Mapping Generative Design

A Comprehensive Exploration of Generative AI's Evolution, Contemporary Application, and Future Potential in the Field of Design

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Abstract

This working paper is part of our research project that aims to explore the impacts of artificial intelligence (AI) on design and culture. This essay aims to map generative design (GD) in terms of its origins, current uses, and possible futures. We investigate how the role of the designer changes in an AI-augmented environment and how GD can be integrated into the creative process. To understand the principles behind generative methods and the design practice itself, we review evolutionary theories of creativity and GD. Based on socio-cultural approaches to creativity and material accounts of agency, we establish a framework where design is understood as an extended and distributed process. We demonstrate that evolution is a good model for creative design, because they can be both framed as optimization. Evolutionary principles, such as selection, mutation, and recombination can be applied to understanding design and creativity which is at the core of human innovation. Optimization problems can be effectively tackled by evolutionary computational methods which are centre to GD. We show that generative tools support both divergent and convergent movements in the design space, therefore they are able to augment the creative process, but they cannot replace the designer. In the second half of the paper we briefly summarize the history of algorithmic approaches, and map current uses of GD, then we formulate our informed predictions regarding generative AI's near future.

Methods

Our research aims to map GD along the following questions: What is GD and what principles is it based on? How can we describe design and creativity in an augmented environment? How does AI affect the design process? How does the role of the designer change in this environment?

To investigate these questions, we conducted qualitative secondary research. First of all, we implemented an iterative search strategy which involved initial searches for the following keywords: generative AI, generative design, parametric design, biomimicry, biomimetics, digital morphogenesis, evolutionary computation, evolutionary algorithms, evolutionary strategies, genetic algorithms. After reviewing titles and abstracts for relevance and then reading selected materials, we employed a citation tracking or 'snowballing' technique, where the reference lists of core articles were scrutinized to discover additional relevant publications. We used the database of Google Scholar, arxiv.org, and Scite.ai which is an AI-assisted research database containing 1.1 billion papers[1]. Additionally, we used a lot

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[1] Nicholson, J. (2022). How to Build a GPT-3 for Science. Future. https://future.com/how-to-build-gpt-3-for-science/

of ‘grey literature sources’ (news articles, public reports, YouTube videos, forum posts), because due to the rapidly evolving nature of AI and the relative novelty of the large generative models, a lot of information is unavailable or outdated in academic literature.

With regard to the theoretical background, after initial exploration of the literature on the philosophical underpinnings of generative design, we decided to use an evolutionary framework to understand design and innovation. The reason for this is that we identified a set of theories in the literature that uses the same evolutionary principles to characterize all three phenomena we are interested in: design, creativity, and AI. This theoretical framework allows us to explain them in the same conceptual space.

Relevance

The relevance of this research lies in the recent proliferation of generative AI (GenAI) models and the questions they raise for the creative industries and society in general. GenAI is currently at the top of the Gartner Hype Cycle[2], and the discussion about AI, which has been limited to academic circles for the past seventy years, has now reached the kitchen tables, as models such as ChatGPT, DALL-E, and Midjourney have gained popularity. Three factors have played a role in the recent wave of AI advances: the vast amount of data available on the internet, the substantial computing power of today's GPUs, and the discovery of transformer models. Large models offer a powerful new way to process data, thus AI acts as a ‘force multiplier’ in our data-driven economies[3]. AI is a pervasive phenomenon that will likely become increasingly large part of our lives in the future. It is forecasted that AI will contribute to a 26% boost in global GDP by 2030[4], and currently, GenAI is the most funded branch of the field. Although generative methods have played a role in design for decades, technological advances now present new opportunities to create unique tools with the latest models, and as additive manufacturing techniques become more widespread, a new era of customization could be on the horizon. Within this evolving context, the role of the designer is increasingly called into question.

Introduction

The idea that tools are extensions of our flawed bodies and minds reverberates through history. In the 17th century, Descartes investigated how the use of lenses can extend the power of sight[5], and Galileo wrote that ‘the very instrument of seeing introduces a hindrance of its own.’[6] The notion that technology can enhance human perception is a cornerstone of the modern scientific project. But Galileo's telescope not only revealed the celestial patterns, but it also facilitated the birth of modern cosmology and the doctrine of the experimental

