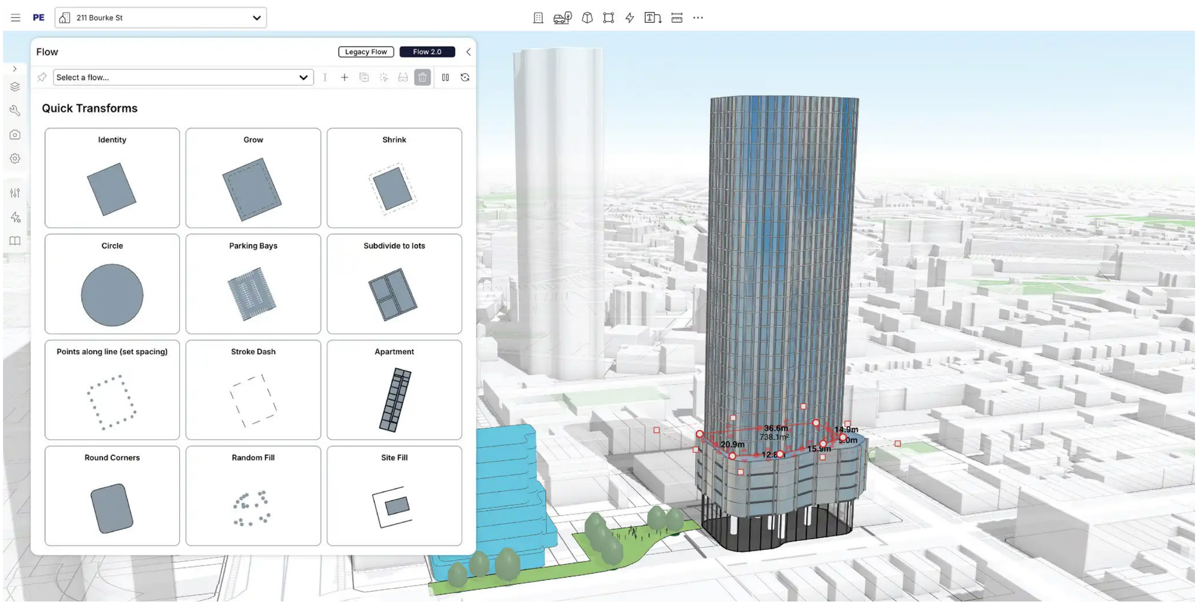


Figure 49. Matrial appliacation flow
www.giraffe.build

EvolveLAB Veras ™

Category : AI visualization add-in

Owner : Chaos

Starting year : 2023

Overview

Veras is an AI-powered visualization application by EvolveLAB designed to help architects generate rapid design imagery directly from their modeling environment. It is positioned as an "AI-powered visualization app" that works across multiple platforms, including SketchUp, Revit, Rhinoceros, Vectorworks, and the web, using the designer's model as the starting substrate for image generation.

Typical outputs

Veras is primarily used to produce fast, prompt-guided architectural images from existing 3D views, supporting ideation, mood exploration, and early visualization without building a full traditional rendering pipeline. Autodesk's app listing describes it as an "AI-powered visualization app" with an AI-based ideation and render engine and optional prompt-based guidance, which aligns with how it is used in practice: generating iterative visual outputs from the same model view to explore alternatives in atmosphere, material expression, and style direction.

How it works

Veras takes a user's model view and combines it with text prompts and tool settings to generate new images that reinterpret the same underlying geometry as a creative substrate rather than a fully resolved render. In this sense, the tool behaves like a controlled image-generation layer applied on top of an existing CAD/BIM viewpoint, enabling fast "what-if" exploration while maintaining a connection to the model's spatial structure. EvolveLAB also documents ongoing feature development such as selection-based workflows in Veras 2.0, indicating an emphasis on more targeted control during generation rather than global, whole-image prompting alone.

Workflow placement

Veras is often used in concept, schematic design, and presentation development. Teams need to quickly explore visual options and share design ideas with clients or internal stakeholders. Its value is greatest before detailed visualization work, such as material creation, lighting setups, and high-quality rendering. It often helps speed up early options, storytelling visuals, and quick client feedback. Its role as an add-in for SketchUp, Revit, and other platforms shows that it is designed to fit within regular architectural modeling workflows instead of replacing them.

Benefits for practice

The main advantage of Veras is its speed. It reduces the time between a design change and a clear image, which allows for cheaper and more frequent iterations in the early stages. Since it integrates with popular design programs like Revit and SketchUp, it helps ease the transition between designing and visualizing. This support enhances quick coordination in discussions where stakeholders need images to assess the direction. EvolveLAB emphasizes using the model as a creative foundation. This highlights the tool's practical use as a fast idea generation and inspiration layer, rather than as a final rendering tool.

Risks & limitations

One main limitation is that the outputs are still just images, not verified technical drawings. Even if they look very realistic, they might show materials, structures, or spaces that are not actually defined in the model. This can be risky if clients see the images as final or guaranteed results. Another issue is that the tool's usefulness depends on how carefully it is used. If teams do not follow clear prompt guidelines, they might create images that look good but do not match the project's direction, making decisions harder. Finally, since this tool only adds an image layer to the model, it does not fix the bigger problem of connecting concept images with detailed BIM data. It helps with visualization but does not replace technical work.

Human oversight

Architects should use Veras outputs as conceptual and communicative images, not as documents ready for compliance or construction. They need to check any suggested design choices,like materials, façade details, structure, openings, lighting, or accessibility,against the real model and project requirements. It's important to set client expectations by making it clear that AI images are for exploration. In the office, using consistent prompts and clear rules for what can be shared outside helps Veras support design thinking instead of just focusing on looks.

Notes

The most important benefit is shortening iteration cycles between modeling and visual feedback; however, it should not be treated as evidence of technical resolution. Architects must manage prompt discipline and reference inputs to maintain consistency, and confirm that any implied construction logic, detailing, and performance assumptions are validated through standard design and consultant workflows.

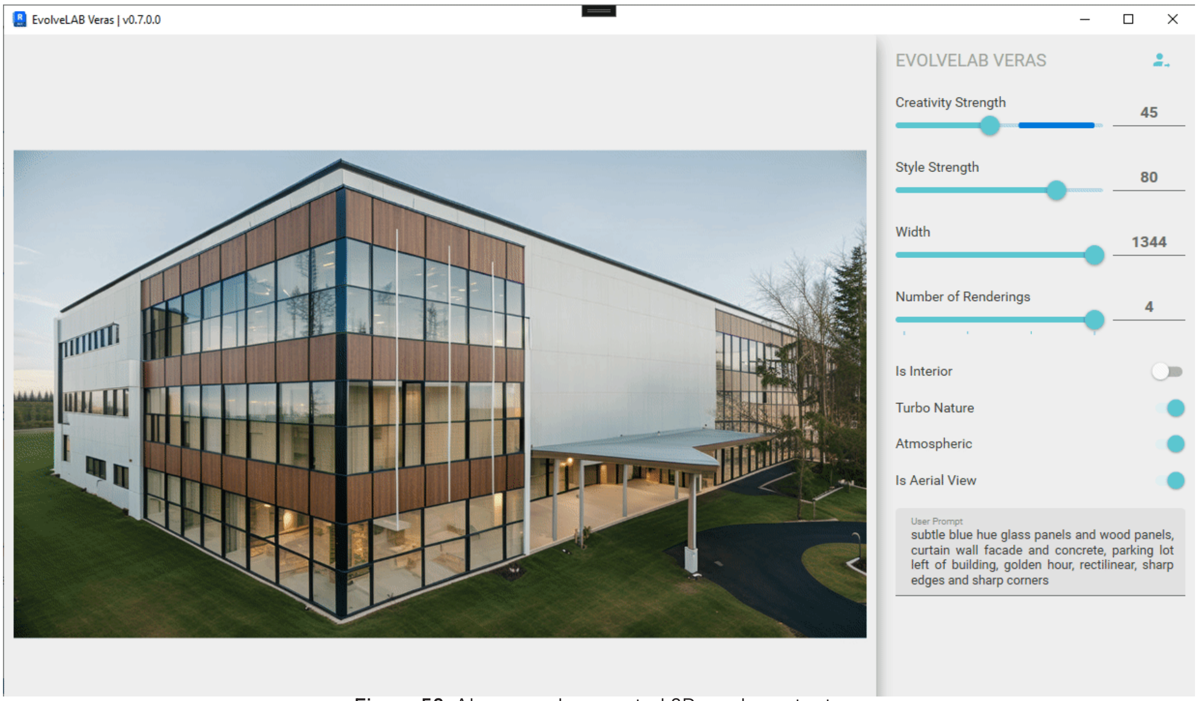


Figure 50. AI powered generated 3D render outputs
www.evolvelab.io/veras

Trimble SketchUp Diffusion ™

Owner : SketchUp

Starting year : 2023

Category : Generative AI rendering

Overview

SketchUp Diffusion was SketchUp's generative AI visualization feature introduced through SketchUp Labs, and it has since been repositioned as AI Render within SketchUp's broader "SketchUp AI" suite. Trimble describes AI Render (formerly SketchUp Diffusion) as a generative AI image creation tool built into SketchUp to accelerate visualization without requiring users to learn complex rendering software or add additional tools to their workflow.

Typical outputs

AI Render combines the active SketchUp model viewport with a text prompt or preset style to create AI-generated images. This supports quick conceptual rendering and mood exploration. SketchUp's help documentation describes it as a tool for making a new AI-generated image based on the current model view. The Extension Warehouse listing presents the same basic function and positions it as a Labs-to-product feature under the AI Render name. In its updated form, Trimble also highlights expanded controls like reference images, inpainting, and negative prompts. These features move it beyond just "one prompt, one image" outputs and allow for more focused iteration.

How it works

AI Render uses the model viewport as a spatial anchor. Then it creates an image based on prompt instructions and style guidelines. This results in a visual interpretation instead of a physically simulated render. SketchUp's guidance explains that prompts are the main way to generate an output. The generated results are saved to a session-based gallery that keeps outputs from the current session and recent history. This setup supports a workflow where users can generate, review, and refine quickly.

Workflow placement

SketchUp Diffusion (AI Render) is best used as a rapid, model-view-based visualization tool to test style, atmosphere, and material direction straight from a SketchUp scene. Its strength is quick iteration using prompts, masking, and optional references, which helps align teams and clients early. It supports—not replaces—core modeling and validated design decisions.

Benefits for practice

By generating images directly from the model view, AI Render reduces the time between a design change and a clear visual. This makes early-stage revisions cheaper and more frequent. Trimble specifically describes the tool as speeding up visualization. It allows designers to concentrate on creative choices instead of learning complicated rendering tools. SketchUp also promotes it as a way to support quick concept visuals during a project's narrative development. This can also improve coordination in conversations with stakeholders. Teams can respond to feedback with new visuals without having to rebuild a full render pipeline.

Risks & limitations

The outputs are still images, not verified technical representations. The tool produces visually appealing results, which can mislead clients or non-technical stakeholders into seeing the output as a final intent or guaranteed buildability. This is true even though it serves as an interpretive visualization layer rather than a validation method. The workflow creates a gap between concepts and technical details: AI Render can improve early communication, but it does not turn images into BIM-ready geometry or structured design data. Therefore, translating these into detailed documentation remains a task for humans. Additionally, privacy and governance issues can emerge. SketchUp services use Trimble identity and wider platform policies that firms must consider when accessing cloud-connected features in professional settings.

Human oversight

Architects should treat AI Render outputs as exploratory concept images and not as final, verified design results. Any decisions suggested by the image, such as materials, openings, structure, lighting, accessibility cues, or contextual fit, must be verified against the actual model and project constraints. Teams also benefit from having internal standards for prompts and presentations to ensure that quick outputs support design thinking and do not lead to inconsistent "aesthetic drift" across iterations. When confidentiality is important, firms should match usage with their internal data governance practices and the platform's privacy expectations.

Notes

Most useful for fast, view-based concept visuals to support reviews and client communication. Use it to explore mood and material direction, then confirm decisions through standard modeling, detailing, and validated rendering workflows.

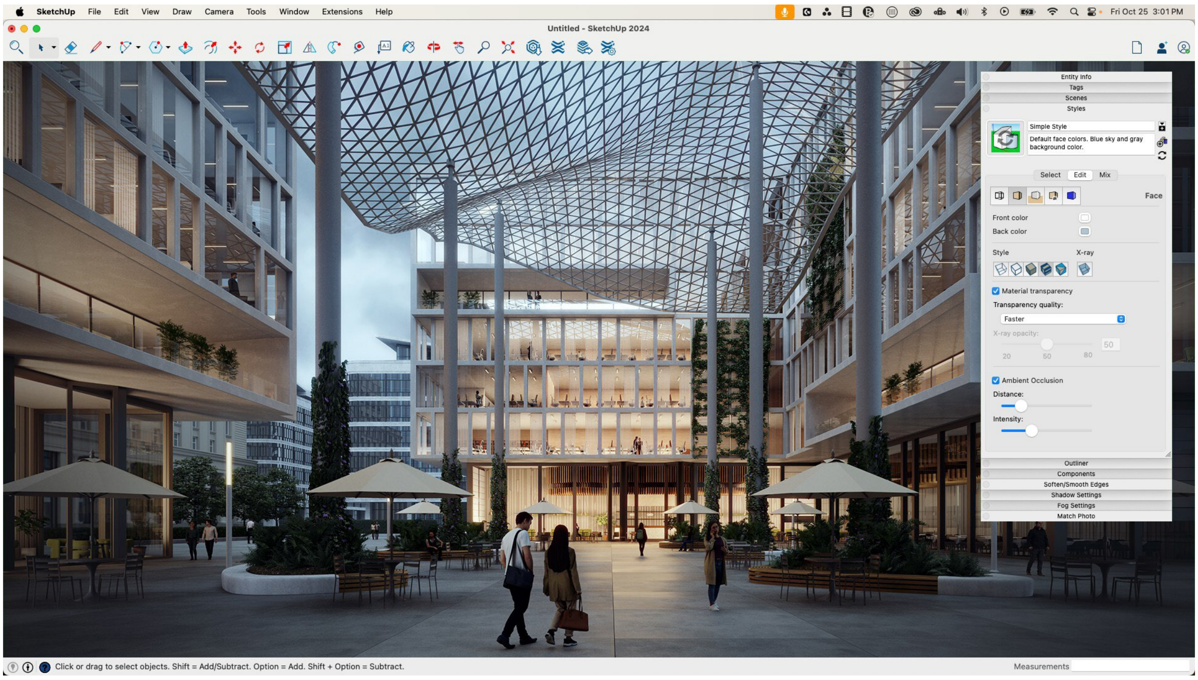


Figure 51. Trimble SketchUp® 3D modeling
www.trimble.com

SPAC≡LY AI

Spacely AI ™

Category : AI visualization

Owner : Spacely AI

Starting year : 2023

Overview

Spacely AI is a generative AI visualization platform positioned for architects, interior designers, and real-estate teams to produce fast, styled renders and edited visuals without requiring a full traditional rendering workflow. It is an AI-powered visualization tool that can generate interior and exterior imagery quickly from sketches, photos, or simplified 3D inputs.

Typical outputs

Spacely AI focuses on creating 2D visual outputs for design communication. Its tool set includes interior and exterior AI rendering from sketches or models, text-to-image generation, style transfer, image editing tools that modify images through prompts, and features that improve quality or extend views. It also offers a SketchUp extension workflow that integrates generative rendering into a familiar modeling context for quick visualization.

How it works

Spacely AI uses prompt based generation and image-to-image workflows. The user provides an input image or model snapshot and then directs the output with style selection and text prompts. The platform offers guidance on prompting, showing that prompts can be used across several features. This suggests a consistent prompt layer that supports creation, editing, and improvement actions throughout the workflow.

Workflow placement

It is mainly used in the concept and schematic phases, when teams need quick visuals to explore options, test alternatives, and communicate their ideas to clients or team members. It also works well during rapid feedback cycles. This approach enables designers to create several presentable variations quickly without having to rebuild a complete render pipeline each time.

Benefits for practice

The main benefit is creating is producing communicable imagery. This can help connect design ideas with understanding. Since the platform has both generation and editing tools, it allows for quick options and faster responses to client feedback. This helps teams make decisions earlier while the design is still flexible. The inclusion of a SketchUp extension also makes the workflow smoother by aligning visualization with typical architectural modeling practices.

Risks & limitations

Spacely AI outputs are visual images, not detailed architectural models. This means they do not include built-in BIM information, valid dimensions, or compliance logic. This raises the risk that realistic images might be seen as finalized or technically sound design choices, even though they are just interpretive representations. Interoperability is also a challenge. Even if the images improve communication, turning the results into coordinated CAD/BIM deliverables still needs architectural judgment and remodeling effort.

Human oversight

Architects should use Spacely AI outputs as concept and communication materials, not as technical proof. Any implied decisions in the imagery, such as materials, openings, structure, lighting, accessibility cues, or spatial proportions, must be checked against the actual project constraints and developed in the appropriate CAD/BIM environment. Clear communication with clients is also essential. AI visuals should be framed as exploratory, ensuring that design responsibility stays with the architect instead of being passed to the tool.

Notes

Figure 52. Spacely AI Residential Exterior Rendering Service
www.spacely.ai

Figure 53. Spacely AI Bedroom Interior Rendering Service
www.spacely.ai

Figure 54 Spacely AI Kitchen Interior Rendering Servicewww. spacely.ai

Figure 55. Generative Render Output www.spacely.ai

ArchiGAN™

Category : Generative design

Owner : Stanislas Chaillou

Starting year : 2019

Overview

ArchiGAN is a research-based generative design framework that uses Generative Adversarial Networks (GANs) for architectural planning. It focuses on creating apartment floor plans and related building designs. This framework is mainly linked to Stanislas Chaillou's work. It showcases a proof-of-concept pipeline that demonstrates how trained models can create realistic plan proposals based on constraints and training data (Chaillou, 2020; Chaillou, 2019).

Typical outputs

ArchiGAN's main outputs are generated plan representations, such as apartment layouts and related intermediate representations in the pipeline. These can be used to quickly explore early planning options. The work outlines a structured "stack" or staged process in which the system generates plan-like outputs. These outputs reflect patterns learned from previous datasets instead of being manually drawn from scratch (Chaillou, 2019; Chaillou, 2020). The public repository linked to the project also presents the approach as a multi-step workflow, not a single one-time generator. This highlights the pipeline nature of the method.

How it works

ArchiGAN uses conditional GAN logic to convert input conditions into plan outputs. It learns patterns from datasets of existing plans. Chaillou connects this method to image-to-image translation concepts, like Pix2Pix-style conditioning. In this approach, constraints and boundary conditions help control the generation process towards realistic arrangements. The workflow outlined in the project materials that help generation follows a series of steps. Each stage influences the next representations, gradually moving toward a cohesive plan output.

Workflow placement

It is mainly used in the concept and schematic phases, when teams need quick visuals to explore options, test alternatives, and communicate their ideas to clients or team members. It also works well during rapid feedback cycles. This approach enables designers to create several presentable variations quickly without having to rebuild a complete render pipeline each time.

Benefits for practice

The main benefit is creating is producing communicable imagery. This can help connect design ideas with understanding. Since the platform has both generation and editing tools, it allows for quick options and faster responses to client feedback. This helps teams make decisions earlier while the design is still flexible. The inclusion of a SketchUp extension also makes the workflow smoother by aligning visualization with typical architectural modeling practices.

Risks & limitations

Hidden errors propagate: small mistakes in an early layout can cascade into major downstream design issues if taken as a base.
Dataset bias: it reproduces the norms of its training examples (culture, unit standards, corridor habits), which can be inappropriate or exclusionary.
False plausibility: plans can look "architectural" while failing basic requirements
Integration friction: converting outputs into buildable documentation still requires full human production and coordination.
No guaranteed compliance: cannot certify safety, accessibility, or regulatory alignment.
Generalization limits: performs best on patterns similar to its dataset; unusual briefs and local housing standards may degrade results.

Human oversight

Define intent + constraints first: program, unit mix, circulation rules, accessibility goals, structural grid logic, cores, egress assumptions.
Validate outputs against reality: dimensions, net-to-gross, daylight potential, fire strategy/egress, accessibility, services routes, constructability.
Check data provenance and fit: what dataset it learned from, what typologies/regions it reflects, and whether that matches your project context.
Translate responsibly: treat images as draft diagrams, then redraw/model properly in CAD/BIM with real dimensions and code logic.

Notes

ArchiGAN is best treated as a proof-of-concept demonstrating how learned patterns from plan datasets can generate plausible planning outputs. In practice, results remain data-dependent and image-based, requiring professional interpretation, validation, and conversion into measurable, code-compliant design documentation before any project use.

Figure 56. Model II output, program for each floor plate
https://developer.nvidia.com/

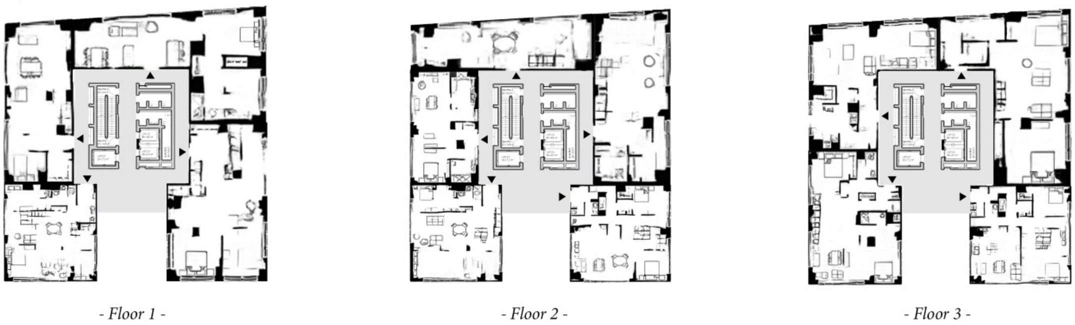


Figure 57. Model III output, furnishing of each individual unit
https://developer.nvidia.com/

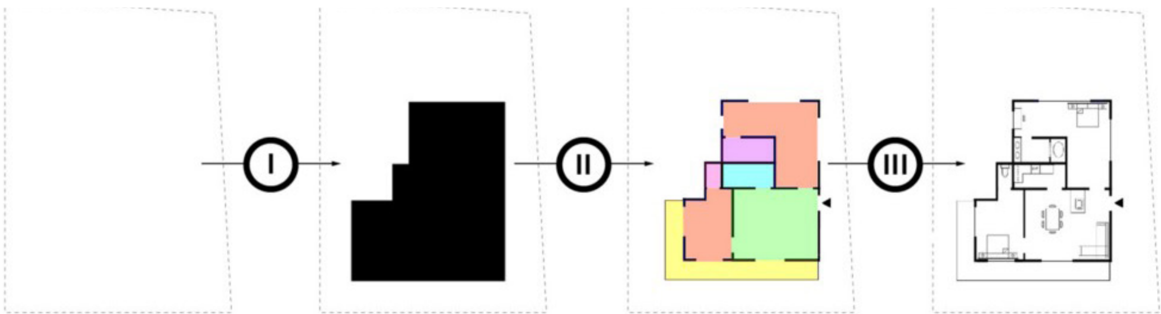


Figure 58. Generation stack in three models
https://developer.nvidia.com/

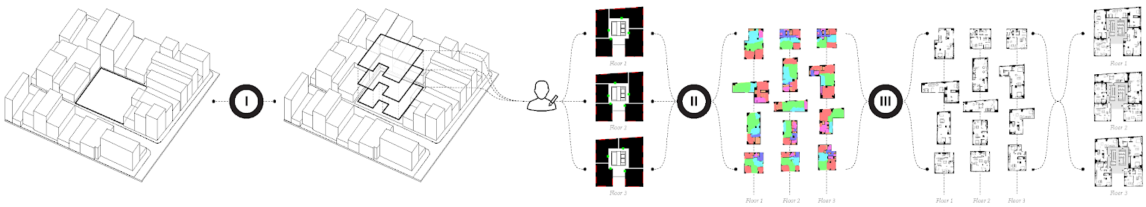


Figure 59. Apartment building generation pipeline
https://developer.nvidia.com/

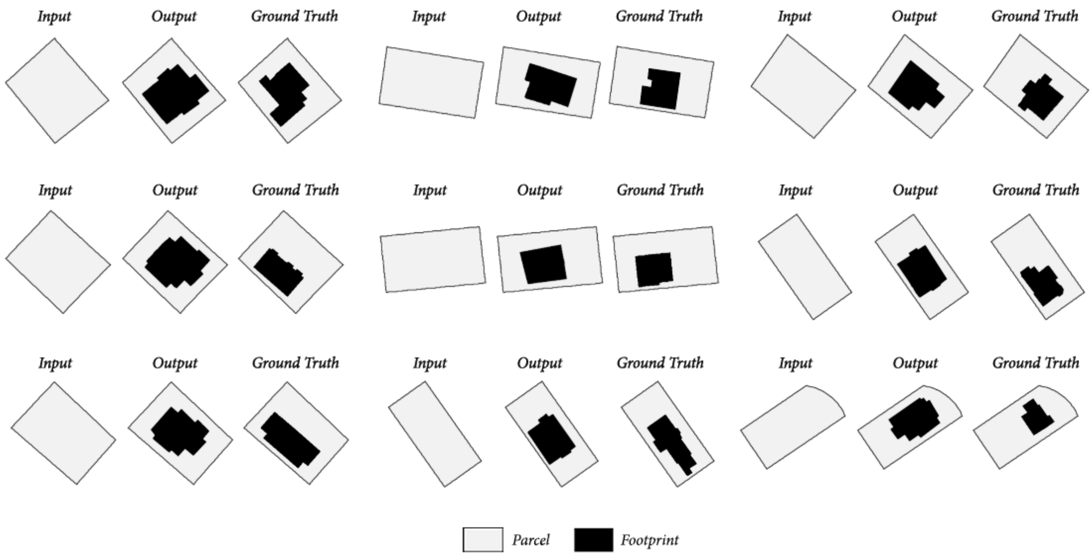


Figure 60. Results of model I
https://developer.nvidia.com/

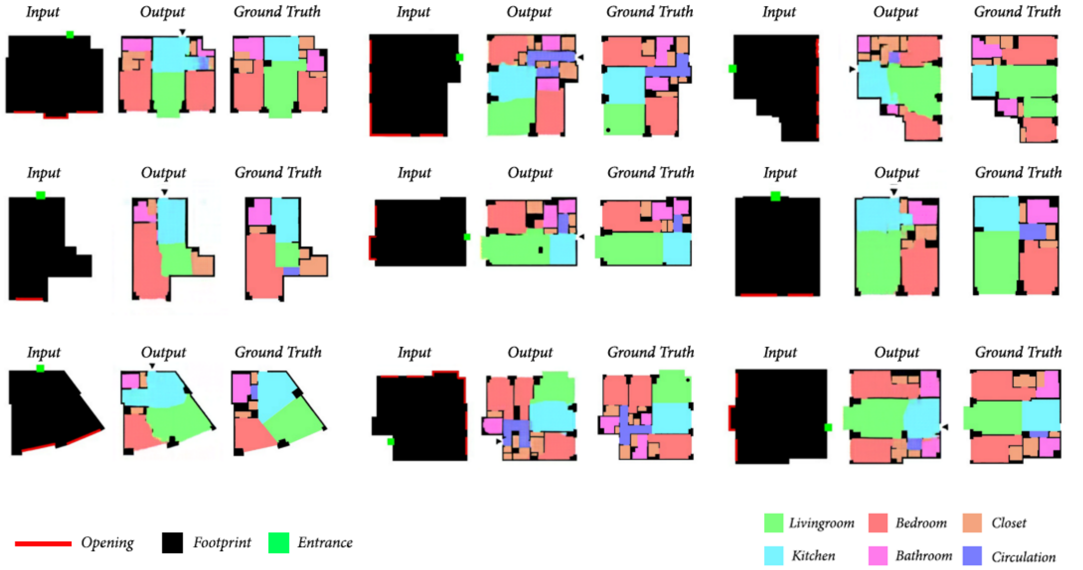


Figure 61. Results of model III
https://developer.nvidia.com/

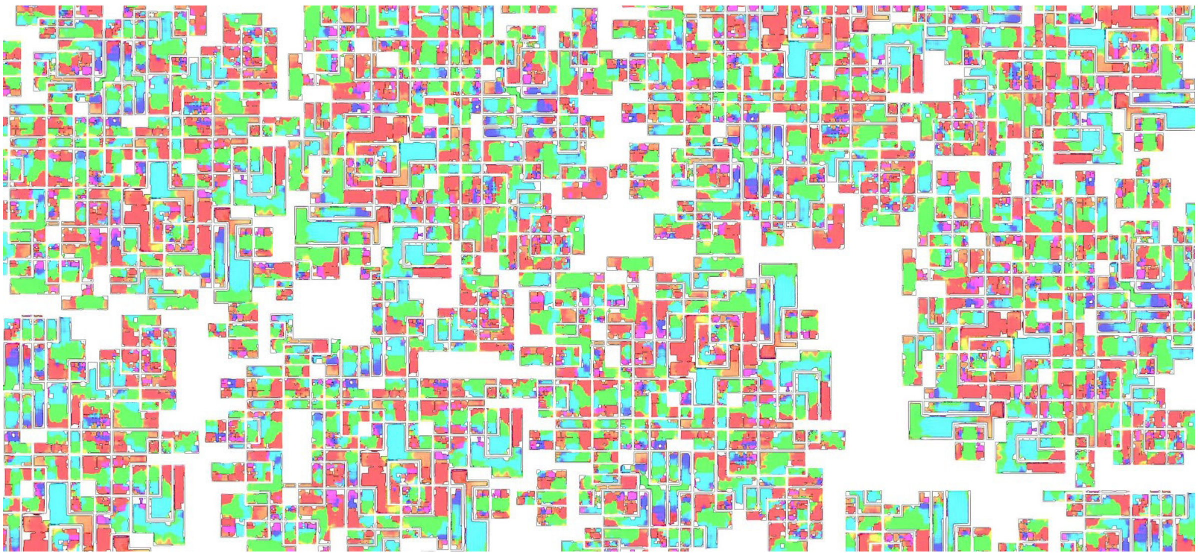


Figure 62. GAN-Generated masterplan
https://developer.nvidia.com/

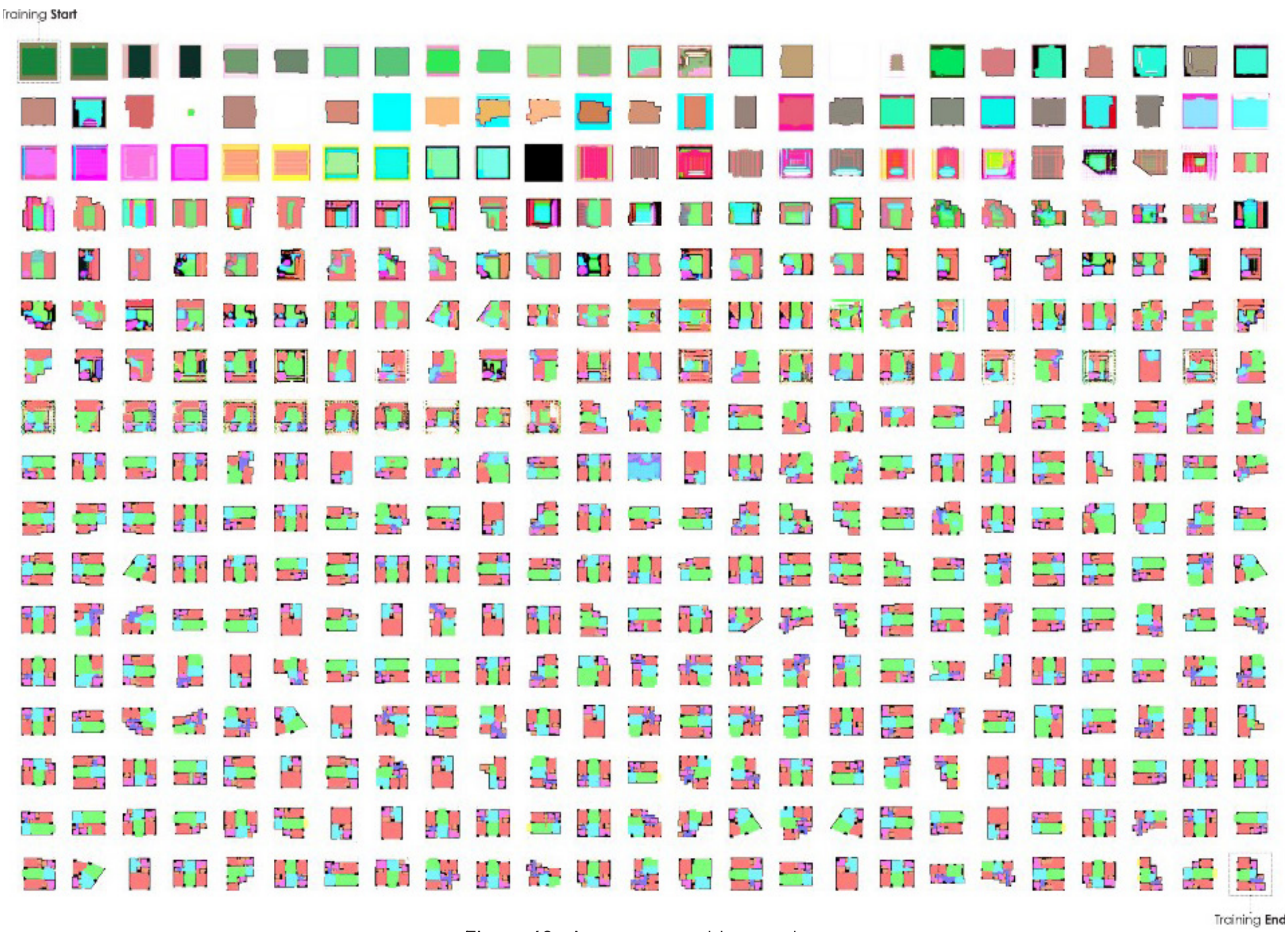


Figure 63. Apartment architectural sequence
https://developer.nvidia.com/

Redefining Architectural Creativity in the Presence of Generative Systems

AI-supported tools have reached a level where they can accelerate architectural workflows a lot, but their role remains assistive rather than independent. After reviewing and testing these platforms, the conclusion is clear: current AI tools are not capable of producing architecture autonomously in any professional sense. They depend on the architect's input to define intent, constraints, and priorities, and they require supervision to decide relevance, feasibility, and appropriateness. Even when the results seem convincing, whether in images, layouts, or documentation, the underlying intelligence is not architectural intelligence. It is a computational pattern. This only becomes useful when it is guided by human expertise, responsibility, and design judgment. But , at the same time, it would be unrealistic and ignorant to see where this path is going. The pace of development in this field is rapid, and the direction is obvious: these systems will be used more frequently and more deeply in practice. As AI tools improve, they will become better at adjusting to structured limitations, learning from feedback, and producing results that match professional expectations a lot more than today This will inevitably reduce workload in several areas, especially in repetitive production tasks, early-stage option generation, visualization cycles, and some types of documentation support. By moving this workload away from architects, these tools can create more time and mental space for the more significant parts of practice. This includes setting clear design goals, making tough decisions amid uncertainty, and balancing priorities among clients, users, regulations, budgets, and context.And for now ,the idea that AI will replace architects or their creativity is far from reality. Architecture involves more than just creating forms or producing correct outputs. It is a cultural practice grounded in interpretation, ethics, negotiation, and responsibility. Architecture requires an understanding of context, values, and human experience, which cannot simply be boiled down to recognizing patterns or optimizing processes. For now, AI will not serve as the author of architecture. it will act as a powerful tool within a human-led process. It can increase speed and capacity, but it still relies on architects to define meaning, assess outcomes, and take responsibility for what is built.And we will explore more of the deeper context in the following chapters.

3.3 Impacts of AI on Architects And Practice

The Definition

To truly understand the impacts of AI we have to define what is an "impact". In this section, the term impact is used as an umbrella concept for describing how AI changes architectural work at multiple levels, from daily workflows to professional identity. Importantly, “impact” does not automatically mean harm or soemthing negative. Instead, it refers to any measurable or observable change in practice and architect's role. This framing is necessary because current evidence shows that AI adoption is happening in the profession. However, implementation is still uneven and remains experimental in many offices that are already influencial today and currrently creating important projects. In this section are grouped by evaluating them. Positive impacts are seen as changes that strengthen architectural practice. This includes improving efficiency, reducing repetitive work, supporting faster iteration, and improving coordination and access to information. Negative impacts are changes that weaken practice or raise risk. These include the role of architect becoming less and less involved on every step of the practice and possibly eliminating/ terminating the occupation of many also o growing pressure on fees and job security, the spread of errors due to rapid generation, and the loss of trust when people misunderstand AI outputs as confirmed decisions are important too. This framing sets the analytical goal. The task is not just to list benefits and risks. It involves distinguishing which changes truly improve architectural practice, which changes create structural challenges, and which changes alter the profession in less clear ways.

Speed and productivity

One of the clearest positive impacts of AI is the reduction of time across early design cycles and tasks. In this thesis, speed means how quickly an initial brief turns into reliable alternatives. Productivity refers to the quantity of design work,options, studies, versions, and visual outputsthat can be generated in a set amount of time. In practice, AI helps by automating parts of workflows that are slow, repetitive, or required many revisions. It also allows for quick creation of similar outputs, which helps with faster review and selection. Architectural tasks do not become automated all at once. They move in stages: first with basic digital assistance, then advancing to systems that can generate, adapt, or execute defined subtasks with less human control (Rafizadeh et al., 2024). This matters for productivity because many work hours go first to necessary but not central work, such as formatting, repetitive drawing, routine documentation, and frequent rework when requirements change.requirements change. The biggest productivity improvements right now are in optioning and iteration, especially during the concept and schematic phases. In both educational and experimental settings, generative AI creates many visual options. And once these options are made, teams can review, critique, and improve them through ongoing feedback. AI also makes it easy to adjust designs based on user input, which speeds up the time from idea to something you can evaluate (Agkathidis et al., 2024). In this setting rather than taking architects out of the process, AI helops them with the pace. Allowing designers to explore more ideas, help them show clients visuals sooner, and reach promising directions faster. In generative design, text-to-image and AI generative systems greatly improve the creation of concept imagery compared to conventional rendering pipelines. This speed boosts exploration by reducing the "cost per iteration," making it easier to compare alternatives, test narratives, and communicate early intentions (Fitriawijaya & Jeng, 2024). The practical consequence is that architects can spend less time waiting for representational outputs and more time evaluating, selecting, and improving design directions, especially when rapid stakeholder feedback is required (Fitriawijaya & Jeng, 2024).

Iteration & exploration

Generative AI enables rapid visual iteration, enhancing both design exploration and communication with clients and stakeholders. Text-to-image workflows visualizes ideas quickly, allowing architects to discuss options, atmospheres, and references with less production time than traditional visualization. AI does more than help with image-based ideas. It also supports structured design exploration through computational and data-driven methods. In designs focused more on performance and optimization, AI helps with evaluation of options and allowing designers to balance their goals like comfort, energy use, geometry, and constraints. This makes it easier to explore designs based on evidence. Architects can quickly test different scenarios and compare more options than they could by hand (Zhong et al., 2024).New hybrid workflows show that AI can connect early design ideas to more detailed architectural work. For example, using sketches or mixed inputs, AI can help turn quick ideas into more developed proposals. These methods let architects explore options while staying involved in decisions, since the tool acts as a translator and amplifier of their intent, not as an independent creator (Li et al., 2024).

Decision Support

Decision support in architecture means using AI to help designers make choices by organizing information, evaluating options, without replacing the human decision-maker. This matters because architectural design is complex: goals change, criterias can conflict, and there is rarely one right answer. Design Decision Support Systems (DDSS) help by offering structured feedback to compare options, while people still frame problems, interpret results, and make final decisions (Schubert et al., 2023). In AI-assisted workflows, decision support is most noticeable when design connects directly to assessment. Recent studies on performance-driven generative design describe a common patern in parametric generation, simulation-based evaluation.This process creates sets of alternatives that show different trade-offs instead of just one “best” solution. These workflows often use multiple optimization and can produce optimal solutions. This helps architects see how improving one factor, like energy use, might make another, such as daylight or comfort, worse. In this way, AI does not make the final decision. Instead, it widens the range of options, helping architects make more accountable choices (Huang et al., 2025).

Communication

Communication in this context goes to two directions,architect–client communication, where the goal is set around ideas & expectations, and communication across project teams, where the goal is coordination, reduction of misunderstandings between disciplines. For clients, generative AI’s main benefit is creating visual options, making it easier to discuss ideas before they are fully developed. A recent study with architects using text-to-image tools found that generative AI speeds up visualization and helping clients taking a more active role by quickly putting their preferences. This changes the feedback process and shortens the time between what client wants and how the architect responds. However, the same study points out a key limitation: AI visuals can look convincing but may ignore what is possible, the project’s context, or real-world limits. Communication only improves when architects clearly present AI results as exploratory and use their own professional judgment to filter them (Schneider et al., 2025). Communication improvements also benefit internal reviews, where design teams need to share their ideas quickly and respond to feedback. Research shows that AI-supported workflows help teams express ideas faster and support ongoing critique, making the “design conversation” stronger by offering more alternatives for discussion (Agkathidis et al., 2024). For project teams and other professionals like consultants, engineers, contractors the main benefit is clear information exchange rather than just image generation. In architecture design decisions involve many people and factors, and decision-support systems help by organizing information, clarifying options, making it clear for everyone involved. AI-assisted communication is most helpful when it turns complex design details into summaries that are easy to share and compare, showing what changes, why it changes, and what effects those changes have on things like performance, cost, or buildability (Schubert et al., 2023).

Sustainability and Energy Efficiency

AI makes a major impact in performance-driven generative design, where it helps create and test design options using environmental simulations. According to a review by Huang et al. (2025), more architects are using AI-assisted systems to improve building performance like energy use, thermal comfort, daylight, and ventilation. With these tools, architects can quickly explore different design choices and weigh differences between sustainability goals, making it easier to find balanced solutions. This means sustainability can shape the building’s form, layout, and orientation from the start, rather than being added later. AI also helps predict energy performance. Machine learning models can estimate a building’s energy needs faster than traditional methods, so teams can test more design ideas. Research shows that AI-based energy prediction supports early decisions by highlighting key factors such as envelope design, orientation, and material choices that affect energy use (Nguyen et al., 2023). AI tools also help reduce waste and use resources more efficiently by optimizing layouts, structures, and material use. AI in sustainable building design can lower the energy consumptipn and improve lifecycle performance, especially when paired with BIM models that track materials and quantities (Attia et al., 2024). But, architects must choose and interpret the right performance metrics and goals. Focusing only on what can be measured risks missing important factors like social impact, cultural context, and long-term flexibility. As research points out, the best results come when AI insights are combined with architectural judgment and ethical responsibility (Zhong et al., 2024).

Hallucinations and Unreliable Outputs

One major flaw of the current AI systems in architecture is their tendency to produce hallucinations. These are outputs that seem convincing but are actually incorrect, incomplete, or inconsistent. Research shows that hallucinations are not rare mistakes, but rather a result of how AI generates responses based on probability instead of verified facts (Ji et al., 2023).Studies on how hallucinations happen show that AI can make up references, misunderstand rules, or create solutions that do not make sense when it works outside its training data (Zhang et al., 2023). In architecture, this might look like wrong dimensions, inaccurate environmental predictions, or attractive designs that do not meet structural or legal standards. Since these outputs often seem very confident, users may find it hard to tell the difference between mistakes and trustworthy information.The risk of hallucinations is even higher during early design stages, when AI tools are often used to speed up idea generation and decisions. Research shows that if these tools are used in complex situations without strong checks, early mistakes can carry through later stages, causing bigger errors and wrong project assumptions (Zhang et al., 2023). This is a serious issue in architecture, where early choices have a big impact on later technical and financial results.The Royal Institute of British Architects recognizes both the benefits and challenges of using AI in architecture, but it does not directly warn against treating AI outputs as final authority (Architects, n.d.). Judgment still rests with the architect (RIBA, 2024). Relying too much on AI without careful review can lead to legal, ethical, and professional risks, especially if incorrect information ends up in final work.From a knowledge perspective, hallucinations show a basic gap between what computers predict and what architects know. AI can mix patterns from data, but it cannot understand context, reason with intent, or make ethical decisions as architects do (Ji et al., 2023). So, just because AI can work on its own does not mean its results are reliable or expert.Solving the problem of hallucinations in architecture requires strong human oversight, careful review, and professional responsibility. Architects need to question AI results, spot uncertainty, and step in when needed. Instead of replacing human judgment, hallucinations make architectural expertise even more important, with architects remaining the final decision-makers in AI-supported design.

Increased Liability and Responsibility

Concerns about hallucinations and unreliable AI outputs raise important questions about liability and professional responsibility in architecture. When AI systems add unpredictable results to design workflows, the need for careful checking and accountability actually grows. Architects must still find, assess, and fix any errors from AI, such as incorrect facts, misleading analyses, or speculative visuals, before using them in project decisions.

Professional organizations make it clear that humans are always responsible for architectural outcomes. The Royal Institute of British Architects says that using AI does not shift liability from the architect to the tool or its developer. Architects are still legally and ethically responsible for following regulations, safety standards, and contracts, even if AI was used in the design process (RIBA, 2024). So, AI does not replace professional judgment; instead, it makes careful oversight, documentation, and critical review even more important.Academic studies support this view. El Moussaoui (2024) explains that AI should be seen only as a tool to support decisions, not as an independent decision-maker. Since AI lacks context and cannot understand norms, it cannot be responsible for design outcomes. Using AI adds new risks for architects to manage, such as checking data sources, reviewing model assumptions, and making sure outputs fit the specific needs of each project.Looking at governance, international guidelines make this responsibility even clearer. The OECD's principles on artificial intelligence say that accountability for AI-assisted decisions must always lead back to people, especially in professional and safety-critical fields (OECD, 2023). These principles highlight that transparency, clear explanations, and human oversight are essential for responsible AI use, which means architects have even more professional duties.New regulations support this trend. The European Union's Artificial Intelligence Act labels many decision-support systems in planning, construction, and environmental assessment as high-risk, and it clearly requires human oversight and risk controls. Instead of lowering professional responsibility, these rules make it official that architects are the final authority for checking, validating, and approving AI-generated results (European Commission, 2023).

Over-Reliance and Reduced Critical Judgment

The risk of using artificial intelligence in architecture is that architects may gradually lose their critical judgment by relying too much on automated platforms. AI tools improve at analysis, options, and suggestions, architects can start letting these systems make decisions for them because they seem efficient and or trustworthy. According to Floridi, as AI becomes a primary tool in design work, there is a growing change in the way people create and trust knowledge, showing a core balance between proven correctness and the broad capabilities of AI systems. Digital systems now shape how we see things, so people often let computers decide what counts as true, even though how these systems work is not always clear. In architecture, this means design choices might be based on what algorithms say instead of careful thinking, especially when AI results look well-optimized or data-driven. According to Clark's theory of extended cognition, tools are not just aids but actually becoming a part of our thinking process, changing where and how we reason (Clark, 2008). When outside systems start to define problems, suggest answers, and judge results, people may hand over not just tasks but also their own judgment. In architecture, this can reduce the chances to question ideas, rethink design problems, or explore concepts more deeply (Clark, 2008). This worry is similar to earlier criticisms of heavy dependence on technology in design. Maldonado (1970) warned that if design becomes focused only on technical systems and capability, then critical thinking as well as ethical obligation may take a back seat to just getting things done. Even though Maldonado wrote before the information age, his point fits today's AI-driven approach, where automation can lead people to accept system-generated answers without thinking them through (Maldonado, 1970). Early ideas about humans and machines working together in architecture also recognized this problem. Negroponte (1970) saw intelligent systems as partners in design, but stressed that real teamwork needs people to stay involved and think critically. If architects stop being actively engaged, machines may end up making more decisions, and architects could become just choosers of options made by AI. Today, this risk is even greater because AI works quickly, handles large amounts of data, and presents results in a convincing way, making it easier to rely on them without question (Negroponte, 1970). It is important to note that relying too much on AI is not because architects are careless, but because today's work requirements push for efficiency. As mentioned earlier, AI speeds up work and opens up new design options. But this speed can also make people less likely to stop and think, especially when fast results are rewarded. When you add the risks of AI making mistakes and the fact that architects are still responsible for the results, the problem grows: architects are encouraged to trust systems that cannot take responsibility themselves.

Deskiling and Dependency on Tools

As AI systems take over tasks that were central to architectural training, such as drawing, modeling, spatial reasoning, and analysis, there is concern that important professional skills could gradually disappear. This risk increases for architects to use automated systems more frequently to create, review, and improve their designs. From a cognitive perspective, tools that start as helpful supports can eventually replace internal skills if people rely on them too much (Clark, 2008). When reasoning, evaluation, and problem framing are handed over to external systems, people may lose the ability to do these tasks on their own. In architectural work, this can manifest as less skill in manual drawing, weaker spatial intuition, and fewer problem-solving methods, especially among less experienced architects (Clark, 2008). Today, this risk is even higher because AI can produce good results much faster than people, so there is less motivation to keep practicing and improving basic skills. In architecture, these concerns can change daily work. Bernstein (2025) notes that , AI can make work more efficient, it may also change the profession that can mostly impact junior architects. Activities that previously helped people build skills, like repeated drawing, modeling, and analysis, are now often automated. This could make it harder for new architects to learn and develop, and over time, the field might depend more on tools and have fewer people with deep expertise (Bernstein, 2025).

Economic Pressure and Job Insecurity

Deskilling and reduced judgment impact more than knowledge; they impact architecture's economic structure. As AI takes over drafting, visualization, option generation, and early analysis, firms rethink staff roles, project fees, and work allocation. These changes add economic pressure, especially for early and mid-career architects. They also raise concerns about long-term job security. Economically, automation is changing professional work by breaking down complex skills into smaller tasks that machines can handle. Susskind and Susskind (2015) note that when professional knowledge is organized and built into digital tools, the value of human expertise goes down. This makes it easier to replace professionals. In architecture, AI speeds up this trend by delivering good results faster and at a lower cost. As a result, firms often focus more on efficiency than on deep expertise. With more tasks automated, firms may rely less on junior architects, who used to do many of the jobs now managed by AI tools (Susskind & Susskind, 2015). Industry reports show that these pressures are already affecting architectural practice. Recent RIBA reports note that architects are worried AI could cause fee compression, job cuts, and more competition as clients expect faster work and lower costs (RIBA, 2024; RIBA, 2025). This economic shift has a greater impact on less experienced architects. As mentioned earlier, AI tools now take over tasks that used to help young architects learn, such as drafting, modeling, and testing ideas. When these tasks are automated, junior roles may be cut before people gain enough experience, which can lead to a cycle of losing skills and becoming dependent on technology (Susskind & Susskind, 2015). Economic pressure and job insecurity are not just side effects of AI adoption. They are part of a larger pattern connected to deskilling, over-reliance on technology, and treating design work as a commodity. AI can make work more efficient and productive, but without thoughtful action from professionals and institutions, it could threaten the long-term stability of architectural practice. To meet this challenge, the field needs both technical changes and shared efforts to protect professional value, support fair labor practices, and rethink how architectural skills are valued as automation grows.