[2] Perri, L. (2023). What’s New in the 2023 Gartner Hype Cycle for Emerging Technologies. Gartner. https://www.gartner.com/en/articles/what-s-new-in-the-2023-gartner-hype-cycle-for-emerging-technologies
[3] Benaich, N. (2023). State of AI Report 2023. StateofAI. https://docs.google.com/presentation/d/156WpBF_rGvf4Ecg19oM1fyR51g4FAmHV3Zs0WLukrLQ/edit#slide=id.g24daeb7f4f0_0_3373
[4] Grand View Research (2023). Artificial Intelligence Market Size, Share & Trends Analysis Report By Solution, By Technology (Deep Learning, Machine Learning), By End-use, By Region, And Segment Forecasts, 2023 - 2030. GVR. https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-market
[5] McDonough, J. K. (2015). Descartes’ Optics. The Cambridge Descartes Lexicon, 550-559.
[6] Galileo, Opere, pp. 289 In: Ihde, 2016

method –providing a new interpretive framework for understanding the world.[7] And as the telescope gave rise to a new view of the world, AI may also give rise to a new epistemic framework. Pasquinelli and Joler investigate this idea in the concept of the 'Nooscope'—'an instrument to see and navigate the space of knowledge.'[8] They borrow the analogy of optical instruments to describe AI as a tool for magnifying and extracting hidden features, patterns, and correlations in vast data. In today's digital economies, data holds a high value, and AI offers new ways of leveraging it. As algorithms sift through huge datasets and map the structures of digital content, they compress data (and the world it represents) into complex statistical models with predictive power that can reveal hidden patterns, optimize solutions, and generate content in various domains. While concerns have been raised about algorithmic governance[9], mass surveillance[10], behavioural nudging[11], and data monopolies[12]; AI has also been utilized to accelerate COVID vaccine research[13], predicting earthquakes[14], fighting cancer[15], and designing high-end sportswear[16], just to name a few. And although generative methods have been part of the design landscape for decades, recent technical breakthroughs and the availability of big data made generative AI much more powerful. The integration of AI in the creative industries has sparked significant interest and debate.[17]-[18]

In the long run, AI may become unavoidable in cultural production, fostering an environment in which human-machine relations must be reframed. As new tools give rise to new interactions and cultural environments, the role of creatives, craftsmen, designers and engineers change. Different technologies require different approaches and skills, while allowing for different ways of thinking and creating. This evolution is mirrored in the questions designers have addressed across various paradigms. Lee[19] argues that while craftsmen of the pre-digital era were mostly concerned about *how* to make things, the

[7] Ihde, D. (2016). Husserl's missing technologies. Fordham Univ Press.

[8] Pasquinelli, M., & Joler, V. (2021). The Nooscope manifested: AI as instrument of knowledge extractivism. AI & society, 36, 1263-1280.

[9] Pasquinelli, M. (2023). The Eye of the Master: A Social History of Artificial Intelligence. Verso Books.

[10] Zuboff, S. (2023). The age of surveillance capitalism. In Social Theory Re-Wired (pp. 203-213). Routledge.

[11] Wagner, D. (2021). On the emergence and design of AI nudging: the gentle big brother?. ROBONOMICS: The Journal of the Automated Economy, 2, 18-18.

[12] Mulligan, C. E., & Godsiff, P. (2023). Datalism and data monopolies in the era of ai: A research agenda. arXiv preprint arXiv:2307.08049.

[13] Sharma, A., Virmani, T., Pathak, V., Sharma, A., Pathak, K., Kumar, G., & Pathak, D. (2022). Artificial Intelligence-Based Data-Driven Strategy to Accelerate Research, Development, and Clinical Trials of COVID Vaccine. BioMed research international, 2022, 7205241. https://doi.org/10.1155/2022/7205241

[14] Saad, O. M., Chen, Y., Savvaidis, A., Fomel, S., Jiang, X., Huang, D., ... & Chen, Y. (2023). Earthquake Forecasting Using Big Data and Artificial Intelligence: A 30-Week Real-Time Case Study in China. Bulletin of the Seismological Society of America, 113(6), 2461-2478.

[15] McKinney, S. M., Sieniek, M., Godbole, V., Godwin, J., Antropova, N., Ashrafian, H., ... & Shetty, S. (2020). International evaluation of an AI system for breast cancer screening. Nature, 577(7788), 89-94.

[16] Burgess, M. (2018). How Nike used algorithms to help design its latest running shoe. Wired. https://www.wired.co.uk/article/nike-epic-react-flyknit-price-new-shoe

[17] Lee, H. (2022). Rethinking creativity: creative industries, ai and everyday creativity. Media, Culture &Amp; Society, 44(3), 601-612. https://doi.org/10.1177/01634437221077009

[18] Sirén-Heikel, S., Kjellman, M., & Lindén, C. (2022). At the crossroads of logics: automating newswork with artificial intelligence—(re)defining journalistic logics from the perspective of technologists. Journal of the Association for Information Science and Technology, 74(3), 354-366. https://doi.org/10.1002/asi.24656