3.4 Sustainability and Environmental Impacts

As the ıse of artificial intelligence grows quickly, it is linked to major environmental impacts. Most of these effects come from the expanding digital infrastructure needed to run AI systems. A recent overview study for Greenpeace by Oeko-Institut Consult reviews about 100 sources to describe the direct environmental impacts of AI, focusing on data centres and AI-specific infrastructure. It examines energy use, greenhouse-gas emissions, water use, resource extraction, and electronic waste (Gröger et al., 2025). Gröger et al. (2025) bring together several datasets and scenario studies to set a baseline for global electricity use by data centres, including those used for cryptocurrency, at about 487 TWh in 2023. They also estimate that AI tasks in data centres used around 50 TWh in 2023, showing that AI already makes up a noticeable part of global digital energy concumption (Gröger et al., 2025). The report highlights that rapid digital infrastructure growth is worsening environmental challenges. Gröger et al. (2025) find that global data-centre electricity demand is increasing at an average compound annual growth rate of approximately 16% from the 2023 baseline, reflecting rapid expansion rather than stability (Gröger et al., 2025). They also note that global data-centre installed electrical capacity reached 55 GW in 2023, and, based on McKinsey's estimates, is growing by about 22% annually. This suggests a doubling of capacity roughly every four years (Gröger et al., 2025).

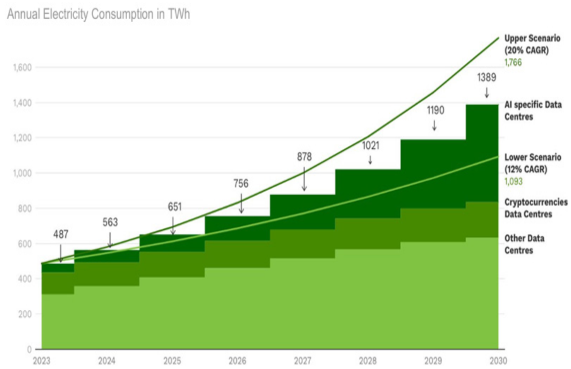


Figure 64. Source: own compilation based on IEA 2025; Deloitte 2024; McKinsey 2024; LBNL 2024; Digiconomist 2025

Artificial intelligence is playing a bigger role in architecture and construction, and this is affecting the sector's environmental footprint. As AI tools become part of design, simulation, and building operations, they influence choices about low-carbon design, lifecycle assessment, and building performance (Płoszaj-Mazurek & Ryńska, 2024). In both buildings and cities, AI is used in smart buildings and digital twins, where ongoing data processing and optimisation depend on constant computing power. Globally, this growing use of AI in building technologies adds to the energy demand of data centres and digital infrastructure, increasing the environmental impacts seen in wider AI studies (Hosseini et al., 2025). Because of this, architecture and construction are not just passive users of AI. They help drive AI adoption and provide the physical infrastructure—like buildings, data centres, and energy systems—that AI needs. This means that assessing architecture is key to understanding AI's environmental impacts. Sustainability frameworks now need to consider not only the materials and operations of buildings, but also the computing resources and digital infrastructure that are becoming part of architectural practice.

3.5 Expanding or Restricted?

After studying and rewieving the current developments of AI , the phenomenons that it brings and the tools that are getting in and becoming a part of our lives , one important question occurs. Is ai expanding our role as architects or is it restring us from further development? The answer is yes and no.However it is for now.We will focus on the current developments but , the future predictions and possible outcomes are important points that we will cover later.First we will see how AI is expanding ou roles as architects. Architecture by nature is a profession that is interconnected with many other disciplines such as engineering ,construction,assesment etc..It is safe to say that even among the same fields , architects most of the time have difficulty with communication , understaing the workflow, design process and professional approach of other architects.And this creates delays in projects, erros in execution and on some cases complete pause of a project.AI here act as a mediator for architects to overcome these issues creating a communication channel for different disciplines to talk with eachother on a more effective spectrum. Maximizing the time , effort and the productivity.This changes the decision making mechanism work on a different level of coherence. This is also supported by automation of the tasks by AI changing the architect's role, moving it towards a higher-responsibility tasks like system integration, judgment, and managing complex digital design systems. Instead of mainly producing drawings and standard outputs, architects now focus on organizing information, bringing stakeholders together, and making sure AI-supported decisions are safe, compliant, and ethically sound (RIBA, 2025).A good example of an expantion is, when assessing sustainability, AI already helps with early decisions. It can quickly predict performance, test options, monitor operations for faults, adapt controls, model retrofit scenarios, and even help with compliance or certification (Ersener & Fokaides, 2025). Now this means architects can now go beyond just designing and handing over a project. Their skills are in active use for data-driven evaluation, managing trade-offs, and thinking about performance over the building's entire life. Often, this work is done together with engineers, data experts, and those who operate the building but with the help of AI an architect can manage a major part of this process.Another important aspect is in representation. Renderings and realistic image outputs of an ongoing project is what "talks the most" with stakeholders and clients. Now we can say that being able to provide a great graphical representation is one of the core requirements of being architect however there are leves to that. The reasons can be discussed but we can say not every architect has the same level of capability in this field. Some are more cpabale and efficient while other may struggle to match the expectation of graphical outcome of stakeholders.Here the responsible use of generative AI plays a crucial role. An architect with the proper knowledge of tools like Stable Diffusion, DALL-E, Midjourney and other nerative AI tools can produce material that can help for stakeholders and clients to visualize what exactly is being made or giong to be made.Creating a fast communication channel between architects and clients working on rapid feedback reports and utilizing all he sources like monet , time and energy in the most productive way possible. Huang (2025) describes this as a move toward "connectionist" generative systems. He says that design thinking is shifting from following set rules to exploring possibilities in a more flexible way, known as "latent space." This means architects now need to focus more on guiding, interpreting, and taking responsibility for AI-generated designs. As these tools quickly create many options, architects must choose, check, and explain which ones are suitable, buildable, and meet client and public needs, rather than just making different design versions (Huang, 2025). This "expansion" means architects are now setting rules for how to use tools, who gets credit, and how to use AI responsibly. This is especially important as AI becomes a regular part of practice, not just something to experiment with.Also with using AI , comes a skill of digital literacy and analysis. Firms will need skills in managing data, reviewing AI outputs, combining different tools, and handling risks like copyright, ethics, and liability. These tasks are more about leadership and governance than basic production work (RIBA, 2025).

There is one key point of this expantion which just keeps it as an expantion rather than a replacement. None of these woud work without the architect. AI is just a cog within the great machine of architectural practice now just like architects.One piece is out ,results the disfucntion of a really complex and a deep process which will inevitably result in failure.The key responsibilities such as public safety, client communication, and professional accountability still belong to architects and are rooted in human judgment.

But AI in architecture just like some other professions poses a significant danger for the professionals.We can not talk about a total take over now as of 2020s but studying the development of AI and It's aggresive pace it is a significant issue for our profession. Many of the AIs positive aspects naturally bring-restrictions to our role.It is important to define the restriction here becasue we are not talking about a Terminator type distopian scenario where we are being restricted by machine intelligence to do our profession it is rather a natural restriction that comes from loosing a skill.Human evolution and evolution of almost all species in the world shows us that when something is not being used , it is eliminated.And in cognitive skills this issue is far more damaging than we think. Because this brings deskilling through over-reliance. As AI systems can now generate design options, images, and text at very low cost, architects may find themselves choosing from AI outputs instead of creating original designs. El Moussaoui (2025) notes that AI changes the traditional economic model, where architects were paid for producing drawings, by making drawings “cheap” and design work easier to commodify. These changes can threaten the profession’s value and independence. Ethical experts also warn that relying too much on automated ideas and optimisation can weaken creative integrity and reduce the motivation to build hands-on skills, unless strong standards for human oversight are kept (Sunil, 2024). Another risk is the black-box effect. Architects are often asked to use AI tools without enough information about how the results are created, what data is used, or what biases or mistakes might be present. The AIA’s research report shows that many people are worried about AI’s lack of transparency and possible errors. There is also concern that AI outputs can seem convincing but still be technically wrong, which is a serious problem in a field responsible for public health, safety, and welfare (Russo, 2025).Then comes the loss of authorship, liability, and workflow control.

Yiannoudes' (2025) systematic review finds that many generative AI outputs remain poorly integrated into CAD/BIM-centered delivery pipelines. These outputs are often raster or non-editable, leading to fragmented workflows and manual hand-offs that limit direct professional usability. The review also highlights broader ecosystem challenges in data sharing, authorship, and liability. These challenges arise when moving from experimental ideation to mainstream practice. AI may soon replace certain forms of "standard design," implying a narrowing of architectural work toward what is harder to automate, while also raising ethical and legal questions about how AI-generated representations are translated into functional and accountable design deliverables (Architects' Council of Europe, 2023). So even now this natural restriction are taking place. Overall for our current time the expantion of AI enables us is more that the restrictions. But keyword here is "now". Based on this study , with the current pace of AI and not enough regulatory oversight the future is not really bright for architects. We will now see the ethical and social aspects of this issue and only then a more clear prediction for the future will be more possible to make.

3.6 Ethical and Social Dimensions

Ethics is a set of moral principles and norms that govern an individual or a group of people to achieve good outcomes, according to Merriam-Webster dictionary(Merriam-Webster, 2025). Ethics provides rules of conduct to society and encourages members to behave in a way that is right, rather than enforced by regulations likegovernment laws. Specifically, ethics examines human behaviors in terms of good and bad, or morally correct and wrong (Bartneck et al., 2021). The ethical principles are determined and developed by society over the years and all members of the society follow ethical behavior to build trust with each other. The Architecture, Engineering, and Construction (AEC) industry has been continually growing over the last decade, which is one of the most influential markets globally. So naturally ethical concerns in AI have been accentuated recently. Ethics is an important aspect that affects the workplace and society, which has also been taken into account in the AEC industry. Researchers have been debating the ethical issues and dilemmas in architecture and construction. However, such ethical concerns in the AEC industry do not consider the presence of AI. For example, the rapidly growing large language models has changed methods to complete job duties in some industries. This raises concerns about job replacement or security issues when applying these emerging technologies. Therefore, it is necessary to investigate the ethical issues of AI particularly in the context of architecture. AI has impacted architectural arena rather dramatically. However, with better tools that are arriving, the architecture industry needs to face a critical ethical dilemma: How do we balance the incredible potential of automation with human creativity and intent, which traditionally has driven architectural design? Probably the most serious ethical issue with AI in architecture is the authorship. While AI design will put out the architecture, it does not seem entirely clear if the person who has provided the input for the architecture is to be credited as the creator, or the creative credit must go to the AI itself, which now seems to create “originally”.Here as architects, we must remember that buildings are more than just functional spaces; they are reflections of culture, identity, and human interaction. Because it is the only way that this credit can be solemnly human. AI can learn the culture, identity, and human aspects but it can not reflect , relate ot represent them in architectural creations. Another issue is the data collection.AI can not operate without data. And here we must ask a question , what is the extent of this data requirement? This is not remark just for the amount but for the confidentiality of the data how much of the private data should be fed to AI and who is giving the guarantee of the safety of these information. Who will be in charge of managing these datasets? In chapter "3.3 Impacts of AI on Architects and Practice" we have stuided the positive and negative impacts of AI, they are directly corelated to the ethical and sociological dimensions. Based on the analysis of the impacts of AI, we identify nine categories of ethical issues marked, including “job loss,” “data privacy,””data security,” “data transparency,” ”decision-making conflict,” “acceptance and trust,” “fear of surveillance,” “reliability and safety,” and “liability.” We will discuss the nine ethical issues of AI and robotics and their implications.

Job Loss

One main reason for job-loss risk is that automation pipelines are replacing tasks. The literature shows that robots and AI systems now help with data capture and model updates, such as collecting site data, registering it to BIM, monitoring progress, and automating work that humans used to do manually (Liang et al., 2023, pp. 26–27). The ethical issue is not just about jobs disappearing, but also about jobs changing or being replaced. Even if automation does not greatly reduce the total number of jobs and sometimes creates new ones, current workers still need to learn new skills to keep up with changing job demands. Helping people through this transition is important to reduce job insecurity.

Data Privacy

In architectural practice, data privacy becomes an ethical issue because AI systems are based more on digital, networked, and cloud-stored data. This data is often spread across many servers, making online software and services more open to privacy problems (Liang et al., 2023, pp. 27–29). This risk concerns not only data about buildings as well as people and projects. AI monitoring and automation collect information from scanners, wearables, and cameras, which is then used for tasks like tracking, documentation, safety, risk analysis, and training (Liang et al., 2023, pp. 27–29). The ethical risk comes when these datasets capture more than intended—such as individuals recorded without consent or confidential project information included by accident—causing worries about weak protection, the spread of sensitive material, and misuse if there is a breach (Liang et al., 2023, pp. 28–29).

Data Security

Data security is an ethical concern in architecture ,AI-driven and digital workflows depend on fast data sharing across connected systems. This makes a complex environment where large amounts of project data move between different people and platforms (Liang et al., 2023, pp. 29–30). Many architecture firms still use traditional storage methods like local devices, office servers, and shared drives.These methods can increase the risk of cybersecurity threats and data corruption during transfer, such as, information theft, viruses, worms, and hacking. These risks are higher when on-site or home-office devices are not well protected and when credentials are shared because of poor security.(Liang et al., 2023).

Data Transparency

Data transparency, explicability, explainability, and interpretability have been discussed in AI and robotics applications as one important aspect to improve human trust. However, AI algo rithms are usually opaque to end-users, i.e., a black box that generates out comes [59, 60, 271]. In particular, the advancement of deep learning makes AI systems more difficult to understand. Bartneck et al. [270] argued that transparency differs from applicability, explainability, and interpretability.

Decision-making Conflict

Decision-making conflicts occur when AI make decisions differently from humans in the same situation. In decision-making scenarios,human workers rely on their experiences and the current situation, whereas AI systems make decisions based on the trained model and the current situation. As a result, they might reach contradictory decisions despite having the same data and conditions. In such cases, resolving these conflicts and making the final decision is more challenging for people because of the conflicted recommendations, and their decision may be influenced by the AI system. These conflicts between humans and AI systems also decrease the team trust dynamic. In addition, most AI systems do not consider the emotional or relational aspects of collaborating workers during the decision-making process, which are important to the performance of human workers. AI systems can also be biased in making decisions due to the training data, which emphasizes the need for fair AI systems.

Acceptance and Trust

Trust in human-robot or human-AI collaboration plays a crucial role in the successful deployment, especially for team performance and safety. When introducing emerging technologies to industries, it is necessary to ensure that human workers trust and accept them. To establish trust, Bartneck (Bartneck et al., 2021) proposed five principles for trustworthy AI, according to European ethical principles for AI, which are non-maleficence, beneficence, autonomy, justice, and explicability. AI and robot systems should not hurt human workers. Instead, AI and robot systems should benefit workers while preserving their rights and authority. Fairness and explicability encourage human workers to understand the outcome of AI systems, which is related to data transparency and decision-making conflicts.

Reliability and Safety

Despite efforts to use AI in architecture over the past decades, their reliability in real-world situations remains a concern. A major challenge in building trust in AI.Without common standards, it is hard to judge how reliable computer vision solutions are in different real-world settings, like various building types or construction sites. Another key challenge for trustworthy AI is the lack of explainability and interpretability. These systems are often seen as a black box, meaning the details of how the algorithms work, such as feature engineering, are usually not clear.

Fear of Surveillance

The fear of surveillance is an important ethical issue as more cameras and sensors are used in the construction industry. While camera systems are now a key part of collecting visual information on construction sites, how well the data is processed still depends heavily on factors such as lighting, weather, and camera placement. Even though on-site sensor use offers many benefits, people are concerned about workers being constantly monitored. Having cameras around and knowing they are being watched can affect how workers feel and how well they do their jobs. Unlike machines, workers do tasks that involve different movements and positions. Knowing they are always being watched by cameras can hurt workers' mental and emotional health and make them feel less trusting.

Liability

Liability means being held responsible or accountable. Machine learning and deep learning are transforming construction by detecting and predicting progress, safety, and quality issues using visual and textual data . Achieving higher accuracy is essential for practical use, not just expanding object detection. Without enough accuracy to earn managers' trust, these systems' liability in practice is questionable.

FOURTH CHAPTER

INDUSTRY ADOPTION OF AI IN ARCHITECTURE EVIDENCE FROM LEADING FIRMS

04

Intro & Selection Logic

In this chapter , we will review some of the leading firns of industry who have alreade been adopting the AI in their official workflow. The importnat topics that we have discussed before such as ethics, rules & regulatons are deeply connected with this chapter because these leading firms are on a course to set the standard of the AI use in architecture. Because the discussion of "application areas" of artificial intelligence in architecture can remain abstract if it is limited to what AI could do in principle. This section reframes the topic as industry adoption of AI to use in their daily work, decision-making, and service delivery. A firm-based perspective is especially relevant to this thesis because architectural assessment is not a single, isolated journey , it is a continuous process of evaluating options, performance, risk, and compliance across the project lifecycle and other disciplines which are involved in the practice.Methodologically the selection of the study firms were made with a logic of how much the AI adoptation/use is being structrulized within the firm that includes if there is a dedicated department ,firm's AI use connects to evaluation practices such as performance analysis, workplace/occupancy insights, optimization, or asset/system monitoring AI in their projects.

Based on these criterias , four firms are selected: Zaha Hadid Architects (ZHA), Foster + Partners, Arup, and MVRDV. ZHA is included because it has an specific research unit, Zaha Hadid Analytics + Insights (ZHAI), dedicate to using data and AI to inform workplace design and performance an area closely related with the assessment. Foster + Partners is selected because its Applied Research + Development (Applied R+D) team is oficially taken the into the position of translating the emerging technologies "out of the lab and into the hands of architects and engineers" . Arup is chosen because their official positioning for the AI and ML are "already at the heart" of their work and it is directly linked to AI for understanding asset performance and improving the workflow. Finally, MVRDV as a design practice that has institutionalized innovation through MVRDV NEXT, an in-house specialist group developing computational workflows and new technologies, explicitly oriented toward making projects more efficient and "data-driven," and publicly engaging with AI integration in design processes through its own events and communications.

ZAHA HADID ARCHITECTS (ZHA)

Name: Zaha Hadid Architects (ZHA)

HQ : London, UK

Founded in : 1979

Zaha Hadid Architects have openly embraced AI as a creative aid across many of their projects. Like many established architecture firms with research and analysis departments, Zaha Hadid Architects in London set up its own group in 2007. Called ZHA Code, it was founded by Shajay Bhooshan, Patrik Schumacher, and Nils Fischer. The group works to develop research and practice together, using their expertise regardless of the specific opportunities, challenges, or issues in each project. Their research helps with every step, from planning to building, for all kinds of buildings, like schools and homes. This means they can create new ways of working that give clients strong, well-made buildings and help the team's designers solve problems quickly.Their research is based on extra-ordinary computational design that has extended to may different fields and now their reach is also including the AI.

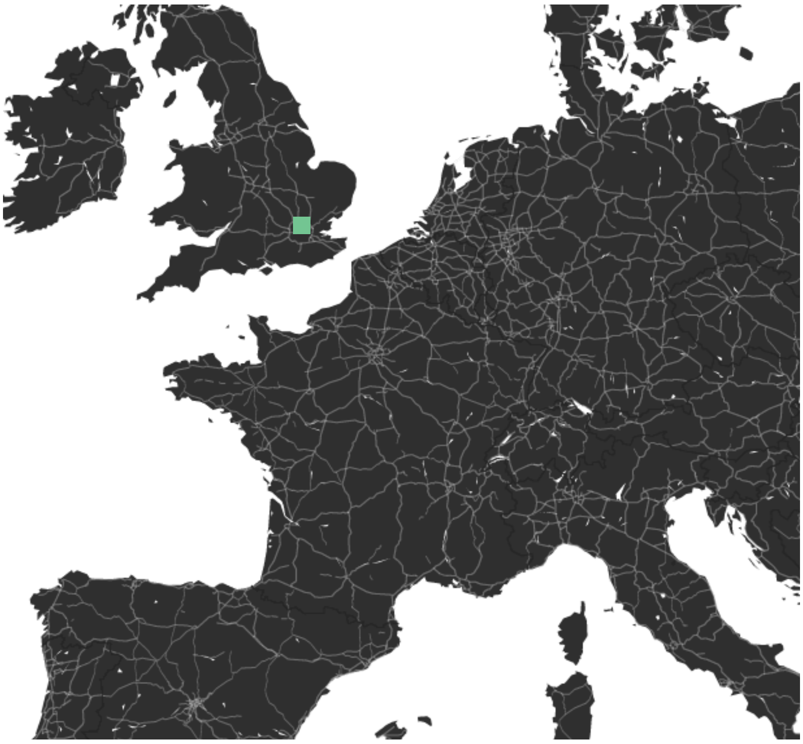


Figure 65. Source: Zaha Hadid Architects , Refik Anadol Studio with OpenAI , DALL-E

Figure 66. At the headquarters of Zaha Hadid Architects in London, Uli Blum, left, and a colleague analyze a visualization of employees' locations and interactions in their office — part of ZHAI, the firm's unit devoted to using A.I. to rethink work spaces.Credit:Jeremie Souteyrat for The New York Times

Figure 67. Using text-to-image AI models that are refined from large base models using custom ZHA training data, to quickly visualise massing options in greater architectural and photographic realism

(Image credit: Zaha Hadid Architects)

By training models to interpret design briefs and generate innovative concepts, ZHA has been able to streamline its creative process without compromising the quality or uniqueness of its designs. Schumacher views AI as an indispensable tool for the firm's continued success in the highly competitive world of architecture. He said "We're not just using AI to speed up processes; we're using it to expand the possibilities of design itself". Generative AI tools like Stable Diffusion and Rhino.ai now play a key role in ZHA's workflow. With these tools, architects can turn simple sketches into refined renderings in just a few hours. In the past, this process would have taken days or even weeks. Working faster lets the firm explore more design ideas, give clients more choices, and shorten project durations. According to Schumacher, the studio normally chooses "10 to 15%" of the AI-generated images to advance to the 3D modeling phase, emphasizing their inherent coherence and suggested three-dimensionality, which aids the modeling process. He also stated that Zaha Hadid Architects has formed an internal AI research team. So how has ZHA's use of AI deveoped? According to Shajay Bhooshan, the gulf between the two-dimensional image and the three-dimensional model are still huge. 'Images are a unified format – there are billions of them. They align with the way computer hardware works. 3D is different,' he says, 'those prerequisites are not there.' Ultimately, ZHA is seeking to create a 'prototype unified file format that would be the 3D equivalent of an image,' something that could be used to train a generative AI.

Figure 68. Experimental results from teaching text-to-image AI to produce structurally and contextually meaningful outcomes (Image credit: Zaha Hadid Architects)

Figure 69. Experimental results from teaching text-to-image AI to produce structurally and contextually meaningful outcomes (Image credit: Zaha Hadid Architects)

Nansha Stadium

As Fischer notes, ‘most of our cities happen without architecture – look at the coast between Hangzhou and Shenzhen, where 40 million people live. In 20 years, we’ll need cities for 600 million people just to match population projections.’ ‘One of the key roles AI will play in our industry is to democratise design, which will be a good thing,’ says Shajay Bhooshan. The idea that complex buildings using the fluid, sculptural forms associated with the studio – and with Zaha’s own artistry and practice – could be generated by a set of parameters is unnerving. However, ZHA are quick to point out that they provide a premium product, innovating through public buildings like stadiums, galleries and transport interchanges. ‘We’re a top tier practice because we never do anything twice,’ says Fischer, ‘our AI toolkit will help us do that. Construction is not rocket science, but pretty much every building is a prototype,’ he adds, ‘AI can overcome the inherent inefficiencies in the construction market.’ ZHA believes the Nansha Stadium could be considered as ‘project zero’ of AI in architecture, a first step towards a new era of computational design that will have broad implications for architecture and urbanism all over the world.

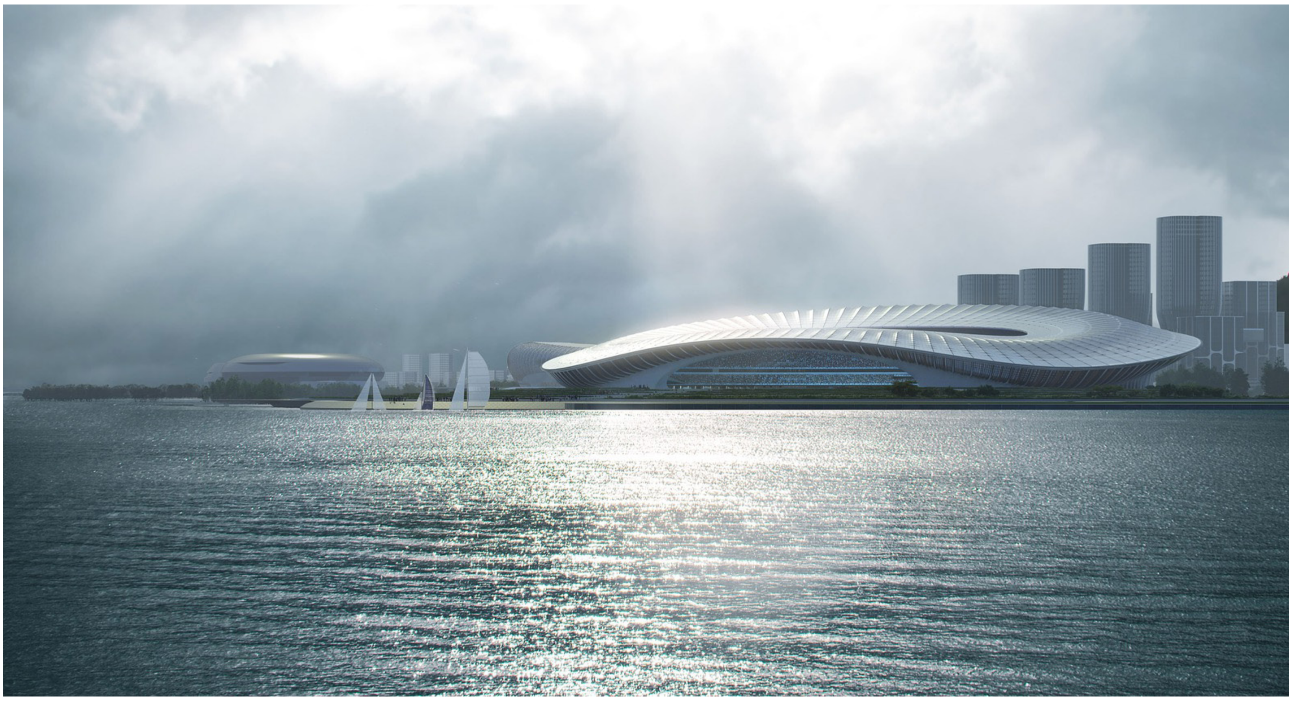


Figure 69. Nansha Stadium The Greater Bay Area Sports Centre
(Image credit: Zaha Hadid Architects)

Figure 70. Nansha Stadium The Greater Bay Area Sports Centre
(Image credit: Zaha Hadid Architects)

Figure 71. Nansha Stadium The Greater Bay Area Sports Centre
(Image credit: Zaha Hadid Architects)

Figure 72. Nansha Stadium The Greater Bay Area Sports Centre construction
(Image credit: Zaha Hadid Architects)

Figure 73. Nansha Stadium The Greater Bay Area Sports Centre construction
(Image credit: Zaha Hadid Architects)

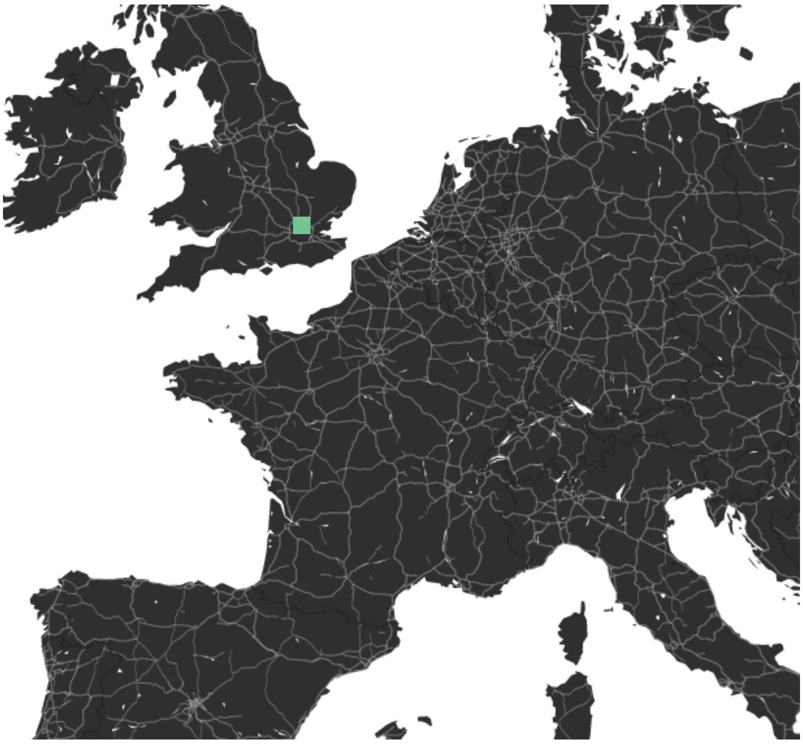
FOSTER+PARTNERS

Foster + Partners

Name: Foster + Partners

HQ : London, UK

Founded in : 1967.



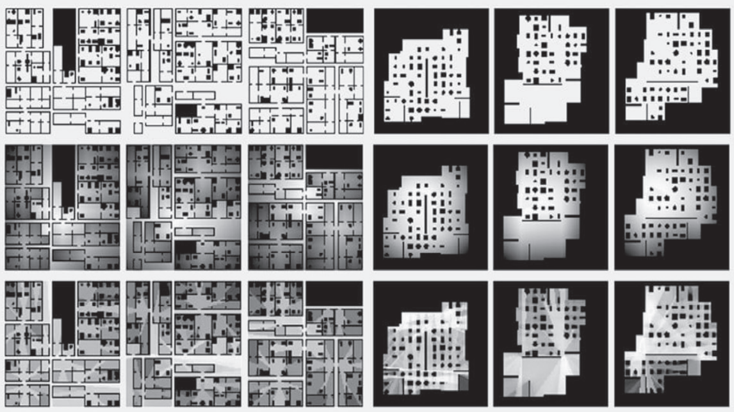


Figure 74. The top row of images shows a sample of floor-plan outputs from the parametric model, showing three compartmentalized (left) and three open-plan work spaces (right). The middle row visualises the output of the spatial connectivity analysis on these floor plans, and bottom row shows the visual connectivity analysis. © Foster + Partners

Foster + Partners has applied AI in both research and real projects, mainly in big scale sustainable masterplans. Foster + Partners approaches AI with a dedicated team. The firm's Applied Research and Development (ARD) team has over 40 researchers (computational designers, data scientists, etc.) exploring the generative design and machine learning in-house. One of their internal platforms, nicknamed "Previz," focuses on generative design research, and the team has developed AI-based tools like "Masque." Masque is an AI-driven space planning tool that automates early-stage floorplan layouts, rapidly producing viable configurations so architects can adapt more freely. But beyond floorplans they also experiment with neural network models that mimic physics simulations. To get real-time feedback on performance issues like structural behavior. In their design process, they utilize predictive analysis like machine learning for urban trends or resource needs ,and generative design algorithms that can create forms based on multiple elements. The firm is known to use custom parametric scripts and AI to test thousands of design options (for facade patterns, layouts, etc.) before selecting the best ones. So Foster + Partners use a lot of AI techniques: generative design tools, neural-network-based simulators, and large data analytics, all controlled by teams to enhance the design process.

The Forestias

The Forestias by Foster + Partners is a contemporary urban living space while integrating residential living with a preserved forest landscape.Built on 785,000 m2 , and completed in 2025 the project stands as an ambitious design showcasing the integration of high-tech tools such as AI and generative design with nature-focused planning. Defining part of The Forestias is the use of AI, which shape both its look and function. Complex AI algorithms analyzed biodiversity at the local level, weather patterns, and environmental factors to create micro-ecosystems that encourage native flora and fauna to thrive through the urban fabric. Generative design tools were used to plan layouts that boost natural ventilation and cut down on artificial energy use, guiding the placement of buildings, green spaces, and water features. The end result is an urban area inspired by nature that feels more like a naturally grown community than a typical city project.

Figure 75. The Forest Pavilion .Source , Foster + Partners.

Figure 76. The Forestias .Source , Foster + Partners.

Figure 77. The Forestias .Source , Foster + Partners.

Figure 78. The Forestias .Source , Foster + Partners.

Figure 79. The Forestias master plan .Source , Foster + Partners.

Figure 80. The Forest Pavilion .Source , Foster + Partners.

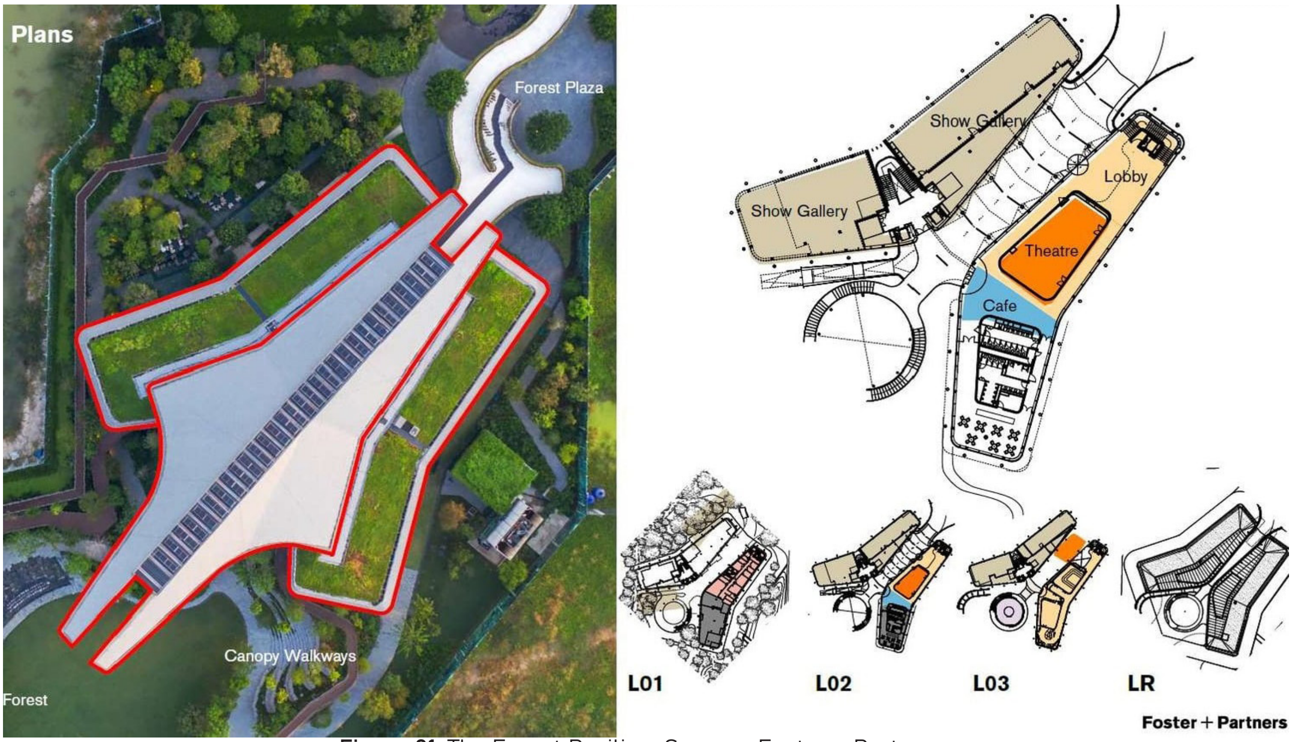


Figure 81. The Forest Pavilion .Source , Foster + Partners.

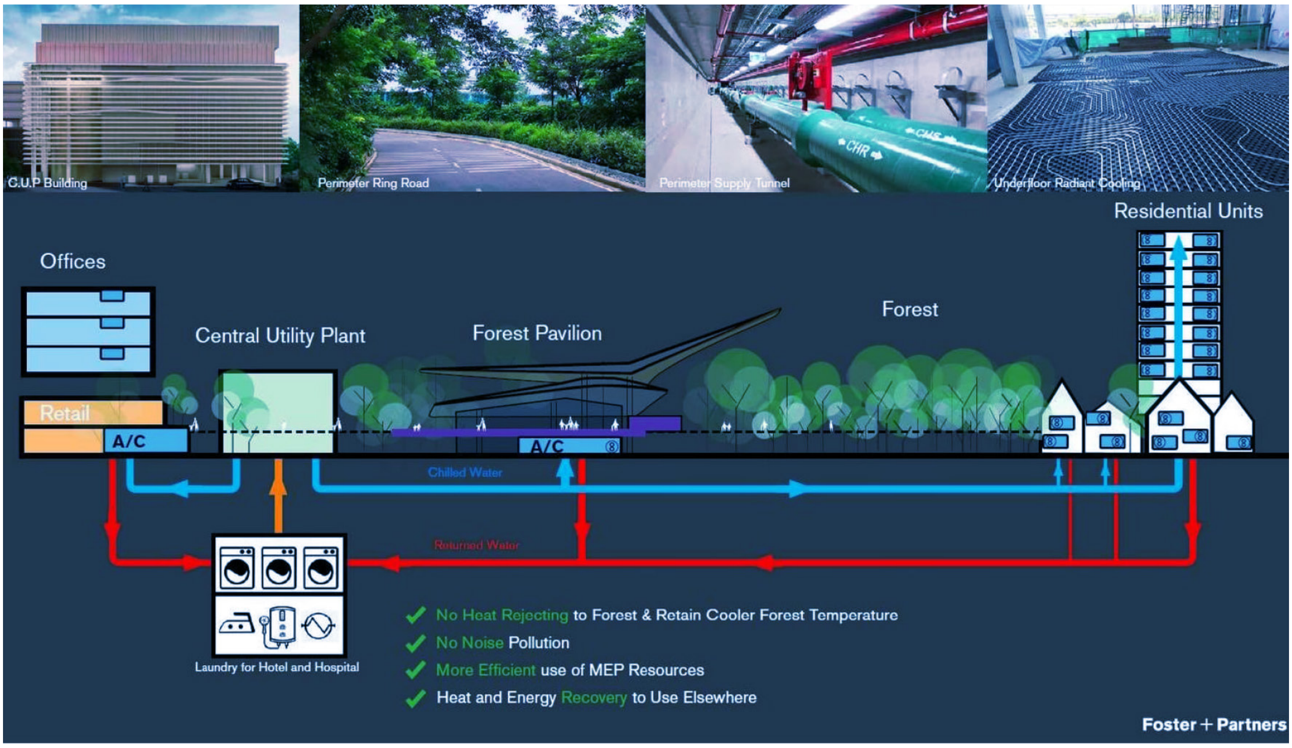


Figure 82.Source , Foster + Partners.

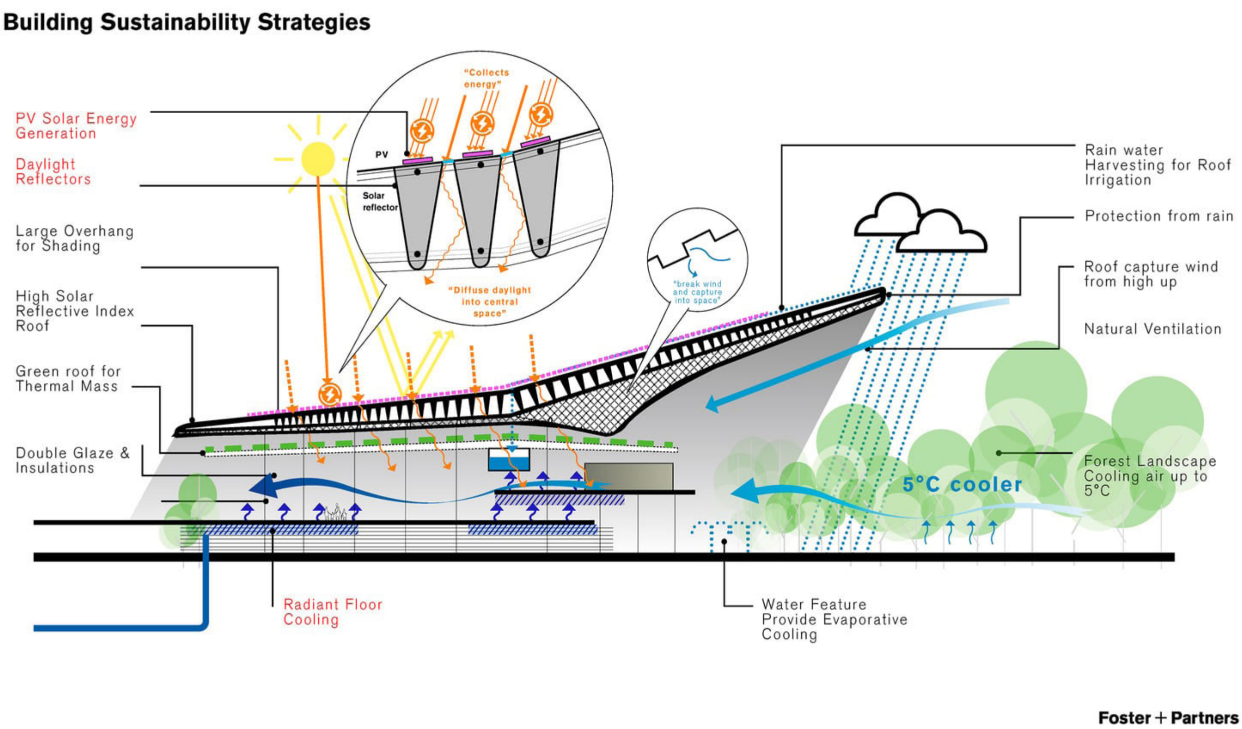


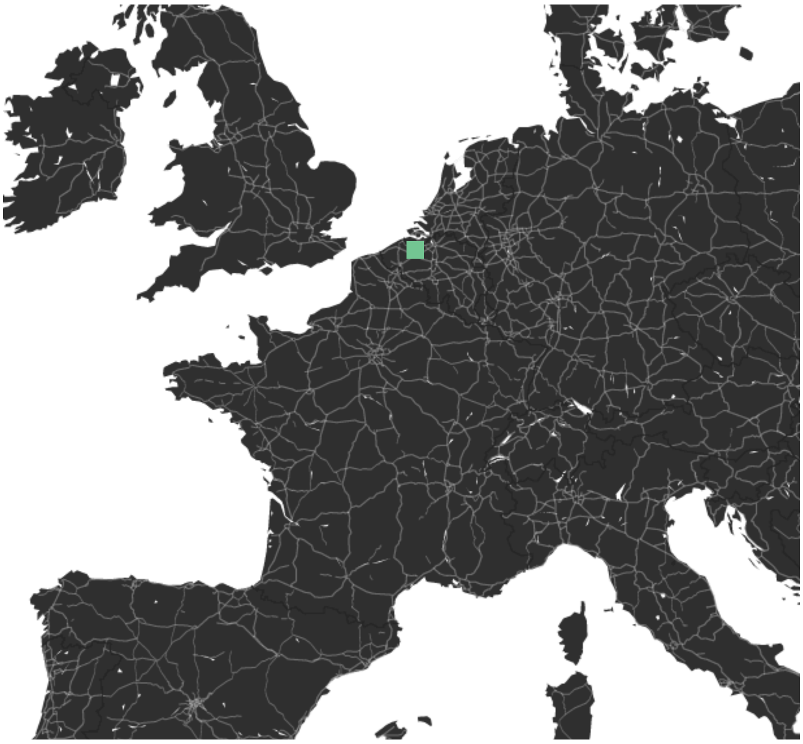
Figure 83.Source , Foster + Partners.

MVRDV

Name: MVRDV

HQ : Rotterdam, Netherlands

Founded in : 1993.



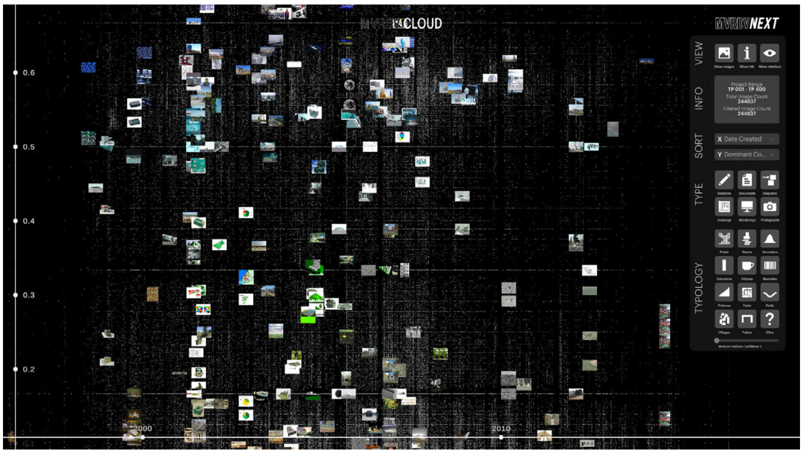


Figure 84.Developed as part of the MVRDVHNI exhibition in 2021, MVRDV Cloud uses computer vision and metadata analytics to map the contents of MVRDV's digital archive to produce new narratives and support the development of future projects by MVRDV.building operations, reduce energy consump-tion, and enhance occupant comfort.

Over the last ten years, the Dutch firm MVRDV has worked to become a data-driven de-sign practice, from analyzing its historical roots to MVRDV NEXT's current research into artificial intelligence. Architect and engineer Freddy Fortich, a researcher at the firm of the same name, examines MVRDV's current AI applications across different phases of the design process, including brainstor-ming, reference research, con-ceptualization, collage design, massing, material assignment, and rendering. Finally, the stu-dio's recent innovative work on customized AI implementation is an importnat aspect. The famous Dutch firm has gained signifi-cance in recent years thanks to its extensive research in compu-ting and architecture, especially for its wroks on data-driven design , an approach that uses data to inform and guide decisi-on-making throughout the pro-cess of creating products, servi-ces, or experiences. This method relies on collecting, analyzing, and interpreting measured data in order to better understand user needs, trends, and the performance of solutions, the firm has long adopted an internal workflow that is always evolving. And , to keep up with the latest technological advancements, the firm has founded a department in named MVRDV NEXT (New Experimental Technologies).This is where they are testing and improving new design workflows, computational design, AI-driven generative design, augmented reality, and virtual reality.They use generative analysis and automated form-finding to expand options and drive design possibilities to its maximum capacity. Among the many AI applications that can be used, they focus on image-based AI, particularly in the brainstorming phase (conceptual phase) and in the customization phase (presentation phase), describing how he implemented machine learning technology within the different stages of the design process.

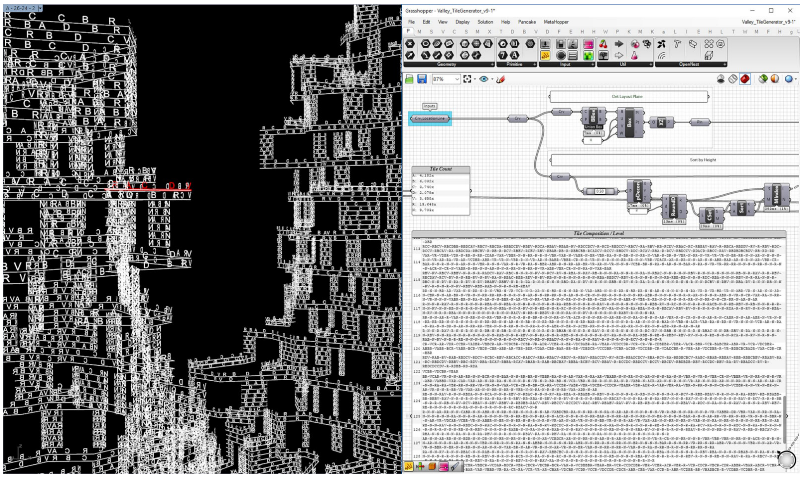


Figure 85. Valley Scripting Grasshopper.MVRDV

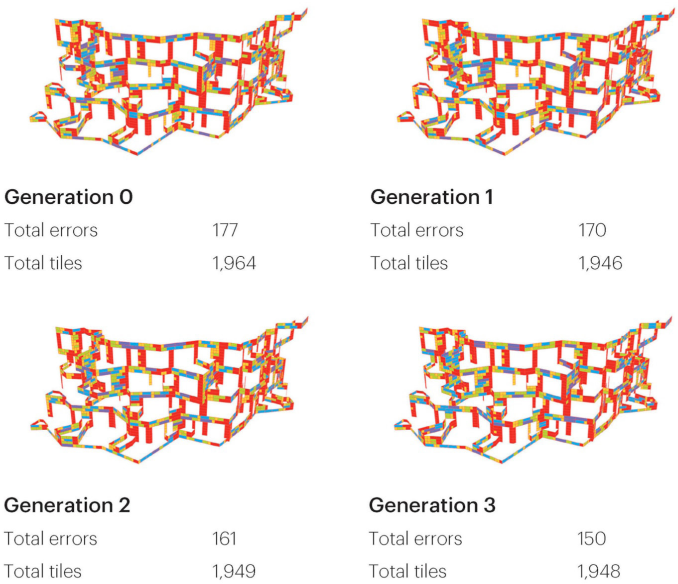


Figure 86. Valley Scripting evolutionary model.MVRDV

The Valley

Valley, the eye-catching, nature-inspired, plant-covered high-rise designed by MVRDV for developer Edge, was officially opened in a ceremony on Friday. The 75,000-square-metre building, which was recently named the world's best new skyscraper by the Emporis Awards, stands out in Amsterdam's Zuidas neighbourhood with its three towers of 67, 81, and 100 metres and its impressive overhanging apartments. Valley is an effort to bring a green and welcoming feel back to the harsh office area of Amsterdam Zuidas. The building has different looks; on the outside, a layer of smooth, mirrored glass matches the business district. Inside this layer, the building looks completely different and more inviting, as if the glass has broken away to show rough rock faces inside, filled with natural stone and plants. MVRDV's technology experts made special digital tools to perfect the building. The Valley outside walls use five set tile sizes: 200, 400, 800, 1200, and 1600 millimetres long. Because the outside walls are not regular, the lengths of the wall sections change, so a tile with a different length is added at the start or end of each row of tiles (at one of the two corners ending each wall section). The pattern is set by these sizes, along with different rules, both technical (like the longest and shortest tile allowed, limits on corners that curve in because of glued tiles, and a minimum space between seams) and visual (like not repeating the same tile more than four times and avoiding seams that line up in a row). The pattern was made by using both computer and manual work. First, a computer program called Grasshopper was used to cover the outside walls with tiles. The line model from the Revit model was filled with letters showing the set tile lengths (A for 400mm, B for 800mm, and so on). The choices for making the pattern are improved using a computer process that tries different options to find the best one. This led to using 800 and 1200 mm tiles more often than 400 and 1600 mm, and to switching the special tiles left and right within the rows of each wall section. Using the feedback from the analysis, architects then adjust the rows by hand to meet all the visual and technical rules.