[19] Lee, B. (2023). Can designers and AI flourish together? In: Flourish by Design (pp. 39-42). Routledge.

digital age was centred around *what* to create, in post-digital times, the main question is *why* –exactly what AI models cannot answer for us.[20] As former head of Nike's generative department pointed out, 'If you cannot explain *why* the image looks like that, it means that you do not have agency, the system created it, not you.'[21] It means that designers need to learn how to create systems that work for them or with them; how to conceptualize their problems algorithmically; how to leverage artificially generated complexity; and how to steer an AI model towards their intended design goals. This paradigm requires designers to create systems that evolve solutions, and to shift focus from a singular solution to the problem-solving loop that creates a variety of solutions. As Daniel Nagy writes 'In order to design like nature, we need to consider how we can design a species. Thus, we will reframe the designer's task from the design of a single physical object with a fixed form (the individual), to the design of systems which encode the full range of formal possibilities for a particular design concept (the species).'[22] Creating design genes that can manifest in different solutions can pave the way for mass-customization. The essential skill here is the ability to conceptualize the idea in terms of relevant parameters that an AI system can explore while the size, the continuity and the variability of the design space is considered. In the co-creation process, the designer's role is to guide a probabilistic semi-autonomous system towards the design goals.

Generative AI

AI systems can be divided into two groups: generative and discriminative models. Discriminative models help to predict a label or outcome based on certain patterns—like a spam filter or a content recommendation engine. In the case of Netflix for instance, the algorithm takes the user's viewing history, browsing patterns, ratings and search queries as input and predicts what kind of shows or movies the user might like. It discriminates between content that is likely relevant and irrelevant for the user.[23]

GenAI, on the other hand, allow the user to create various content like text, image, video, audio, 3D model, a function, or any kind of synthetic data. The simplest method to identify a generative system is by examining its output: if it is a category, a label, or a binary yes-or-no answer, then it is considered discriminative AI. Conversely, if the output comprises a new instance of data, such as a floorplan, a protein, an optimized surface, or a sentence, then it is classified as generative AI. The input may include text, images, or parameters. The model processes this input to generate a series of probabilistic outputs, which are designed to approximate the patterns observed in the training data.

The new wave of GenAI is largely the result of the discovery of Generative Adversarial Networks (GANs). GANs are a class of AI algorithms used in unsupervised

[20] Wolfram, S. (2023). What Is ChatGPT Doing... and Why Does It Work?. Stephen Wolfram. https://writings.stephenwolfram.com/2023/02/what-is-chatgpt-doing-and-why-does-it-work/

[21] Csuros, D. (2022). Co-creating with Machine Intelligence – An Interview with Lysandre Follet. Designisso. https://designisso.com/2022/10/25/co-creating-with-machine-intelligence-an-interview-with-lysandre-follet/

[22] Nagy, D. (2017). The design space. Medium. https://medium.com/generative-design/step-1-generate-6bf73fb3a004

[23] Matthew, J. R. (2020). Netflix and the design of the audience: The homogenous constraints of data-driven personalization. MedieKultur: Journal of media and communication research, 36(69), 052-070.

machine learning, implemented by a system of two neural networks contesting with each other. One is trained to generate images, and the other to distinguish between real and fake images. As they compete, they become better over time in generating realistic pictures[24]. GANs were introduced by Ian Goodfellow and his colleagues in 2014[25], who got the idea over a beer, as they talked about machines that would generate photos by extracting the statistical distribution of the training data.[26] The idea of GANs has led to the training of the so-called foundational models[27] in different domains like GPT, Midjourney or MusicGen.

GenAI models, particularly those that use techniques like GANs, make probabilistic predictions. This means their output is not strictly deterministic, as they generate samples from probability distributions. However, within their probabilistic frameworks, generative AI models operate consistently in how they apply randomness. For a given state of the model and a set of inputs, they will generate outputs that (while not identical every time) will fall within an expected range of variation. In other words, they are deterministic in their approach to introduce non-determinism.

Convolutional Neural Networks (CNNs) are a class of deep neural networks, typically applied to analyzing visual imagery. They are known for their capability to detect and recognize patterns in images, making them ideal for tasks like image classification, object detection, and more. A CNN architecture is characterized by its use of convolutional layers that apply a convolution operation to the input, passing the result to the next layer. This enables the network to build a hierarchy of learned features from the visual data.