Figure 87. Top view.Source:MVRDV

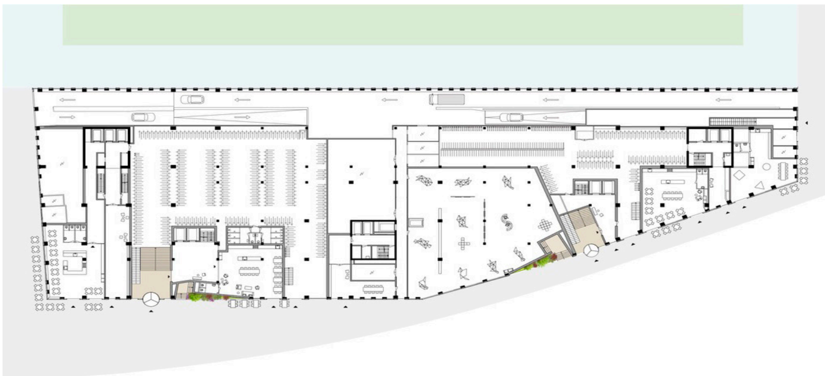


Figure 88. Ground Floor Plan.Source:MVRDV

Figure 89. 1st Floor Plan.Source:MVRDV

Figure 90. 4th Floor Plan.Source:MVRDV

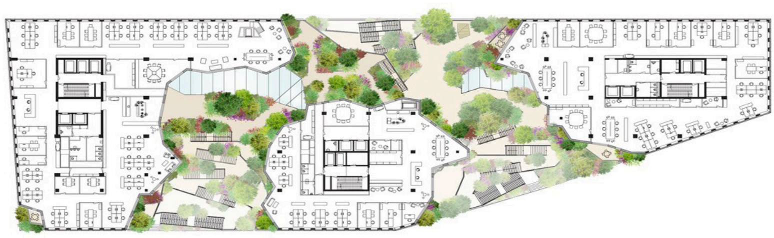


Figure 91. 5th Floor Plan.Source:MVRDV

Figure 92. 10th Floor Plan.Source:MVRDV

Figure 93. 15th Floor Plan.Source:MVRDV

Figure 94. Apartment 10th floor north tower (left)
Apartment 9th floor north tower (right).Source:MVRDV

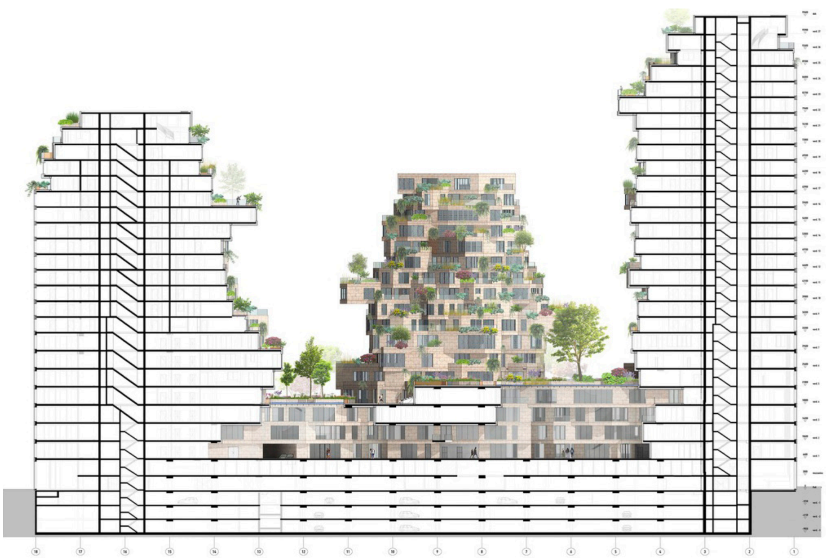


Figure 95. Section.Source:MVRDV

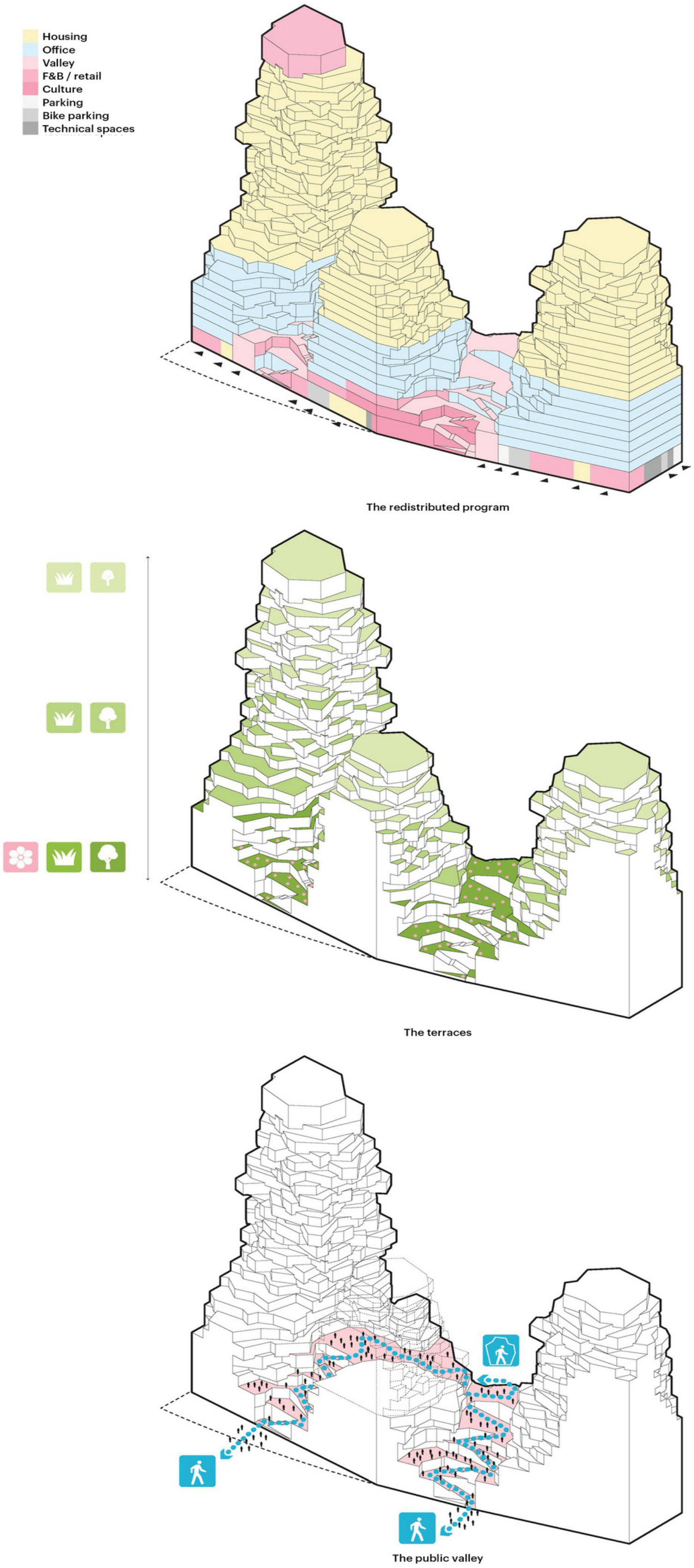


Figure 96. From top to bottom
The resdistrubiton diagram
The Terraces
The Public Way.
Source:MVRDV

Figure 97. Photo Collage of The Valley Towers
by Ossip van Duivenbode

Figure 97. Aerial View of The Valley Towers
by Ossip van Duivenbode

Figure 97. The Valley Towers
by Ossip van Duivenbode

ARUP

Name: Zaha Arup Group Limited

HQ : London, UK

Founded in : 1946.

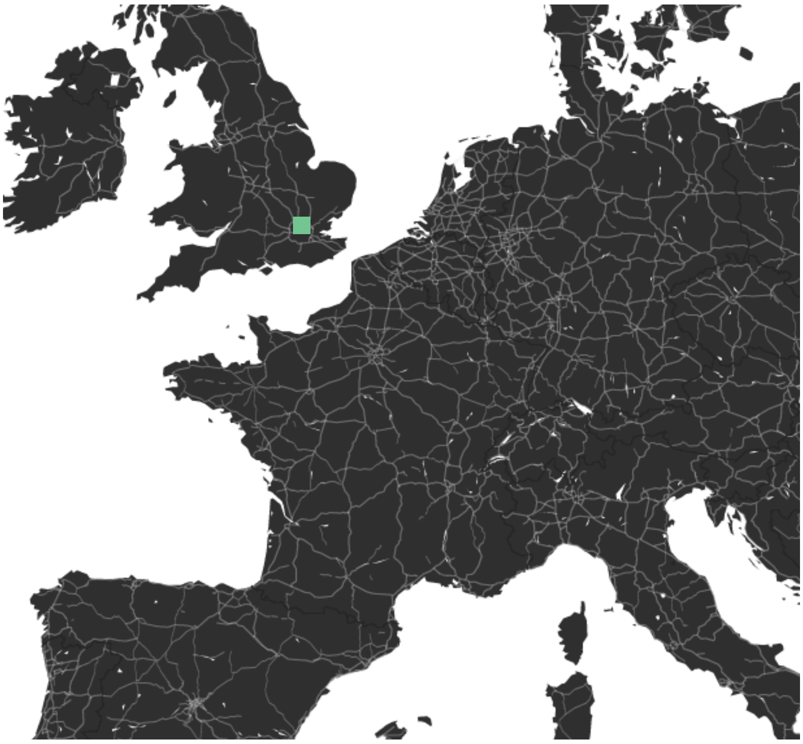


Figure 98.NEURON by ARUP ,Neuron leverages cutting-edge AI and machine learning to optimize building operations, reduce energy consumption, and enhance occupant comfort.

Arup has a formal Data Science & AI team. Arup's organizational structure includes a dedicated group focused on data, analytics, and artificial intelligence in the built environment. In fact, Arup has a Global Director of Data Science & AI (Tom Heath) leading firm-wide AI strategy. This team (part of Arup's Digital Services) develops and deploys AI soluti-ons for design, engineering and operations – for instance, using machine learning to design low-carbon energy networks or to create "digital twin" models for infrastructure. The purpose of Arup's AI unit is to augment the firm's deep domain exper-tise with cutting-edge AI tools, aligning with Arup's aim to be an "AI-first" organization (meaning AI is applied in everything they do). This is an interesting state-ment becasue that's not about AI leading what they do, it's about them using AI in everything they do The Data Science & AI group at Arup works on both internal projects and client services. Their work includes building custom software, such as AI to-ols for sustainability analysis and knowledge-management chatbots. Arup uses AI to improve how buildings and city systems are designed, operated, and assessed. Arup has created the Neuron in-house smart building platform, which brings together data from sensors and building dashboards with AI and machine learning to study how the building works, predict energy use, improve systems, and help spot problems early and fix them before they happen (Arup, n.d.).Under their "Digital solutions and tools" Arup has developed multiple AI/ML-enabled digital tools.First one is Neuron, Arup's smart building app where the "brain" uses AI + machine learning to analyse, optimise and automate operations (e.g., energy forecasting, early fault detection, predictive maintenance).Next there is Fuse.AI. A digitial data platform basically using large language models to store and access up to half a million documents and act as a "ProjectGPT" for complex project delivery.Another significant one is Terrain. Arup's land use analysis solution that uses machine learning and automation to satellite imagery for planning, scenario testing, and environmental risk/opportunity assessment.Then we have Uheat. An urban heat tool, developed to analyse cities using satellite imagery + open-source climate data; Arup's "Urban Heat Snapshot" (built using UHeat) highlights the role of machine learning + satellite imagery in identifying hotspots and modelling interventions. highlights the role of machine learning + satellite imagery in identifying hotspots and modelling interventions.Finally we have Mass Energy.It uses AI-driven genetic algorithms to rapidly explore thousands of building-energy design options (running EnergyPlus models programmatically) to meet sustainability targets and compare options. (Arup, 2025)

One Taikoo Place

One Taikoo Place is a Grade A office tower in Taikoo Place, Quarry Bay (Hong Kong Island), developed by Swire Properties as a key part of the Taikoo Place redevelopment. It was completed in September 2018 and designed by Wong & Ouyang, with Arup providing multidisciplinary engineering services. Arup's teams in building design, ground engineering, exterior design, sustainability, civil engineering, fire safety, and digital services have worked together to make this important building, which was created to be very efficient and environmentally friendly for our long-term partner Swire Properties. This helps make the eastern part of Hong Kong's one of the top business areas in the city.They have used their in-house developed digital building management platform Neuron and made the city's first AI-enabled, data driven smart building. The platform analyses and learns from large historical data sets to automatically discover trends and perform energy forecasts, optimise building systems, detect faults and allow predictive maintenance.

Figure 99. Source: Gustafson Porter + Bowman.

Figure 100. Source: Gustafson Porter + Bowman.

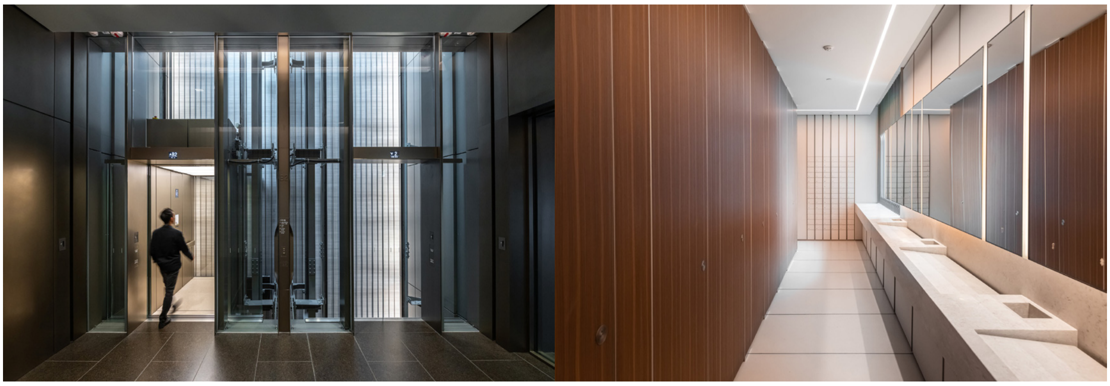


Figure 101. Source: Gustafson Porter + Bowman.

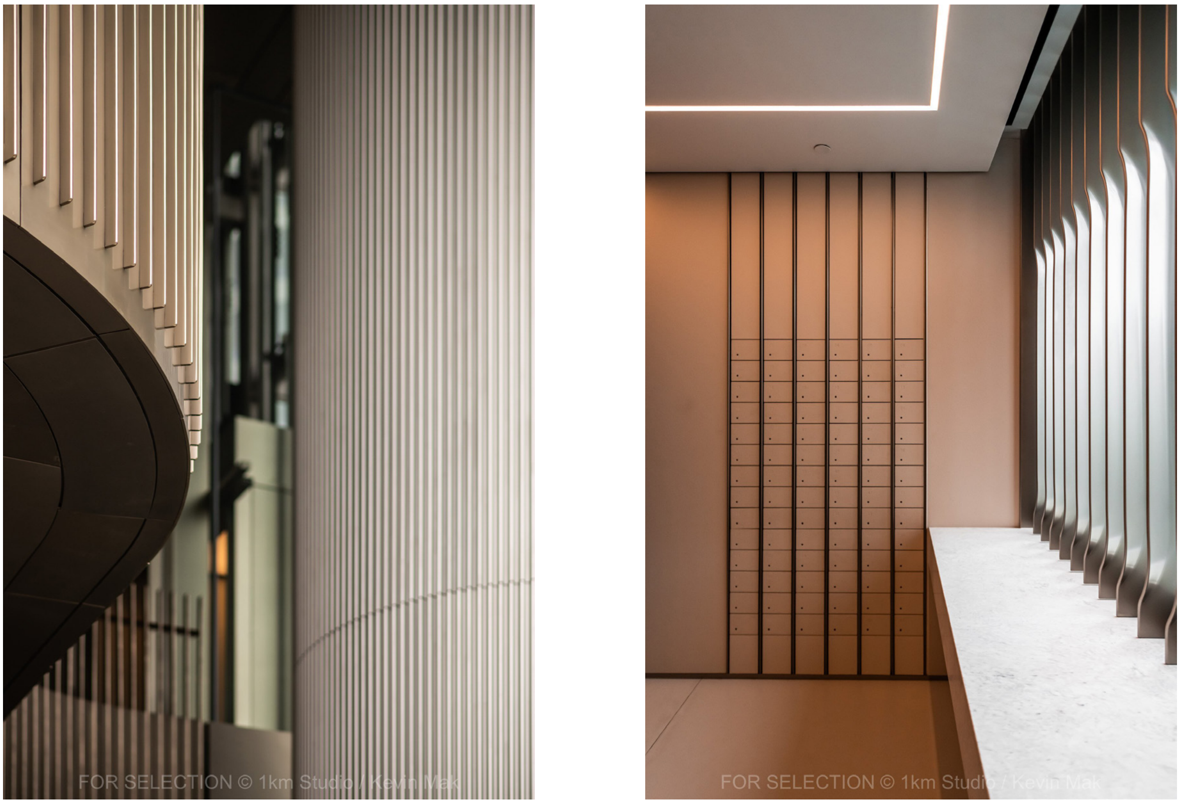


Figure 102. Source: Gustafson Porter + Bowman.

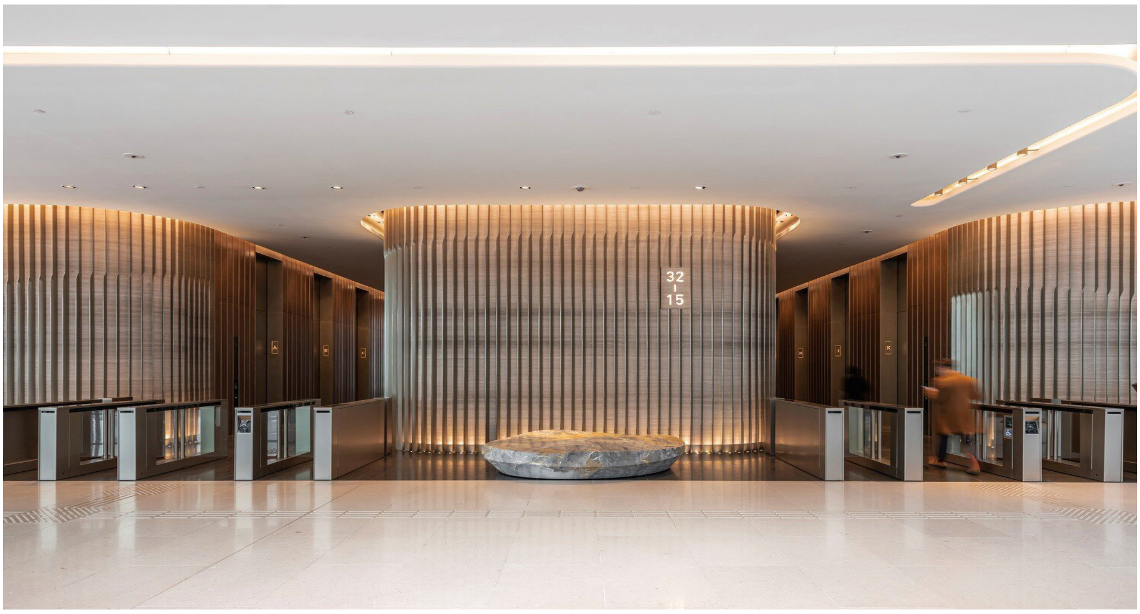


Figure 103. Source: Gustafson Porter + Bowman.

FIFTH CHAPTER
CASE STUDIES

05

5.1. Introduction

This chapter presents a carefully selected set of architectural case studies that demonstrate how artificial intelligence, powerful computational tools, and data-driven methods are used in modern architecture. Building on the ideas, technology, and professional issues discussed earlier, the case studies help turn theory into concrete examples, showing how AI-based processes work across the design, building, and review stages.

The selected projects cover different sizes, types, and locations, including research buildings, big public areas, and buildings shaped by digital technology. Instead of seeing artificial intelligence as a single or independent system, these examples show how it works together with people, using computer methods to help with design ideas, checking how things work, improving materials, and making choices.

Each case study is examined with attention to:

The specific AI-related tools or computational strategies employed,

The type of data and simulation frameworks informing design and assessment,

The interaction between human expertise and automated systems, and

The architectural outcomes and limitations generated by these processes.

This chapter looks at both the possibilities and limits of AI shown in real-life examples. Its goal is to give a careful look at AI as a working part of architecture, not just as a technology for the future. The case studies help show how artificial intelligence changes how architecture is reviewed, affects what professionals are responsible for, and changes how we judge the quality and success of buildings.

The case studies analyzed in this section include a diverse range of projects, both in terms of geographic location and design strategy:

MX3D Smart Bridge (Amsterdam, Netherlands)

Al Wasl Plaza (Dubai, United Arab Emirates)

Morpheus Hotel – Zaha Hadid Architects (Macau, China)

DFAB House – ETH Zurich (Dübendorf, Switzerland)

The Vessel – Heatherwick Studio (New York City, United States)

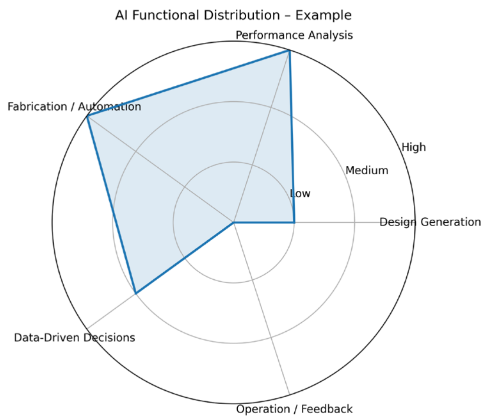
PlanIT Valley (Porto, Portugal)

The Smog Free Tower (Rotterdam, Netherlands)

These projects were selected not only for their architectural value but also for their ability to demonstrate how artificial intelligence and computational systems influence contemporary architectural design and assessment. The case studies represent different applications of AI, including generative design, robotic fabrication, performance optimization, and data-driven decision-making, across a range of scales and contexts. Together, they allow a comparative understanding of how human expertise and algorithmic processes interact in real architectural projects, highlighting both the potentials and limitations of AI integration in practice.

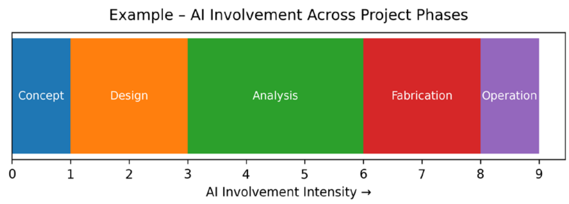
Radar Diagram Explanation

The radar diagram gives a general view of how artificial intelligence is used in the main phases of each project. It shows how much AI is involved in design generation, performance analysis, fabrication, data-driven decision-making, and operation, using a simple low, medium, or high scale. Using the same axes for all case studies makes it easy to compare how AI is integrated, but it does not suggest exact numbers.



Phase Bar Diagram

The horizontal phase bar diagram shows the relative level of artificial intelligence involvement across the main stages of the architectural process. Segment length indicates qualitative intensity of AI use, allowing a clear comparison of when AI intervenes within each project without implying quantitative measurement.



5.2. MX3D Smart Bridge

Original function: Pedestrian bridge and experimental research infrastructure

Date of construction: 2017–2018

Location: Amsterdam, Netherlands

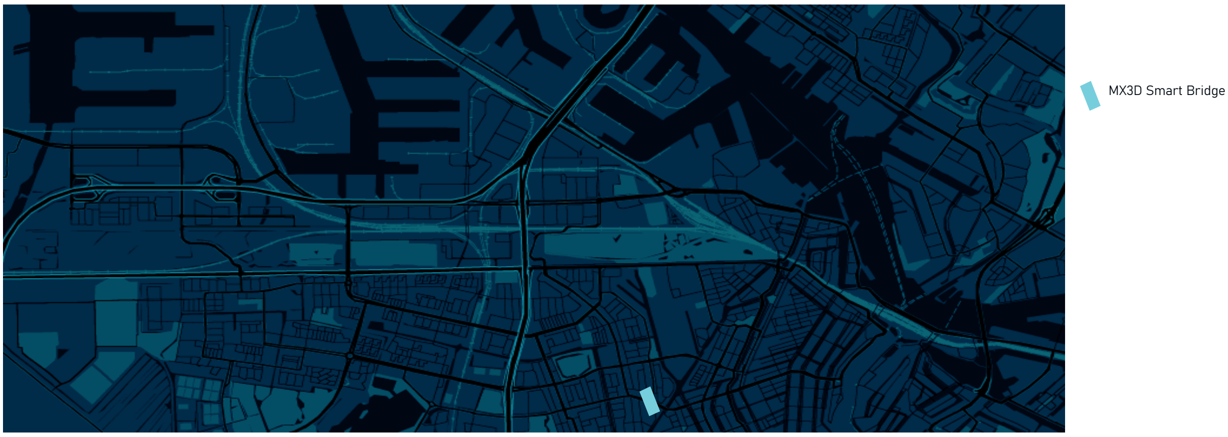


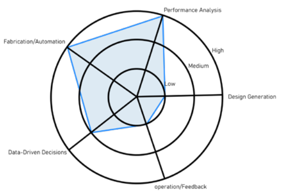
Figure 104. Joris Laarman's 3D-printed stainless steel bridge
https://www.dezeen.com/2021/07/19/mx3d-3d-printed-bridge-stainless-steel-amsterdam/

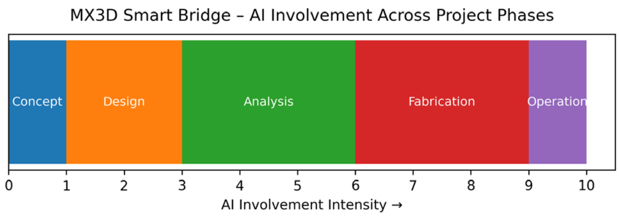
Figure 105. Joris Laarman's 3D-printed stainless steel bridge
https://www.dezeen.com/2021/07/19/mx3d-3d-printed-bridge-stainless-steel-amsterdam/

Figure 106. Joris Laarman's 3D-printed stainless steel bridge
https://www.dezeen.com/2021/07/19/mx3d-3d-printed-bridge-stainless-steel-amsterdam/

Figure 107. Joris Laarman's 3D-printed stainless steel bridge
https://www.dezeen.com/2021/07/19/mx3d-3d-printed-bridge-stainless-steel-amsterdam/

MX3D Smart Bridge intensity of AI involvement





The MX3D Smart Bridge is a major project that uses artificial intelligence, computational design, and robotic fabrication in modern architecture and infrastructure. Designed to be both a pedestrian bridge and a research platform, it shows how AI supported system can change architectural assessment by bringing together design, structural evaluation, fabrication, and post-construction monitoring in one process. Built between 2017 and 2018 and placed over a canal in , the bridge marks a move from traditional step-by-step construction to a more data-driven and feedback-based approach (MX3D, 2018; Dezeen, 2021).