Evolutionary computation (EC)—which includes genetic algorithms, evolutionary strategies and evolutionary algorithms—are a subset of generative AI, typically used to solve optimization and search problems that do not require the kind of pattern recognition ANNs are designed for—although they are often applied together.[28] EC is the primary method in GD. It can be described as the application of evolutionary principles to find new design solutions. These algorithms generate a variety of solutions by applying mathematical functions derived from evolutionary concepts of genes, populations, inheritance, selection, recombination, mutation and fitness.[29] EAs are often used to optimize shape, structure, and

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[24] CyberVenturer (2017). MidJourney: The AI Art Tool That's Taking the Internet by Storm. Medium. https://medium.com/@business_money/midjourney-the-ai-art-tool-thats-taking-the-internet-by-storm-714ca94f3f11

[25] Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014). Generative Adversarial Networks. In arXiv [stat.ML]. arXiv. http://arxiv.org/abs/1406.2661

[26] Giles, M. (2018). The GANfather: The man who's given machines the gift of imagination. Technology Reviews. https://www.technologyreview.com/2018/02/21/145289/the-ganfather-the-man-whos-given-machines-the-gift-of-imagination/

[27] A termed coined by the Stanford Institute for Human-Centered Artificial Intelligence's (HAI) Center for Research on Foundation Models (CRFM). It means general purpose models trained on huge data, such as GPT, BERT, DALL-E. 'Homogenization' is a concern because flaws of foundational models can propagate through all other apps using them. https://crfm.stanford.edu/

[28] ANNs and EAs are used together in breast cancer detection. Fogel, D. B., Wasson, E. C., Boughton, E. M., Porto, V. W., & Shively, J. W. (1997). Initial results of training neural networks to detect breast cancer using evolutionary programming. Control and Cybernetics, 26, 497-510.

[29] Fogel, D. B. (1999). An introduction to evolutionary computation and some applications. In K. Miettinen, M. M. Mukela, P. Neittaanmaki, & J. Periaux (Eds.), Evolutionary algorithms in engineering and computer science (pp. 23-41). Wiley.

topology within the constraints provided by the designer. The iterative process of mutation, crossover, and selection aligns well with the exploratory nature of GD.

Evolutionary algorithms in design

Algorithms are simple 'recipes' on how to do things, and they are as old as humanity. The Oxford dictionary of English defines it as 'a process or set of rules to be followed in calculations or other problem-solving operations.'[30] Even orally transmitted rules of rituals and other ancient practices can be considered as algorithms; however, their true potential was hidden until the 19th century. Charles Babbage's idea of the Analytical Engine was one of the first attempts to conceptualize a mechanical computer that could loop instructions. Ada Lovelace, who worked with Babbage, is often credited with creating the first algorithm intended to be processed by a machine, making her the first computer programmer.[31]

Another important milestone was Darwin and Wallace's presentation of the evolution theory that demonstrated the power of algorithms in nature. In the 20th century, researchers started pondering on the general use of algorithms, which led to the development of the first electrical computers in the 1940s and a deeper understanding of the field. Dennett[32] characterizes algorithms by three features: (1) substrate neutrality which means that algorithms are independent of their medium (e.g. a recipe remains the same recipe regardless if it is written or spoken), (2) underlying mindlessness which refers to the fact that the steps of algorithms are very simple and complexity emerges only on the system-level (e.g. a neuron fires or not, but the whole network can do complex tasks), (3) and determinism, because algorithms guarantee a result if applied correctly (but unpredictable properties can emerge on large scale application).

Evolution is a prime example of the power of algorithms. Ever since Darwin and Wallace proposed the theory, the Darwinian framework has inspired a wide range of research, from economics[33] to architecture.[34] Secondary type of Darwinism (or universal Darwinism[35]) refers to the application of evolutionary principles to explain developmental processes beyond the evolution of life forms.[36] It provides a generalized model that can be applied to any field that involves the generation of variations, a selection process and some kind of recombination method. Deriving computational principles from evolutionary processes is obvious, since evolution itself can be framed as a set of algorithms that creates a diverse variety of solutions and selects among them.[37]

Design, engineering, and architecture are fields that benefit significantly from the application of evolutionary principles. Nature has always been an inspiration for design, with

[30] Stevenson, A. (Ed.). (2010). Oxford dictionary of English. Oxford University Press, USA.
[31] Aiello, L. C. (2016). The multifaceted impact of Ada Lovelace in the digital age. Artificial Intelligence, 235
[32] Dennett, D. C. (2013). Intuition pumps and other tools for thinking. WW Norton & Company. p. 135
[33] Nelson, R.R. and Winter, S.G. An evolutionary theory of economic change. Harvard University Press, Cambridge, MA, 1982.
[34] Agkathidis, A. (2016). Generative design. Hachette UK.
[35] Dawkins, R. and Bendal, D.S. Universal Darwinism. in Evolution from Molecules to Men, Cambridge University Press, Cambridge, 1983, 403-425.
[36] Simonton, D. K. (1999). Creativity as blind variation and selective retention: Is the creative process Darwinian?. Psychological Inquiry, 309-328.
[37] Dennett, D. C. (2013). Intuition pumps and other tools for thinking. WW Norton & Company. pp. 135