Initial Construction Process

In traditional bridge construction, most structural controls and assessments are usually carried out before building begins. With the MX3D Smart Bridge, evaluation continues throughout the bridge's entire life. Here, artificial intelligence does not act as an independent designer. Instead, it supports people by analyzing data and helping with decisions during design, robotic building, and ongoing performance checks.

Project Context and Design Approach

The MX3D Smart Bridge was first built to serve as a pedestrian bridge, but its main goal is to explore how a large scale metal 3D printing construction can affect architecture and structure. Designers used parametric modeling, which let them adjust the bridge's shape to meet structural needs and fabrication limits. Although people guided the design, computer tools helped designers and engineers study complex shapes that would be hard to analyze with traditional methods (Oosterhuis & Bier, 2019).

Robotic Fabrication and AI-Supported Production

The most important aspect of this bridge is that its fabrication was carried out by robotic metal manufacturing. Robotic arms were used to shape molten stainless steel layers, producing the structure with an unconventional form. This process required a continuous control to regulate geometric accuracy. AI assisted tools were also used to track the fabrication conditions and making adjustments to parameters in real time making sure that the structural stability during printing remains (Gibson et al 2015).

Structural Monitoring and Data-Driven Assessment

The MX3D Smart Bridge has a large network of sensors that constantly collect data on strain, vibration, displacement, and environmental factors. AI-based systems then analyze this information, so engineers can track the bridge's performance both in real time and over long periods. This ongoing monitoring means the bridge is assessed even after it is built, making it more like a living system.

Human–AI Interaction and Responsibility

One of the main success of the bridge is how it shows a hybrid workflow between people and AI. Designers and engineers kept the control and responsibility, while AI added analysis and precision.

Relevance to AI-Based Architectural Assessment

The MX3D Smart Bridge ,as a case study, shows how artificial intelligence is changing architectural assessment by making evaluation part of design, construction, and operatio. The project shows that AI's main value is in supporting ongoing verification, monitoring, and adaptation, rather than acting independently . Combining computational simulation, robotic fabrication, and real-time data analysis, the it sets an example of how architectural assessment can be carried out as a continuous and a data-driven process.

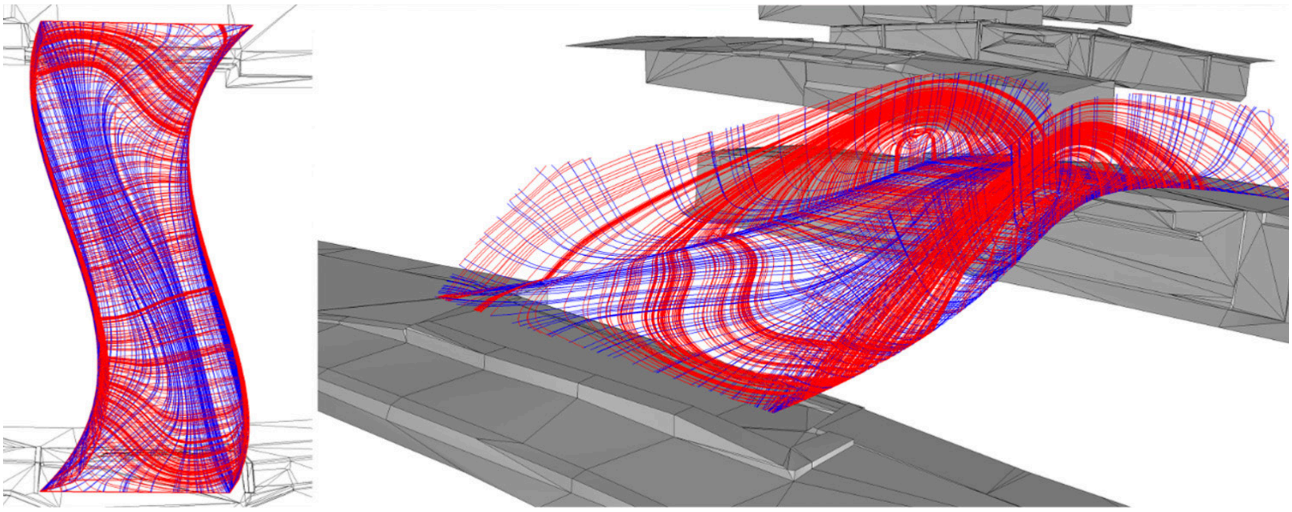


Figure 108. MX3D Smart Bridge
http://mx3d.com/smart-bridge

Figure 109. MX3D Smart Bridge
http://mx3d.com/smart-bridge

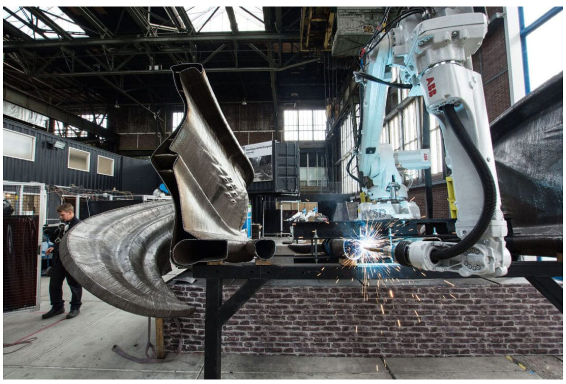


Figure 110. MX3D Smart Bridge
http://mx3d.com/smart-bridge

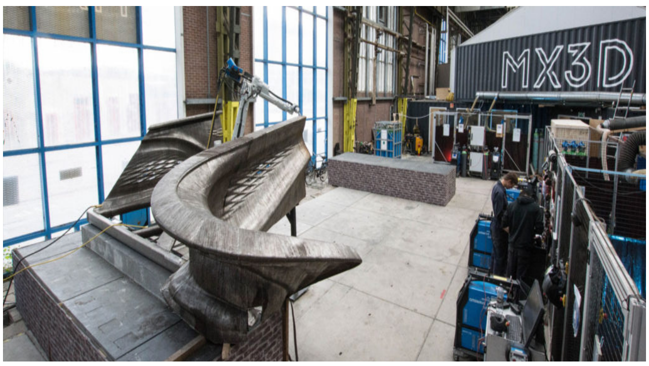


Figure 111. MX3D Smart Bridge
http://mx3d.com/smart-bridge

5.3. Al Wasl Plaza

Original function: Public plaza and central gathering space for Expo 2020

Date of construction: 2016–2020

Location: Dubai, United Arab Emirates

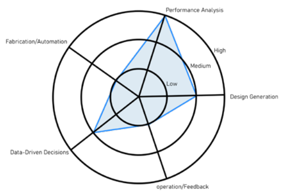
Figure 112. Al Wasl Plaza Dubai Expo 2020
https://www.riba.org/explore/awards/international-awards/middle-east-awards/al-wasl-plaza/

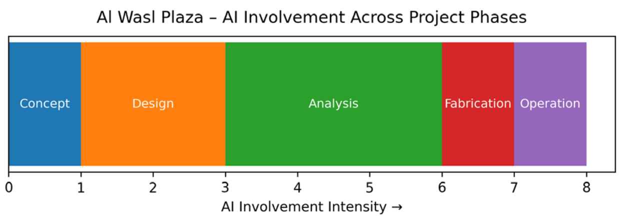
Figure 113. Al Wasl Plaza Dubai Expo 2020
https://www.riba.org/explore/awards/international-awards/middle-east-awards/al-wasl-plaza/

Figure 114. Al Wasl Plaza Dubai Expo 2020
https://www.riba.org/explore/awards/international-awards/middle-east-awards/al-wasl-plaza/

Figure 115. Al Wasl Plaza Dubai Expo 2020
https://www.riba.org/explore/awards/international-awards/middle-east-awards/al-wasl-plaza/

Al Wasl Plaza intensity of AI involvement





Al Wasl Plaza is the center of Expo 2020 Dubai. This large scale project relied on advanced computational design, environmental simulation, and data-driven assessment. The plaza was created as a monumental public space for large gatherings, performances, and events. Its expansive steel dome combines striking architecture with climate-responsive features. Built between 2016 and 2020, the project shows how artificial intelligence-supported tools help architects mainly by evaluating environmental performance and optimizing designs, rather than by generating forms on their own (RIBA, 2021).

Context and Project Overview

The original function of Al Wasl Plaza is that of a public plaza and central node within the Expo 2020 masterplan, designed to accommodate large gatherings, events, and daily pedestrian flows. The defining aspect of the project is its large steel dome, which spans the plaza without internal supports and functions as shading device and an urban landmark. According to the Royal Institute of British Architects, the project aimed to combine the openness and climatic protection, responding directly to Dubai's high solar radiation and extreme temperatures (RIBA, 2021).

Computational Design and Environmental Performance

At Al Wasl Plaza, artificial intelligence is mainly linked to environmental analysis and design focused on performance. Designers used parametric modeling to make the dome's shape responsive, so they could test changes in lattice density, curvature, and orientation. With AI-assisted simulation tools, they studied solar exposure, daylight, and thermal comfort in different design versions, which helped them improve the building based on real data (Kolarevic & Malkawi, 2015). Instead of creating the form on its own, AI acted as a tool that processed large amounts of data and gave performance results to guide design choices. This approach matches broader ideas in performative architecture, where computational analysis is a key part of design thinking, not just something added later (Oxman, 2017).

Structural Logic and Digital Assessment
Building the dome's structure took careful coordination between its shape and engineering requirements. Designers and engineers used computer models to keep checking load paths, member sizes, and structural backup as the design changed. AI-based optimization tools helped them assess how efficient the structure was, so the dome could span a large area, use less material, and still meet safety standards (Zhang et al., 2019).

Construction, Fabrication, and Limits of AI Integration
AI and computational systems were used during the design and analysis, their role during fabrication and construction was more limited. The dome was realized using digitally coordinated but largely conventional fabrication and assembly techniques. Digital models guided precision manufacturing, yet real-time AI-driven automation played a secondary role compared to projects centered on robotic construction.

Human–AI Interaction and Architectural Responsibility
During the project, people stayed in charge of architectural authorship . Architects reviewed simulation results, evaluated the performance data and made the final choices about form and materials. AI tools helped make assessments more thorough and reliable, but professional judgment always came first.

Relevance to AI-Based Architectural Assessment
Al Wasl Plaza is a good example of how artificial intelligence is changing architectural assessment, especially through environmental analysis and performance checks on a large scale. The project shows that AI's main value is not in creating striking shapes, but in helping architects carefully test and improve their designs based on climate, structure, and space. In this way, Al Wasl Plaza shows an approach to using AI that is thoughtful, fits the context, and supports professional standards.

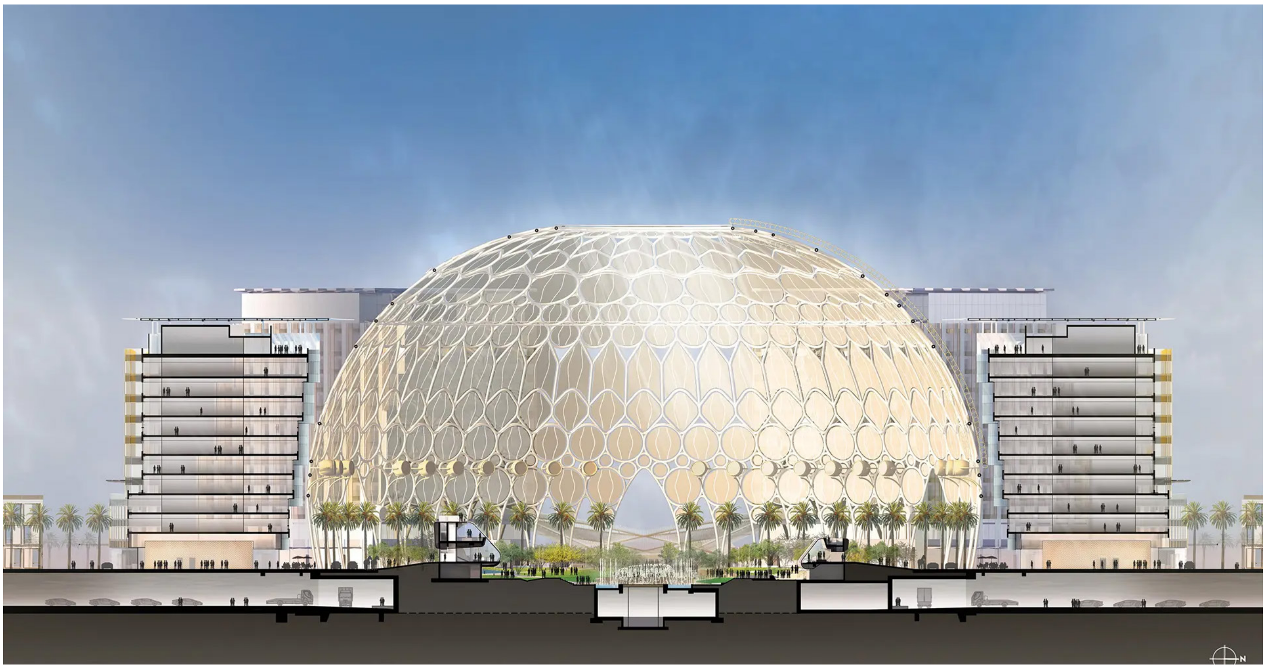


Figure 116. Adrian Smith and Gordon Gill Architecture
https://www.riba.org/explore/awards/international-awards/middle-east-awards/al-wasl-plaza/

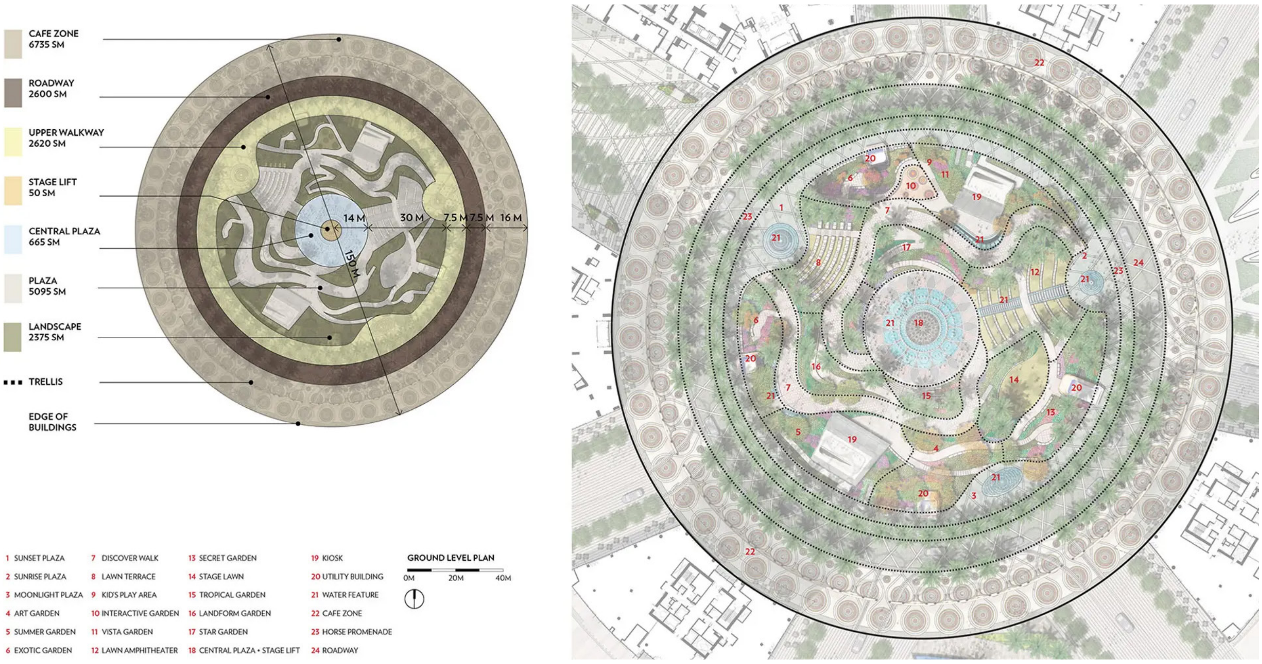


Figure 117. Adrian Smith and Gordon Gill Architecture
https://www.riba.org/explore/awards/international-awards/middle-east-awards/al-wasl-plaza/

5.4. Morpheus Hotel

Original function: Hotel and hospitality building

Date of construction: 2013–2018

Location: Macau, China

Figure 118. Image credits Virgile Simon Bertrand https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

Figure 119. Image credits Virgile Simon Bertrand https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

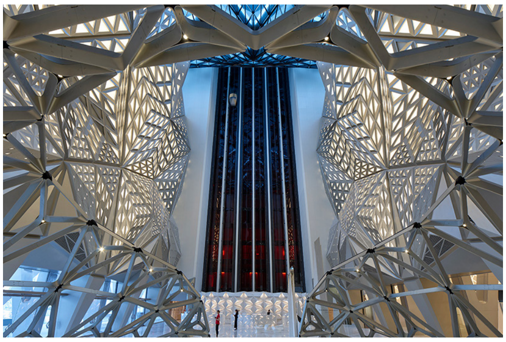


Figure 120. Image credits Virgile Simon Bertrand https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

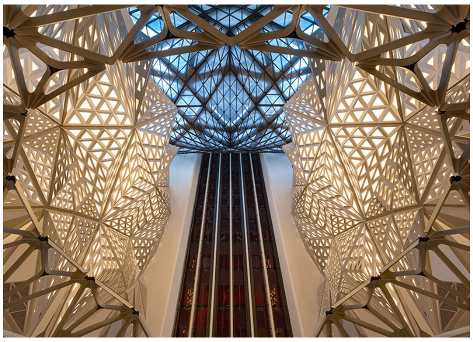
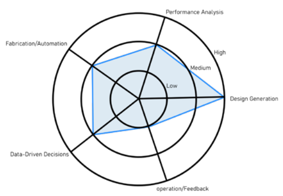
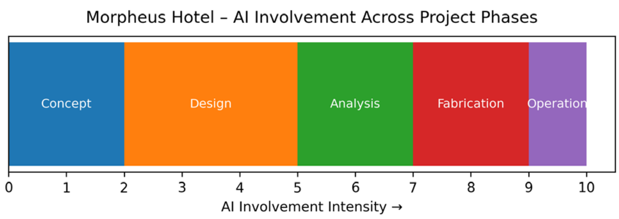


Figure 121. Image credits Virgile Simon Bertrand https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

Morpheus Hotel intensity of AI involvement





The Morpheus Hotel is a unique example of large scale architecture where advanced computational design, algorithmic modeling, and AI-supported assessment played a key role in creating a complex building. Designed by Zaha Hadid Architects and finished in 2018, it serves as a luxury hotel in Macau. While many projects use the artificial intelligence mainly for environmental optimizations or automatins of tasks, Morpheus shows how AI can help manage geometric complexity, assess structures, and streamline design on a large scale.

Context and Project Overview

The Morpheus Hotel is designed for hospitality, but its architecture aims for more than just meeting basic needs. As a free-form high-rise, it breaks away from typical tower designs by combining structure, enclosure, and circulation into one system. Its exoskeleton acts as both the main support and a key visual feature, forming large internal voids and atria that define the hotel's spatial experience (Schumacher, 2016).

Computational Design and Environmental Performance

In the Morpheus Hotel project, artificial intelligence played a key role in design generation and structural assessment. Designers used parametric and algorithmic systems to create and improve the exoskeleton's shape. This approach helped them explore complex forms while still managing the building's structural performance.AI-based optimization tools checked load distribution, stress points, and geometric continuity across thousands of different structural parts, which allowed the design to be improved step by step. Instead of working as an independent designer, AI acted as a bridge, turning the architect's ideas into structures that could actually be built.This approach shows a move toward what is called performance-driven form-making, where architectural design develops through ongoing feedback between the building's shape and how it is evaluated (Kolarevic, 2018).

Structural Logic and Digital Assessment

The exoskeleton of the structure required a high level of integration between architectural and engineering models. Computational assessment tools helped designers and engineers to evaluate the structural behavior for the entire building, making sure that the stability was intact while preserving the form. AI-assisted analysis supported decisions regarding member thickness, node geometry, and material distribution, reducing redundancy while maintaining safety margins .

Construction, Fabrication, and Limits of AI Integration

AI had a central role during design and assessment. The construction of the Morpheus Hotel was digitally coordinated but used mainly the conventional fabrication methods, including prefabricated steel components and precise on-site assembly. Computational models were used extensively to rationalize complex geometry into buildable elements, ensuring dimensional accuracy and coordination across trades

Human–AI Interaction and Architectural Responsibility

During the project, people were in the complete charge of architectural authorship. Designers set the formal intent, organized spaces, and gave meaning to the work. AI-supported systems helped by offering analysis and feedback. This teamwork highlights a main point of this thesis: artificial intelligence helps architects handle complex tasks, but it does not take away their creative or ethical responsibilities.

Relevance to AI-Based Architectural Assessment

The Morpheus Hotel is an example of how AI is changing architectural assessment. AI helps evaluate and realize complex geometric and structural designs. In this project, AI's main value is not just in automating tasks or monitoring buildings after they are built, but in helping balance creative design ideas with what is actually possible to build. Morpheus shows how AI can be part of the design process itself, making assessment a natural part of creating new architecture.