countless examples ranging from da Vinci's flying machines to Archimedes' screw, from self-healing materials[38] to natural ventilation systems inspired by termite mounds.[39] But universal Darwinism has much to offer to design theory as well, in the form of formalized evolutionary principles that can be applied to understanding the creative process. Victor Papanek, design theorist, has considered the "handbook of nature" as a primary source of inspiration for design. He wrote that 'Through analogues to nature, man's problems can be solved optimally. … To put it more simply: to study basic principles in nature and then apply these principles and processes to the needs of mankind.'[40]

Engineers, architects, and craftsmen of the past have often borrowed ideas from the natural world, but the systematic formalization and engineering application of nature's principles only gained momentum in the 1950s. One of the pioneers was Otto Schmitt, an American biophysicist, who investigated the possibility of transferring ideas from nature to technology, a concept he later called 'biomimetics'.[41] Along these lines, Ingo Rechenberg[42], German researcher in the field of bionics, developed 'evolution strategies' in the 1960s. Evolution strategies are optimization techniques that use evolutionary principles to find the best solution to a problem –where 'best' typically means a solution that minimizes or maximizes a goal function set by the designer. They aim to solve complex engineering problems, like topology optimization or aerodynamics. Evolution strategies operate by creating a population of individual solutions and then iteratively applying the following manipulations:

Selection: Choosing the best-performing individuals from the current population according to some fitness criterion.

Mutation: Introducing random changes to the individuals to create "offspring".

Recombination: Combining features of individuals to form one or more offspring.

Survivor selection: Some form of selection process to determine which individuals remain in the population for the next generation.

The general idea is to mimic the process of natural selection where only the fittest individuals are chosen to reproduce, leading to the improvement of the population over successive generations. Rechenberg and his team have created mathematical formulations of these principles and applied them successfully to problems such as aerodynamic optimization (Fig.1). Independently from the German group, David Goldberg, American computer scientist developed the idea of genetic algorithms – 'procedures based on the

[38] Sun, Q., Gao, X., Wang, Q., Shao, R., Wang, X., & Su, J. (2022). Microstructure and self-healing capability of artificial skin composites using biomimetic fibers containing a healing agent. Polymers, 15(1), 190. https://doi.org/10.3390/polym15010190

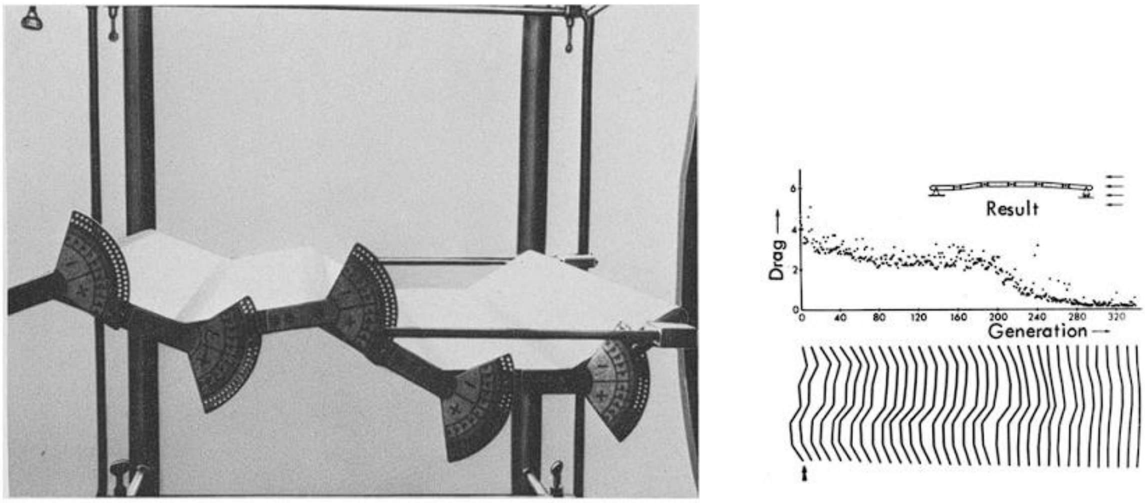
[39] El Ahmar, S., & Fioravanti, A. (2015). Biomimetic-computational design for double facades in hot climates. Bob Martens Gabriel Wurzer Thomas Grasl Wolfgang E. Lorenz, 687.