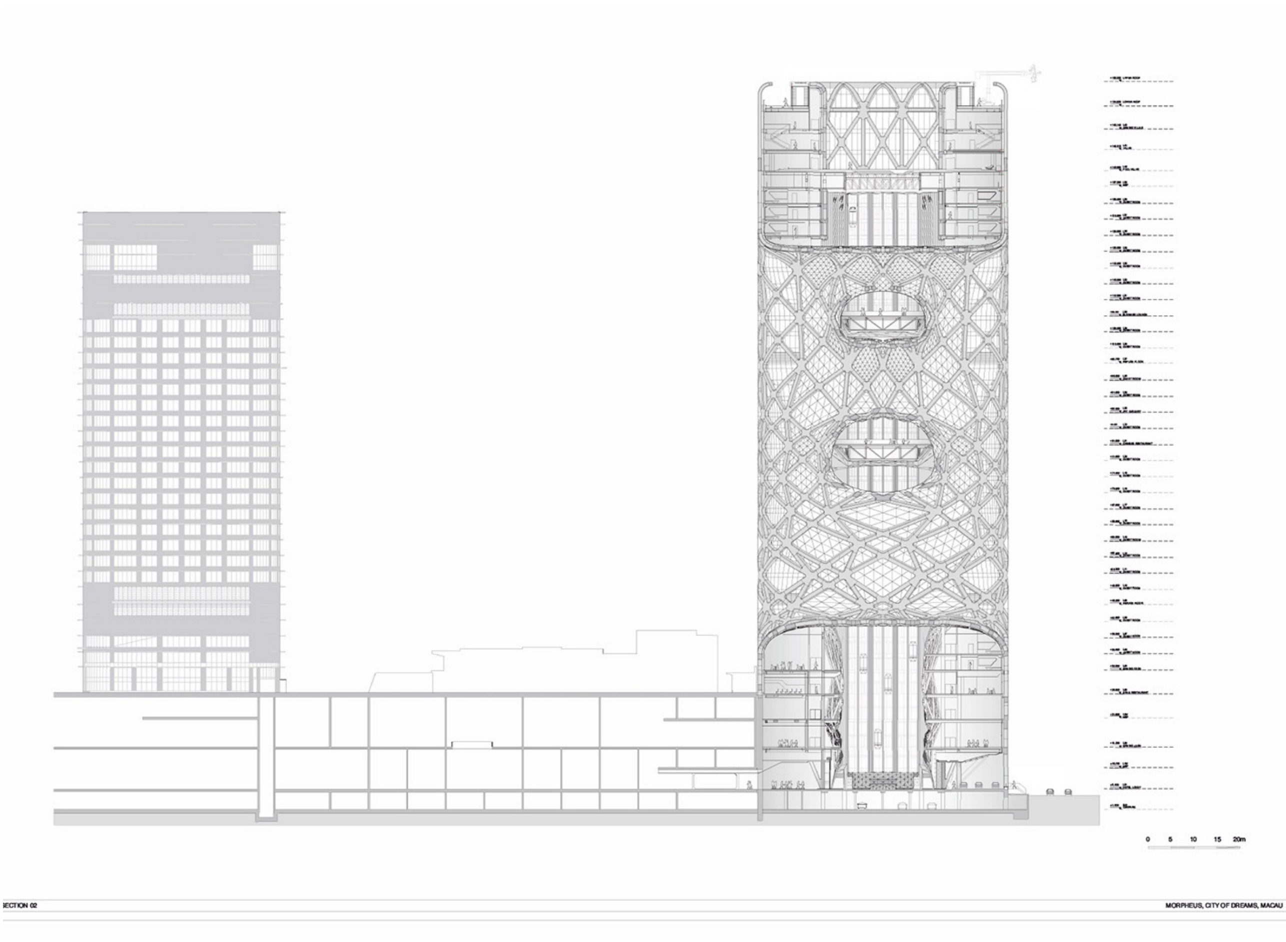


Figure 122. Image credits Virgile Simon Bertrand
https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

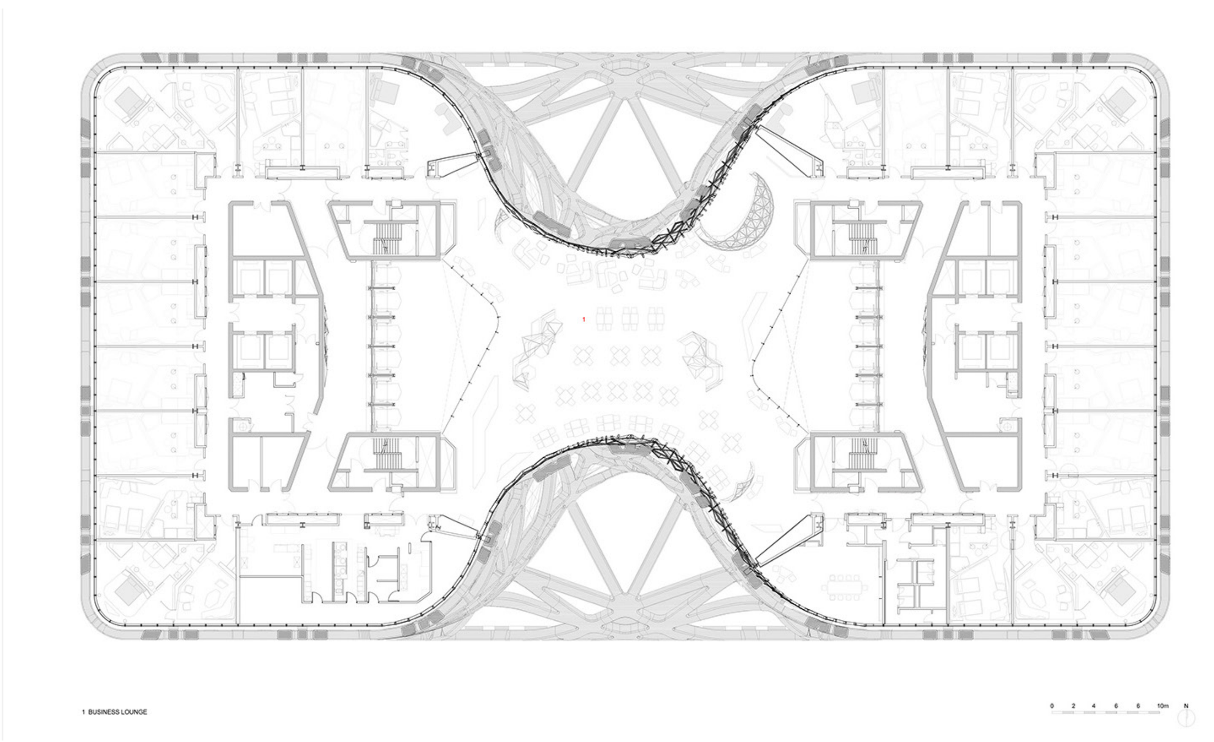


Figure 123. Image credits Virgile Simon Bertrand
https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

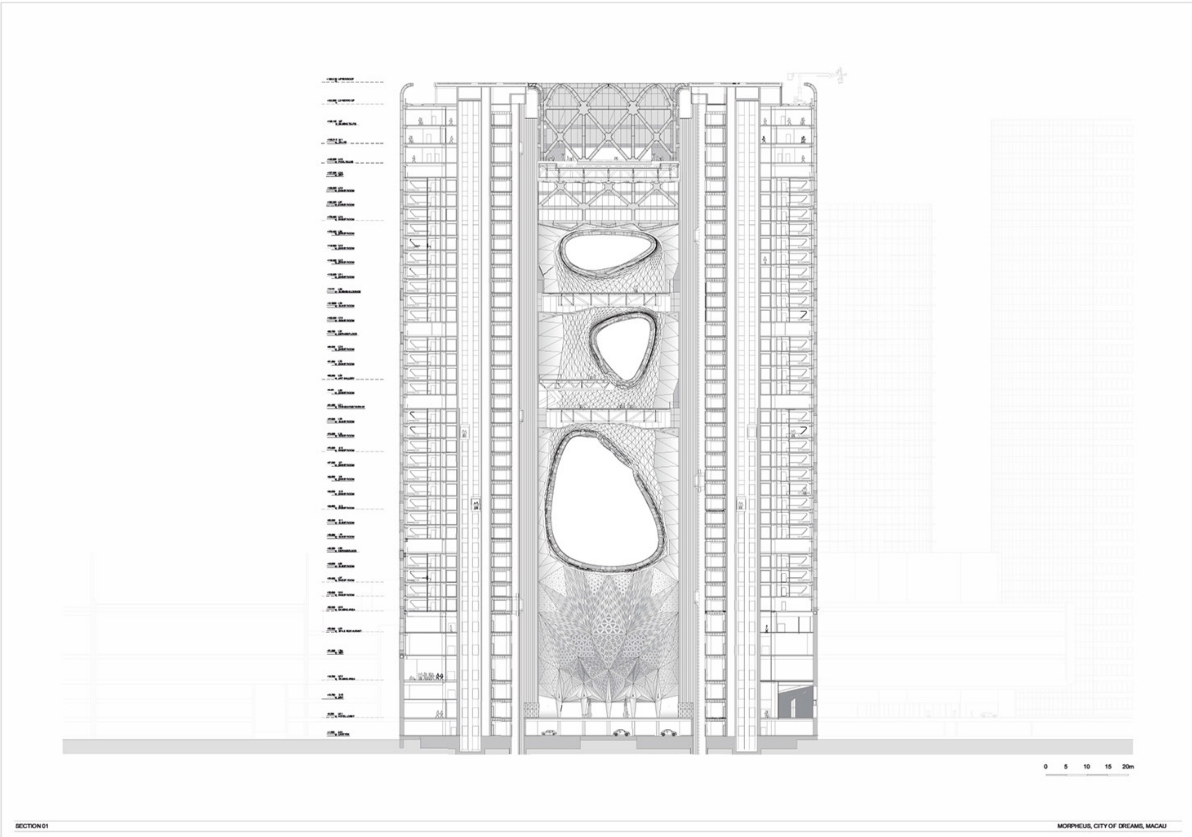


Figure 124. Image credits Virgile Simon Bertrand
https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

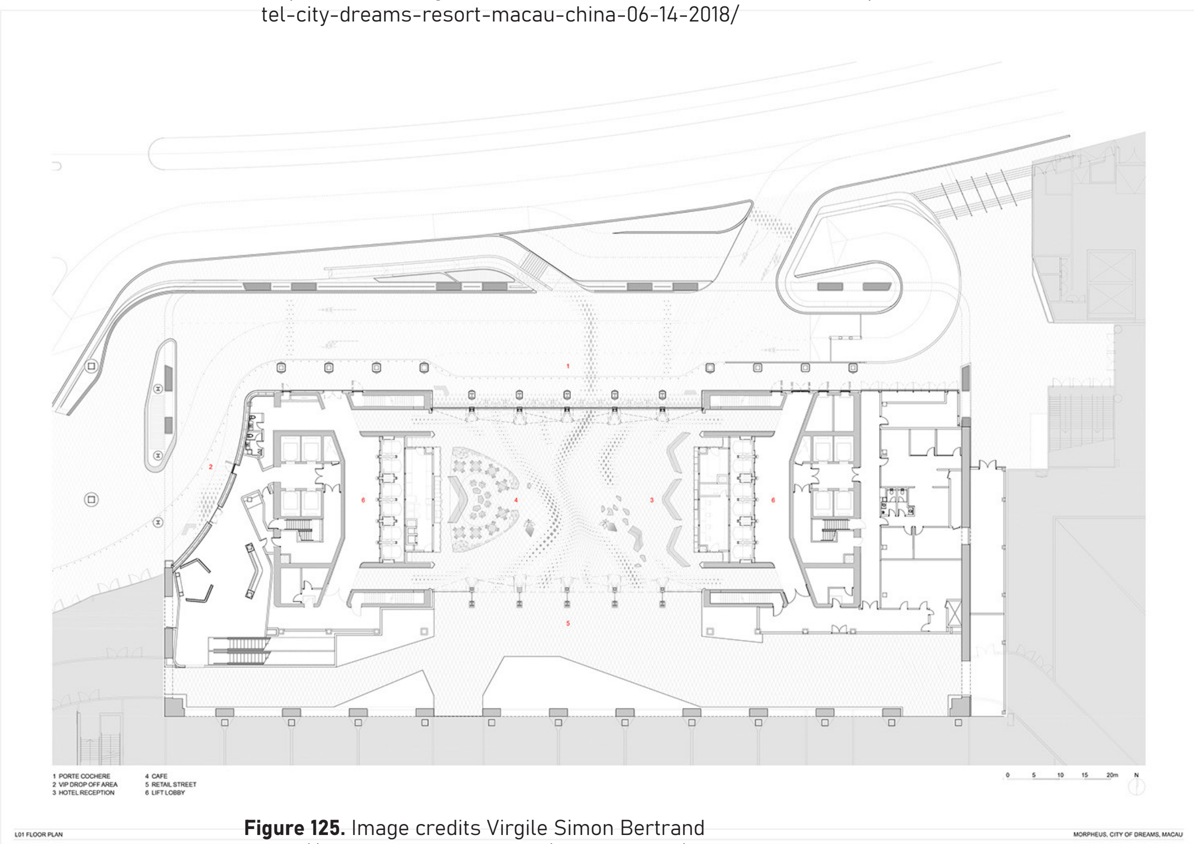


Figure 125. Image credits Virgile Simon Bertrand
https://www.designboom.com/architecture/zaha-hadid-morpheus-hotel-city-dreams-resort-macau-china-06-14-2018/

5.5. DFAB House

Original function: Experimental residential and research building

Date of construction: 2017–2018

Location: Dübendorf, Switzerland

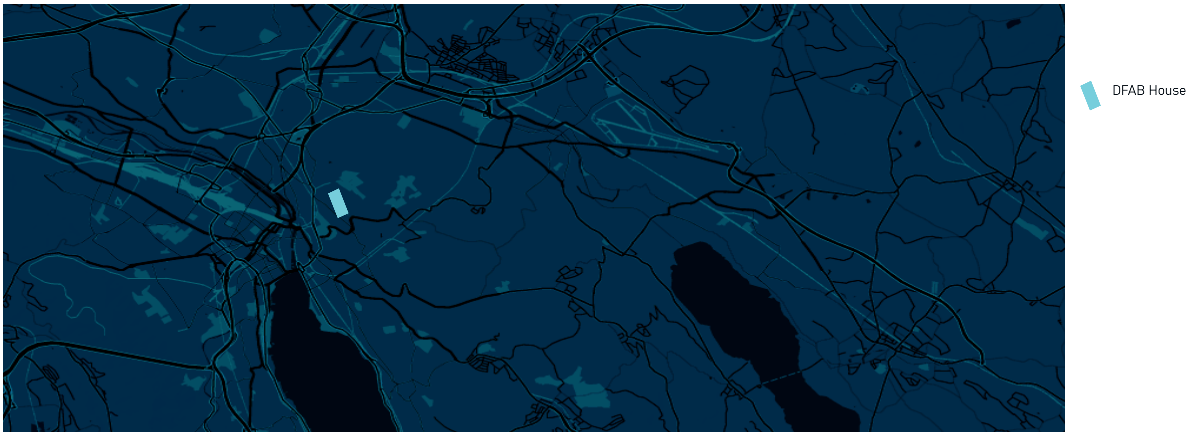


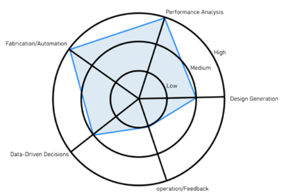
Figure 126. Image credits Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

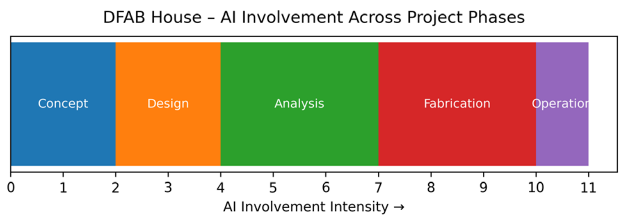
Figure 127. Image credits Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

Figure 128. Image credits Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

Figure 129. Image credits NCCR Digital Fabrication / Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

DFAB House intensity of AI involvement





The DFAB House represents a case in contemporary architecture where AI and robotic fabrication, data-driven assessment are not just supporting tools but foundational components of the design and construction process. Developed as part of the research agenda of ETH Zurich, the project was completed in 2018 in Dübendorf, Switzerland, and functions as an experimental residential building and a demonstrator of digitally enabled construction. DFAB House positions architectural assessment at the center of innovation, using AI-supported systems to evaluate material behavior, structural performance, and constructability in real time.

Context and Project Overview

DFAB House was conceived within a wider research initiative aimed for exploring the future of digital building process. Rather than prioritizing the visual impact, the project was designed to test how computational intelligence could help with new construction methods. The building incorporates multiple experimental systems,including robotic formwork, additively manufactured components, and automated timber assembly,each evaluated through AI-supported assessment tools.

Computational Design and Environmental Performance

Artificial intelligence is central to the fabrication processes in DFAB House. Robotic systems were used to create complex structural and architectural elements that are hard or impossible to make with traditional methods. AI-assisted control systems managed robotic formwork for concrete parts, keeping the shapes accurate and adjusting to how the material behaved during casting (Dörfler et al., 2019). In DFAB House, assessment is built into the construction process, not just the design stage. The fabrication process produces data that is checked right away, so adjustments can be made if there are any deviations or unexpected material changes. This feedback-based approach marks a major change in architectural assessment, as performance is checked continuously instead of only after the fact.

Structural Logic and Digital Assessment

Structural assessment is closely connected with material intelligence. The team used AI-supported simulation tools to study the efficiency in new construction systems. These simulations guided choices about geometry, reinforcement, and assembly, helping to reduce the material use while keeping the structure strong .

Construction, Fabrication, and Limits of AI Integration

Even though AI and robotic systems are used a lot in the project of the DFAB House , it is still guided by people. Architects and engineers set the research goals, decide on performance standards, and make sense of the computational results. AI helps improve accuracy and expand what can be assessed, but it does not take the place of professional judgment.This collaborative relationship reinforces the idea that AI functions most effectively as a cognitive extension of human expertise, particularly in experimental contexts where uncertainty is high.

Human–AI Interaction and Architectural Responsibility

The DFAB House is a demonstration of how the artificial intelligence changes the way architects work, but does not take away human responsibility. While AI systems and robots are important for building and testing, people still lead the design, make ethical choices, and decide what happens. Architects and engineers set goals, decide on standards, and use AI feedback to help them, treating AI as a tool for better evaluation instead of letting it act on its own.

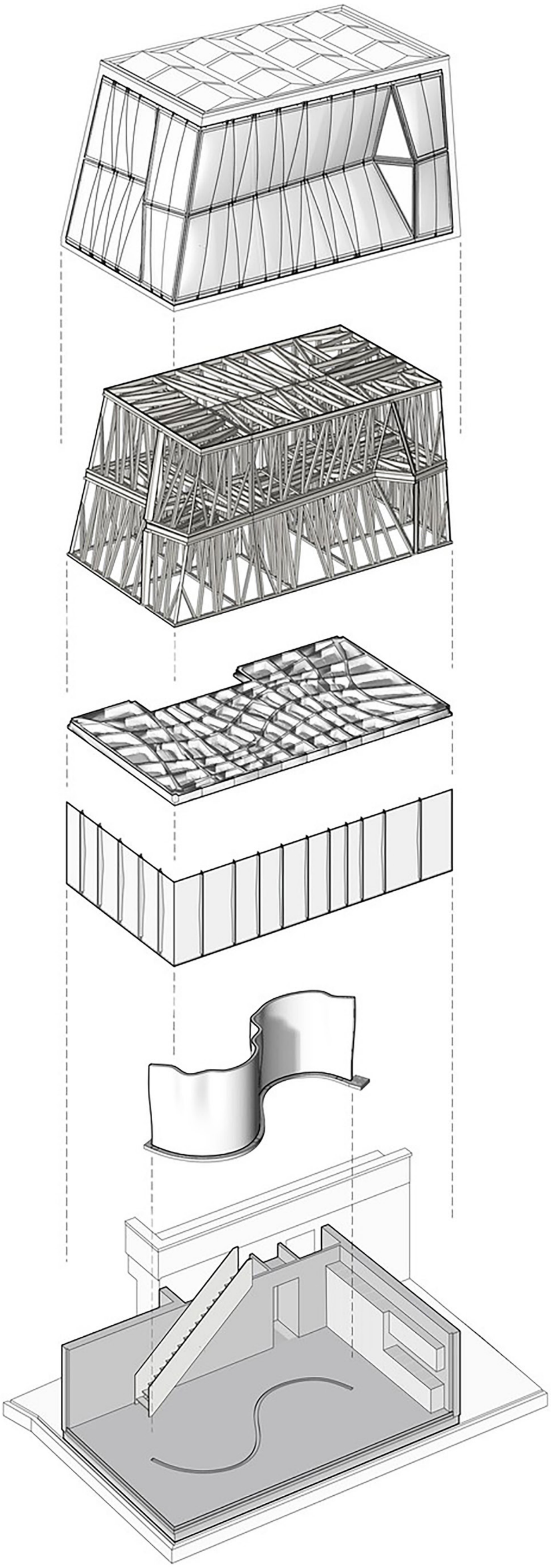
Relevance to AI-Based Architectural Assessment

The DFAB House shows that how artificial intelligence can change architectural assessment by making evaluation part of the material production and construction. This project moves assessment beyond just rules, turning it into a flexible process that can react to real-time conditions. DFAB House stands out because it works with the real world regulations and is actually used, showing that AI assessment can be used in practical architecture, not just in theory. This approach could lead to building practices that are more responsive, efficient, and intelligent.

Figure 130. Image credits Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

Figure 131. Image credits Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

Figure 132. Image credits Roman Keller
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication



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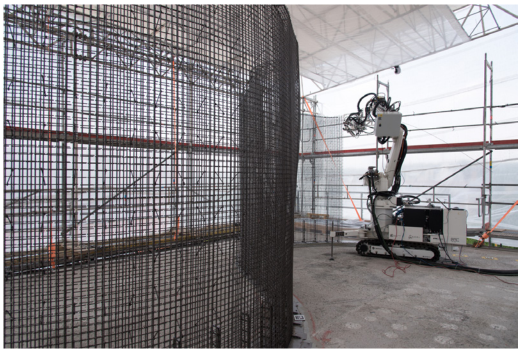


Figure 50. Image credits NCCR Digital Fabrication
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

Figure 134. Image credits NCCR Digital Fabrication / Roman Kelle
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

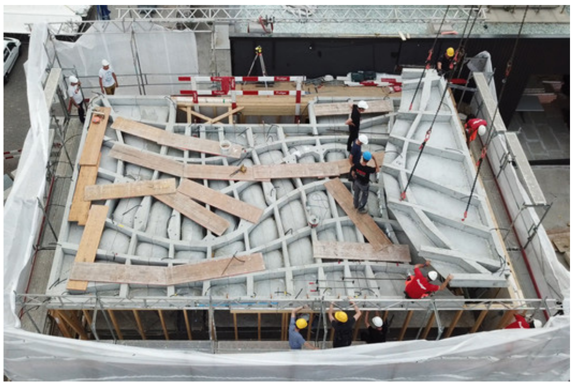


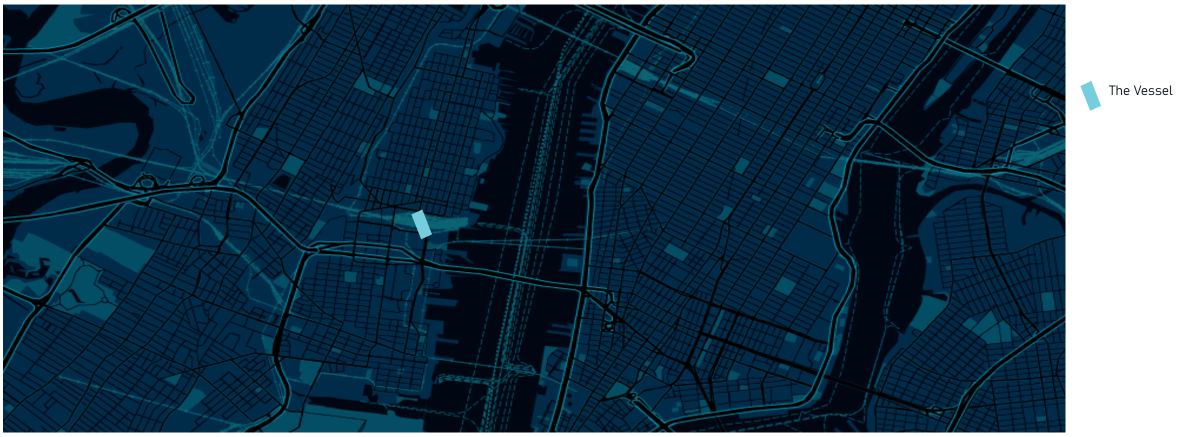
Figure 135. Digital Building Technologies (dbt), ETH Zürich / Tom Mundy
https://www.archdaily.com/942221/dfab-house-eth-zurich-plus-ncc-r-digital-fabrication

5.6. The Vessel

Original function: Public landmark and circulation structure

Date of construction: 2016–2019

Location: New York City, United States



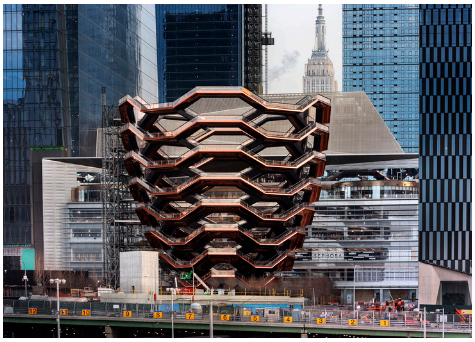


Figure 136. Image credits Michael Moran
https://www.archdaily.com/913699/vessel-public-landmark-heat-herwick-studio

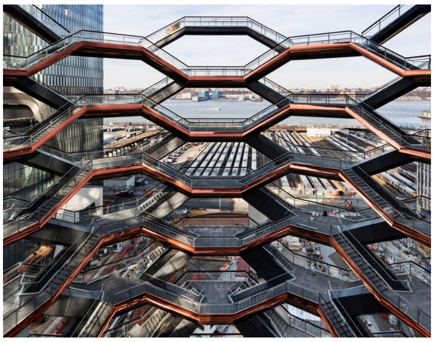


Figure 137. Image credits Michael Moran
https://www.archdaily.com/913699/vessel-public-landmark-heat-herwick-studio

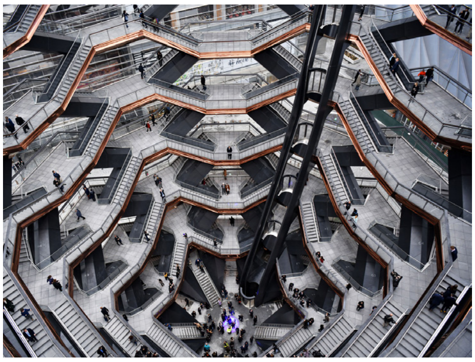


Figure 138. Image credits Michael Moran
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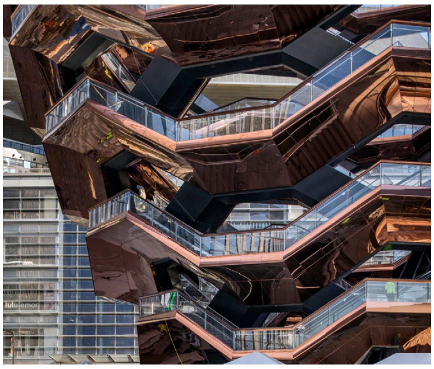
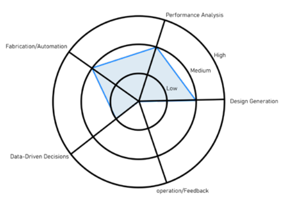
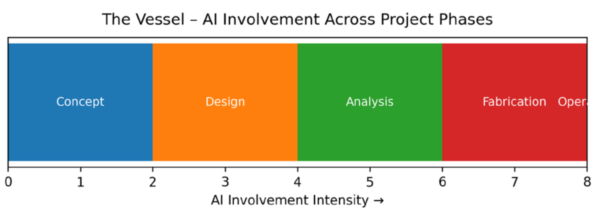


Figure 139. Image credits Michael Moran
https://www.archdaily.com/913699/vessel-public-landmark-heat-herwick-studio

The Vessel intensity of AI involvement





The Vessel is a large-scale public landmark and circulation structure located within the Hudson Yards redevelopment in New York City. Designed by Heatherwick Studio and completed in 2019, the project represents a contemporary architectural work in which advanced computational design and AI-supported digital coordination were essential to managing geometric complexity and constructability.The Vessel illustrates AI's role in geometric rationalization, repetition management, and architectural assessment related to feasibility and coordination (Heatherwick Studio, 2019).

Context and Project Overview

The Vessel is a public circulation and gathering structure, a centerpiece inside a large urban development. Rather than enclosed spaces, the project prioritizes movement and visual connectivity. This role brought in some specific difficulties for assessment process, particularly in related to the circulation, and geometric consistency.

Computational Design and Environmental Performance

In The Vessel , AI is mainly used for algorithmic aspects and assessment. Architects have used parametric systems to handle geometric differences in repeated elements, which helped them review how people move through the space, the rhythm of the layout, and how parts depend on each other. AI tools analyzed large sets of data about geometry, tolerances, and how pieces fit together, making it possible to keep improving the system (Oxman, 2017). Unlike the Morpheus Hotel, where algorithms shape the structure directly, AI in The Vessel acts more as a tool to keep things consistent, spot problems, and handle the complexity of many components. The project's radar diagram shows that AI played a moderate role in generating designs and analyzing performance, but was more important for coordinating data and making decisions.

Structural Logic and Digital Assessment

The structural system of The Vessel required a precise integration between architectural and engineering constraints. AI supported assessment tools were used to evaluate structural data across the entire building. AI-supported simulations enabled designers and engineers to assess structural feasibility while preserving the project's form based goal.

Construction, Fabrication, and Limits of AI Integration

The Vessel was built using the standard construction methods, but with digital coordination. Steel parts were made off-site with the help of detailed digital models, then put together on site in a specific order. AI assisted workflows enabled to turn complex shapes into parts that could be built which lowered construction risks.

Human–AI Interaction and Architectural Responsibility

During the project, people led the way in both authorship and responsibility. Designers set the main ideas, planned the spaces, and decided on the experience of the building. AI tools helped by checking if ideas were possible, accurate, and well-coordinated. Therefore the responsibility lies not in assigning decision-making to intelligent systems, but the managing of complex computational processes that support architectural input.

Relevance to AI-Based Architectural Assessment

The Vessel serves as a case study of showing how the artificial intelligence changes architectural assessment by improving the coordination. The project demonstrates that AI can help with complex architectural systems that need precise and consistent work across many parts and helping multiple actors to communicate with each other on a clear frequence. However, it also shows that AI assessment is mostly limited to the design and construction stages, with little use in environmental or operational areas.

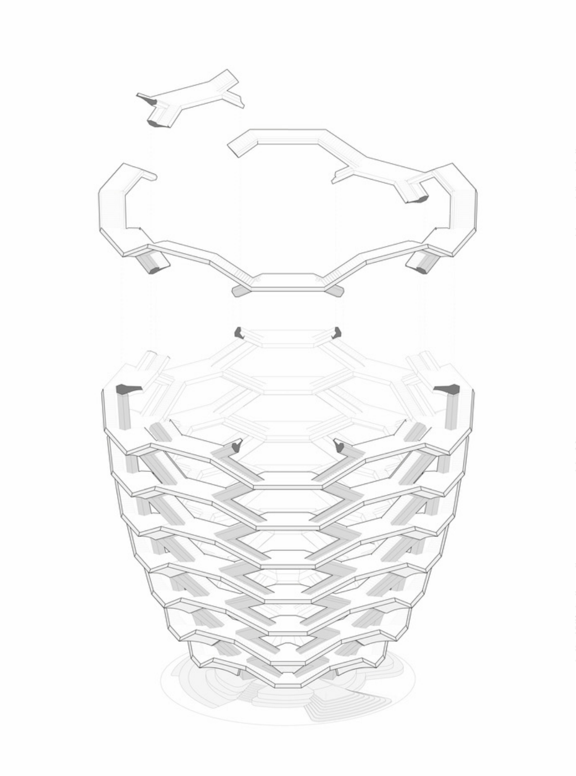


Figure 140. Image credits Heatherwick Studio
https://www.archdaily.com/913699/vessel-public-landmark-heatherwick-studio

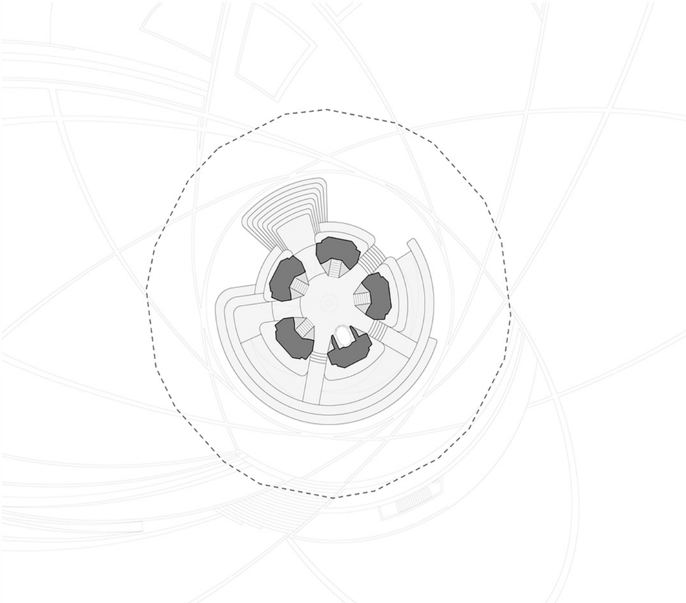


Figure 141. Image credits Heatherwick Studio
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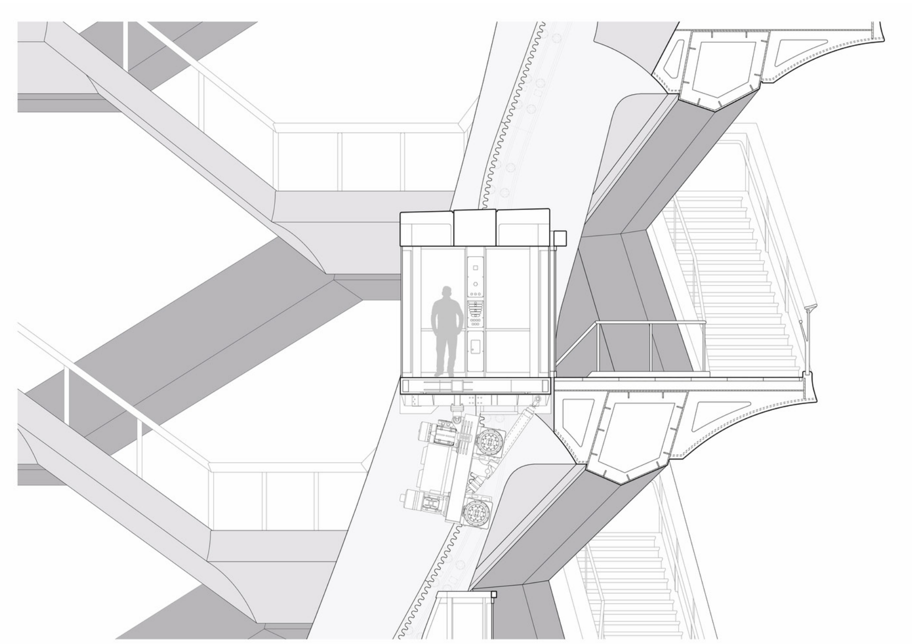


Figure 141. Image credits Heatherwick Studio
https://www.archdaily.com/913699/vessel-public-landmark-heatherwick-studio

5.7. Google Bay View Campus

Original function: Corporate workplace and research campus

Date of construction: 2017–2022

Location: Mountain View, California, United States

Figure 142. Image credits Iwan Baan
https://www.archdaily.com/985328/google-bay-view-big-plus-heat-herwick-studio

Figure 143. Image credits Iwan Baan
https://www.archdaily.com/985328/google-bay-view-big-plus-heat-herwick-studio

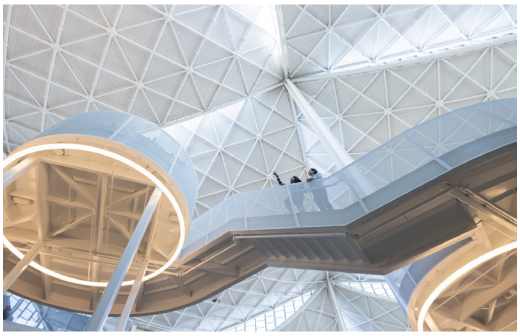
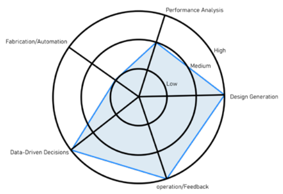
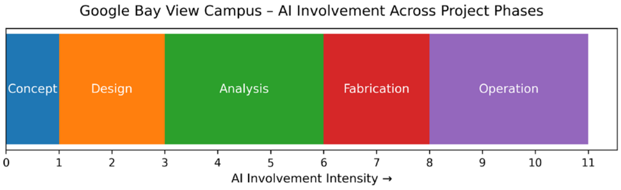


Figure 144. Image credits Iwan Baan
https://www.archdaily.com/985328/google-bay-view-big-plus-heat-herwick-studio

Figure 145. Image credits Iwan Baan
https://www.archdaily.com/985328/google-bay-view-big-plus-heat-herwick-studio

Bay View Campus intensity of AI involvement





The Google Bay View Campus marks a major change in modern architecture by bringing together artificial intelligence, data-driven design, and ongoing environmental assessment for a large corporate site. Bjarke Ingels Group (BIG) and Google designed the campus, which was finished in 2022 in Mountain View.In most architectural projects, AI is used to handle complex shapes or help with building processes. At the Bay View Campus, AI is mainly used to assess environmental performance, improve operations, and optimize the building over time.

Context and Project Overview

The Google Bay View Campus was designed as a workplace and research center, with offices, collaboration areas, and support spaces. Its most notable feature is the large, wavy roof canopies that hold solar panels, provide shade, and give the campus its unique look.Beneath these canopies, flexible interior spaces are organized to support evolving work patterns and environmental responsiveness

Computational Design and Environmental Performance

At Bay View Campus, artificial intelligence is mainly used for environmental simulation and performance-based assessment. Designers used parametric and computational tools to study solar exposure, daylight, thermal loads, and energy flows across the campus. AI-powered simulations handled large sets of data about climate, how people use the buildings, and how the buildings are oriented. This helped designers test and improve their ideas at different scales. Instead of creating designs on its own, AI worked as an analytical tool, letting designers compare different options. For example, the shape of the roof canopies was tested for how well they support solar panels, provide shade, and let in daylight. This method shows a larger trend toward performance-based design, where building shapes are shaped by ongoing feedback between simulation and decision-making .

Structural Logic and Digital Assessment

The Bay View Campus structural system needed careful teamwork between architects and engineers. They used digital models to study how the structure would respond to different weather and loads, making sure the large roof was visually coherent and efficient .AI-supported evaluation tools carried out the integration of structural logic with environmental systems, reinforcing the project's emphasis on performance assessment.

Construction, Fabrication, and Limits of AI Integration

Digital coordination was important during construction. The main use of AI at Bay View Campus, though, is in daily operations.The buildings have advanced data tracking systems that collect the real-time data on multiple environmental and structural aspects.AI-based management systems have analyzed this data to adjust ventilation, lighting, and thermal conditions dynamically, supporting continuous optimization of building performance

Human–AI Interaction and Architectural Responsibility

Even with the extensive use of AI, architectural responsibility of the Bay View Campus belomgs to the humans. Designers and engineers define performance objectives, within the Bay View Campus remains human. Architects have defined performance and sustainability goals while AI systems manage optimization within the constraints also provided by the archiects. Human oversight is essential in interpreting performance data and making strategic decisions about building behavior.

Relevance to AI-Based Architectural Assessment

Google Bay View Campus is a great example of how AI is involved in architectural assessment by going beyond design and construction. The project highlights AI's capacity to support environmental intelligence, adaptive performance, and evidence-based evaluation. And creating an on going feedback data loop constantly gathering information about the building and its environment by using AI Unlike projects focused on geometric or fabrication innovation, Bay View illustrates a model in which AI enables architecture to function as a responsive and continuously assessed system.

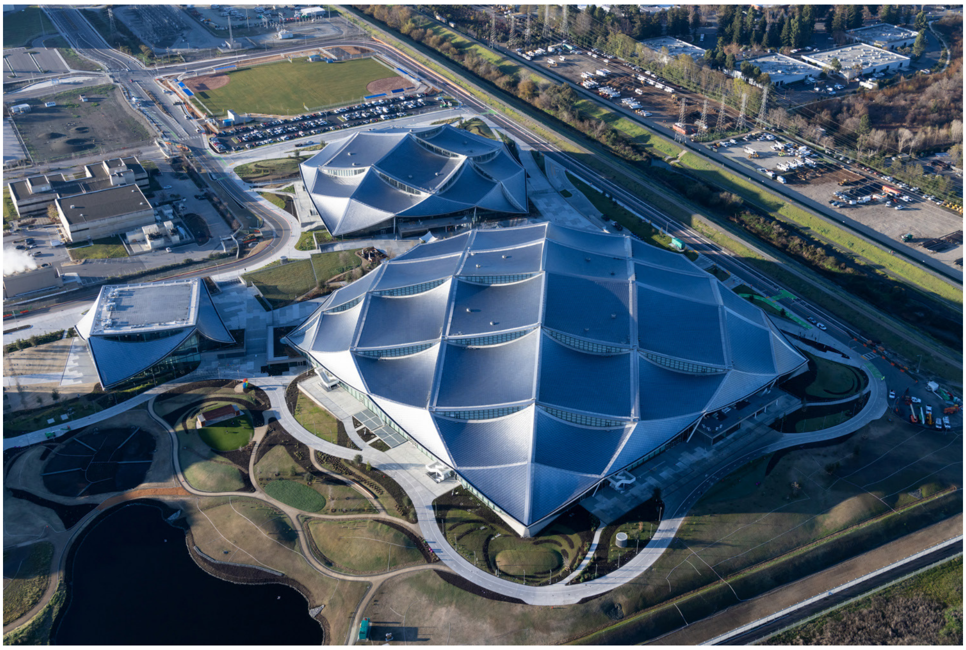


Figure 146. Image credits Iwan Baan
https://www.archdaily.com/985328/google-bay-view-big-plus-heat-herwick-studio

Figure 147. Image credits Iwan Baan
https://www.archdaily.com/985328/google-bay-view-big-plus-heat-herwick-studio

5.8. Smog Free Tower

Original function: Air purification installation and environmental awareness structure

Date of construction: 2015

Location: Rotterdam, Netherlands

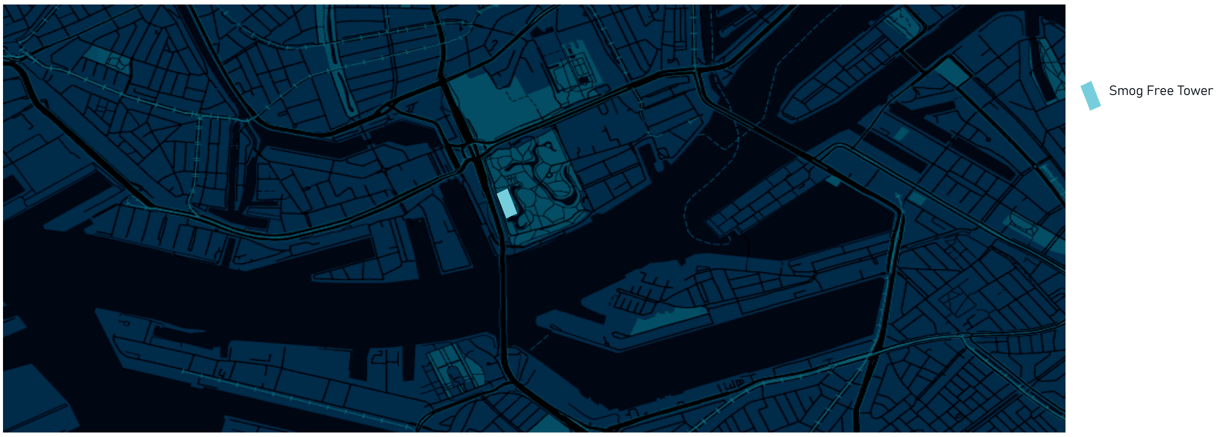


Figure 148. Image credits Studio Roosegaarde https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

Figure 149. Image credits Studio Roosegaarde https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

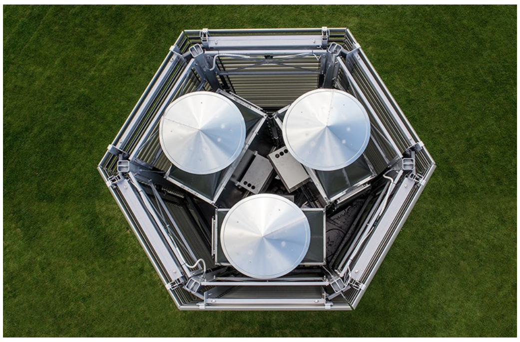
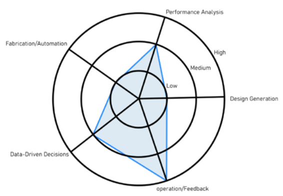
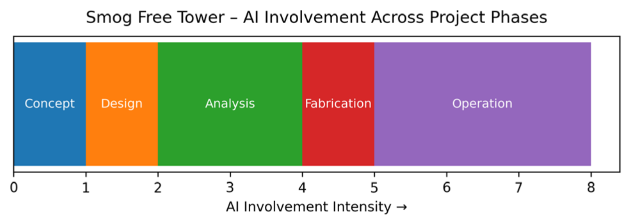


Figure 150. Image credits Studio Roosegaarde https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

Figure 151. Image credits Studio Roosegaarde https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

Smog Free Tower intensity of AI involvement





The Smog Free Tower is an environmental installation designed to actively remove air pollution from urban environments and raising public awareness of air quality issues. Developed by Studio Roosegaarde and first installed in Rotterdam in 2015, the project represents a specific type of architectural intervention where AI and data-driven assessment works primarily at the level of environmental monitoring. Unlike large and complex buildings that are mostly using the AI for their operations and management, the Smog Free Tower works as a compact, urban-scale device, making it a valuable case for examining how AI reshapes architectural assessment through real-time environmental data and continuous feedback.

Context and Project Overview

Smog Free Tower is basically an air purifier. The tower uses patented ionization technology to capture fine particulate matter (PM2.5 and PM10) from the surrounding air, releasing cleaner air back into the urban environment. While architecturally minimal in form, the project is conceptually positioned at the intersection of design, environmental science, and urban activism (Roosegaarde, 2015).

Computational Design and Environmental Performance

Artificial intelligence within the Smog Free Tower project is not primarily concerned with generating architectural form but with measuring, interpreting, and communicating environmental data. Sensors embedded within the tower continuously monitor air quality parameters, including particulate concentration and purification efficiency. AI-assisted algorithms process this data to evaluate system performance and identify temporal patterns related to traffic, weather, and urban activity (Chen et al., 2017). In this context, architectural assessment shifts away from predictive simulation toward evidence-based evaluation. Rather than estimating environmental performance through models alone, the Smog Free Tower relies on real-time data to validate its effectiveness. This operational feedback loop positions AI as an analytical layer that translates environmental phenomena into actionable information, reinforcing the role of architecture as an interface between technology and urban conditions.

Structural Logic and Digital Assessment

Structurally, the Smog Free Tower is relatively simple compared to other case studies in this chapter. However, its architectural significance lies not in structural innovation but in the integration of environmental systems and digital evaluation mechanisms. The tower's design accommodates sensors, filtration components, and data interfaces within a compact vertical form, enabling continuous performance monitoring without compromising accessibility or visibility.

Construction, Fabrication, and Limits of AI Integration

Fabrication and construction of the Smog Free Tower rely on conventional manufacturing techniques, with limited AI involvement during production. The most significant application of artificial intelligence occurs during the operational phase, where continuous data collection and analysis guide system calibration and performance reporting. AI-based monitoring enables the tower to adapt to fluctuating environmental conditions, optimizing purification efficiency over time (Zhao et al., 2018).

Human–AI Interaction and Architectural Responsibility

Human–AI interaction in the Smog Free Tower project is characterized by a clear division of roles. Designers define the conceptual framework, ethical intent, and public-facing narrative of the installation, while AI systems manage data processing and performance evaluation. Architectural responsibility remains human-led, particularly in interpreting environmental data and translating technical results into public discourse.

Relevance to AI-Based Architectural Assessment

The Smog Free Tower is an example of how artificial intelligence can change the way we assess architecture by focusing on how buildings perform, using real-time data, and measuring their impact on the environment. This project leads to a greater idea of what architecture can be, showing that it can act as an active part of the environment with an ongoing AI based evaluation. Unlike projects that mainly look at form, structure, or space, the Smog Free Tower shows how we can judge architecture by its environmental results and how it involves the community. This example shows that AI can make architectural practice more flexible, helping us find new ways to assess buildings that support ecological responsibility and urban resilience.

Figure 152. Image credits Studio Roosegaarde
https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

Figure 153. Image credits Studio Roosegaarde
https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

Figure 154. Image credits Studio Roosegaarde
https://www.designboom.com/technology/daan-roosegaarde-smog-free-tower-rotterdam-09-07-2015/

5.9. Analysis

The analysis of the case studies presented in this chapter shows us that AI influences architectural assessment in multiple ways, varying from project scale, typology, and lifecycle phases. AI emerges as a comes out as an infrastructure that reshapes how architectural performance is assessed. Across the cases, AI works mainly as a mediating system that supports decision-making, rather than as an autonomous design agent. An important pattern observed is the assessment across project phases. In projects like MX3D Smart Bridge and DFAB House, AI is merged with analysis and fabrication processes, allowing performance checks to happen at the same time as making materials. This mixes the usual steps of checking the design and building, turning assessment into a process that uses feedback to improve. In contrast, projects like Al Wasl Plaza and the Morpheus Hotel use advanced tools mostly during the design and planning stages, where they look at how complex the environment and shapes are before making final building decisions. he Google Bay View Campus and the Smog Free Tower show a shift toward using live data to track how buildings affect the environment, how much energy they use, and how their systems work while people are using them. Instead of just making guesses, this way lets architects keep checking and improving how buildings work as time goes on. Finally, the cases prove us that AI changes how we judge architecture by focusing more on how well things work together and how risks are handled, instead of just following traditional rules.Finally, the case studies show that AI mainly affects architectural assessment by making it possible to evaluate projects over longer periods, at different scales, and with greater complexity. Assessment is now less of a separate step and more of a continuous process that is part of design, construction, and operation. This shift views architectural intelligence as adaptable, data-driven, and centered on practical methods. It influences job roles, responsibilities, and our criteria for good architecture.

SIXTH CHAPTER

CONCLUSION

06

CONCLUSION

In conclusion, this thesis examined how artificial intelligence is changing architectural assessment, not just not just limiting it to a set of tools, but as a wider shift in how assessment is carried out with the modern day architectural process. In the past, assessment usually happened near the end of design development or during technical checks. The evidence in this study shows that AI supported tools and workflows are speeding up a move towards a continuous assessment, where evaluation happens earlier, more often, and during more stages of a project than before. A key finding is that AI most commonly function as a mediating layer rather than being a autonomous design creator. In practice, AI does strengthen the capacity to manage the complexity of the multidisciplinary nature of architecture while leaving responsibility for objectives, priorities, and value judgments to only human minds. In this sense, AI contributes to a reconfiguration of architectural workflow setting a but a redistribution of tasks between human expertise and Artificial intelligence.Another important aspect is that AI enabled assessment has a reocurring pattern. AI and advanced computational methods increasingly support early design exploration by enabling rapid evaluation of options . This reduces the delay between formal exploration and technical verification, allowing assessment to operate as part of the creative process . In digitally coordinated workflows, assessment is integrated with production. Rather than checking performance only after design completion, evaluation is increasingly linked to real-time monitoring. The study indicates that AI changes what architects must be good at. As AI assisted assessment becomes more common, the architect's role is increasingly involved with interpreting results, questioning assumptions, and maintaining coherence between performance metrics and project intent.And these require a certain set of sklllills for the digital literacy. Since AI-supported systems can produce outputs that might appear authoritative, there is an increasing need for transparency in how these results are being generated, what data they rely on, and what limitations/risks they have. This is especially relevant where evaluation outputs certain decisions with ethical or social impact that can not be translated by AI alone. Therefore, the core contribution of this thesis is not the claim that AI "replaces" architectural judgment, but that it restructures decision-making and makes the quality of human oversight more important, not less.One important limitation of this thesis which should be adressed that it is the absence of direct, hands-on AI applications or a comperehensive first-hand implementation experience within a real design or assessment workflow. So the discussion relies primarily on secondary sources, documented case studies, and conceptual analysis. Some interpretations are therefore influenced by the author's current level of knowledge and familiarity with specific tools and methods, and they should be read as indicative rather than a definitive point. Future works can strengthen the reliability of these findings through a direct experimentation with AI tools and systematic comparison between AI-supported outputs and traditional evaluation methods.This thesis shows that AI is transforming architectural assessment by enabling continuous, data-informed evaluation across design, construction, and operation. Its benefits depend on critical human oversight, transparency, and ethical accountability.

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