[40] Papanek, V. (1985). Design for the real world, secondary edition, Thames & Hudson, pp. 168

[41] Schmitt, O. H. (1969, August). Some interesting and useful biomimetic transforms. In Third Int. Biophysics Congress (Vol. 1069, p. 197).

[42] Ingo, R. (1973). Evolution strategy: Optimization of technical systems by means of biological evolution. Fromman-Holzboog. Stuttgart, 104, 15.

mechanics of natural selection and genetics'[43]—that relied on genetic inheritance and crossover (combining parts of two parent solutions to produce new ones). Since the seminal work in biomimetics, the field of evolutionary computation has grown to be quite interdisciplinary, addressing complex challenges with enhanced algorithms, hybrid approaches and distributed computing, and incorporating of the designer's insights through inventions like the interactive evolutionary computation algorithms.[44]



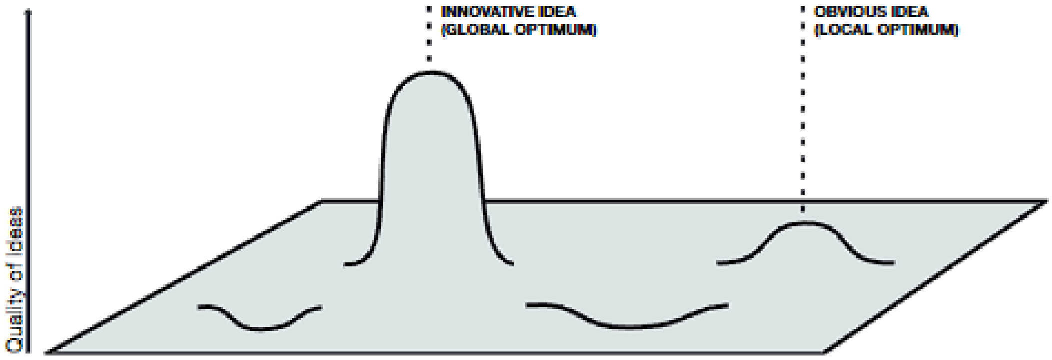
1. Figure Left: Articulated plate in the wind tunnel to imitate Darwinian evolution Right: The result of optimization.

Design as optimization

But why is evolution a good model for creative design? What are the common features? The answer lies in the fact that design and evolution both can be framed as optimization problems.[45] Majority of design problems we encounter are multi-dimensional—they involve multiple factors to consider at the same time. When architects create a floor plan, for instance, they take into account space requirements, natural light, traffic flow, ventilation, acoustics, costs, regulations, etc. These factors can be captured in parameters and constraints, and it delineates the 'design space' which refers to the range of all possible solutions or design configurations defined by the parameters and constraints. Optimal solutions are the ones that best satisfy a set of performance criteria which is determined by the designer, and survive the selection process—similarly to natural selection where the fittest individuals are most likely to survive and reproduce. Complex problems with many factors create a huge design space where optimal solutions are hard to find, because we cannot take into account every factor at once and view the problem holistically. Therefore, we break it down into a series of smaller decisions and try to find optimal solutions through

[43] Goldberg, D. E. (1994). Genetic and evolutionary algorithms come of age. Communications of the ACM, 37(3), 113-120.
[44] Takagi, H. (2001). Interactive evolutionary computation: Fusion of the capabilities of EC optimization and human evaluation. Proceedings of the IEEE, 89(9), 1275-1296.
[45] Thoring, K., & Müller, R. M. (2011, October). Understanding the creative mechanisms of design thinking: an evolutionary approach. In Proceedings of the Second Conference on Creativity and Innovation in Design (pp. 137-147).

heuristics, and the time-consuming process of iteration and testing.[46] In other words, design and evolution are essentially search processes to identify optimal solutions.



2. Figure Local and global optimum in the design space. Moving away from local optimum lowers the performance at first. Source: Thoring, K., & Müller, R. M. (2011, October). Understanding the creative mechanisms of design thinking: an evolutionary approach. In Proceedings of the Second Conference on Creativity and Innovation in Design (pp. 137-147).

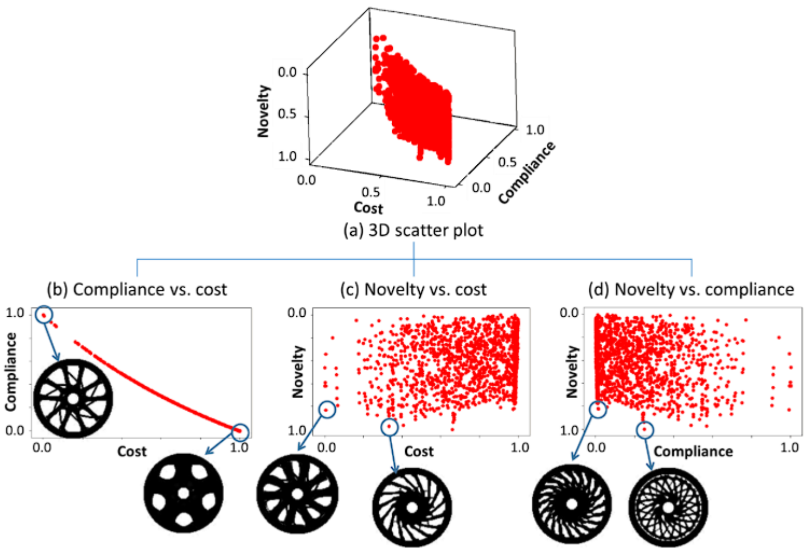
Problems that lack complexity delineate a small design space which is easier to explore, thus optimal solutions can be found without generative methods. For example, the basic design of combs, pencils, knives are more-or-less permanent for thousands of years, because they are optimal solutions to simple problems, and they cannot be improved in the basic form and structure. On the other hand, urban design or aerodynamics are rich, multi-dimensional problems, where complexity of the design space often exceeds the limits of the human mind, therefore they benefit from algorithmic methods. We can still design viable solutions for complex problems without algorithmic tools, but globally optimal solutions are harder to find. In the design space, the highest performing solutions (e.g. the floor plans that best satisfy the criteria) are closer to the global optimum, and the less optimal, 'good-enough' solutions (that still do the job) create local optima (Fig.2). In most cases, evolution and design are stuck in these pockets of local optima. Evolution does not create perfect solutions, because sub-optimal traits can be inherited, and it cannot start over—although the complexity overcomes limitations.[47] Similarly, design is influenced by existing solutions, which are often sub-optimal but accepted ways of doing things. Invention is challenging because breaking out of a local optimum involves navigating through numerous sub-optimal

[46] Nagy, D. (2017). Learning from nature. Medium. https://medium.com/generative-design/learning-from-nature-fe5b7290e3de

[47] For example, the blind spot in our visual field which is the result of the optic nerve passing through the retina to exit the eye, which is a sub-optimal evolutionary trait that we inherited. The brain fills in the gap, so we do not experience it typically.

solutions; however, there is a chance to discover a different paradigm that performs significantly better than the previous one.

Exploration of the design space is therefore key for invention. Exploration consists of idea-generation, a divergent process that is characterized by intuitive movement between alternative solutions and novel affordances. It is followed by a convergent phase through a selection process, often based on heuristics and implicit knowledge. Ideas can be crossed and mutated until something new and meaningful emerges. However, even with great effort, only a small fraction of the design space can be explored by traditional methods. Even design experts tend to evaluate only a few original ideas, then stick to one of them even in the face of the difficulties that arise later.[48] After initial exploration of possible solutions, a selection process takes place, when ideas are evaluated, and the best-performing designs are retained for iteration. However, in case of complex design spaces, it is rarely evident which solution is optimal. Since it is humanly impossible to analyse high-dimensional problems holistically, we simplify each decision-making process to two or three factors and try to optimize within these limits, ignoring other aspects that may lead to unwanted consequences later. Generative design methods could immensely help in both the divergent and convergent aspects, because they excel in optimization—in generating a variety of solutions quickly and selecting the best-performing ones (Fig.3).



3. Figure Visualized design options by three attributes: novelty, cost, and compliance. Source: Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019). Deep generative design: Integration of topology optimization and generative models. Journal of Mechanical Design, 141(11), 111405.

Evolutionary creativity

Evolutionary theories of creativity can be traced back to the mid-20th century. In 1960, Campbell proposed that blind variation and selective retention are crucial in creative thought processes and highlighted the importance of trial and error. He also emphasized the role of evolution-like processes in problem-solving.[49] This account was further developed by

[48] Cross, N. (2004). Expertise in design: an overview. Design Studies, 25(5), 427–441.

[49] Campbell, D. T. (1960). Blind variation and selective retentions in creative thought as in other knowledge processes. Psychological Review, 67(6), 380–400. doi:10.1037/h0040373

Simonton[50], who collected experimental evidence from different research fields and concluded that that 'the overall creative process must be inherently Darwinian'. A formalized model was introduced by Hybs and Gero[51] who outlined an evolutionary process model of design based on three similarities evolution and design share in common: (a) cyclicity, (b) embeddedness in an environment, and (c) continuity by inheritance. As they suggest, design is 'an iterative cyclic process of generation and refinement of partial design solutions which are evaluated using a model of the actual environment.' This involves a phase of (1) idea generation that builds on existing design knowledge, (2) an evaluation and selection phase that identifies the best ideas, and (3) a phase that involves 'design cross-over' and 'design mutation'. The idea of 'design genes' were also introduced to conceptualize how different design plans can be crossed and mutated and selected, just as genes in natural evolution. Along these lines, Thoring et al.[52] investigated the principles and methods of IDEO's design thinking from a Lamarckian perspective and applied evolutionary theory to explain the effectiveness of these methods. They showed that the sequence of divergent and convergent phases in the deign process—an important concept in design thinking—can be best explained in evolutionary terms of generation (through mutation and combination), selection, and retention. If we view creativity as a process that operates according to evolutionary principles, it is easy to see how evolutionary computation could augment it by supporting ideation and selection with different algorithmic tools, like topology optimization or generative models.[53]

Creativity is traditionally associated with new ways of achieving goals, involving the manipulation and combination of ideas.[54] In psychological literature creativity is often viewed as a process that takes place within the individual; however, social and cultural theories, such as those articulated by Csikszentmihalyi[55], Amabile[56] or Simonton[57] suggest that creativity results from the interaction between individuals and their social environment. Csikszentmihalyi, for example, proposed the 'systems model of creativity' which is based on the interactions between the individual, the domain, and the field. The domain consists of all available concepts, methods, questions etc., and the field includes all individuals working on ideas defined by the domain. Simonton argues that at the macro level of creativity, innovative ideas are a result of a stochastic search process across the

[50] Simonton, D. K. (1999). Creativity as blind variation and selective retention: Is the creative process Darwinian?. Psychological Inquiry, 309-328.

[51] Hybs, I., & Gero, J. S. (1992). An evolutionary process model of design. Design Studies, 13(3), 273-290.

[52] Thoring, K., & Müller, R. M. (2011, October). Understanding the creative mechanisms of design thinking: an evolutionary approach. In Procedings of the Second Conference on Creativity and Innovation in Design (pp. 137-147).

[53] Oh, S., Jung, Y., Kim, S., Lee, I., & Kang, N. (2019). Deep generative design: Integration of topology optimization and generative models. Journal of Mechanical Design, 141(11), 111405.

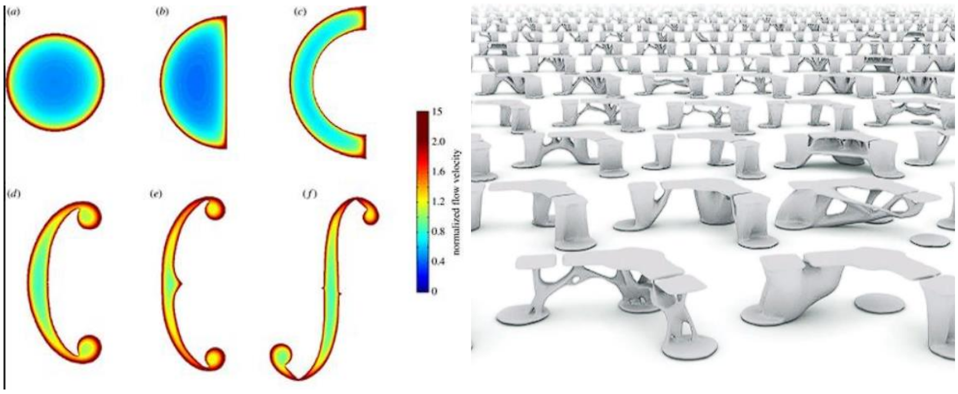
[54] Bown, O., & McCormack, J. (2011). Creative agency: A clearer goal for artificial life in the arts. In Advances in Artificial Life. Darwin Meets von Neumann (pp. 254–261). Springer Berlin Heidelberg.

[55] Csikszentmihalyi, M. 1999. Implications of a systems perspective for the study of creativity. In Sternberg, R. J., ed., The Handbook of Creativity. New York: Cambridge University Press. 313–335.

[56] Amabile, T. (2011). Componential theory of creativity (pp. 538-559). Boston, MA: Harvard Business School.

[57] Simonton, D. K. (2003). Scientific creativity as constrained stochastic behavior: the integration of product, person, and process perspectives. Psychological bulletin, 129(4), 475.

field. He draws on the phenomenon of 'multiple discoveries'[58] to show that instead of being the result of an individual's scientific brilliance, scientific innovation is the unavoidable consequence of sociocultural processes. At the micro level, he explains, 'The disciplinary ideas making up each creator's sample are then subjected to free, relatively unconstrained, or quasi-random recombination, with the aim of finding original and useful permutations.'[59] And while these permutations eventually lead to innovative ideas, the macro level of creativity can be seen as a stochastic search process where certain innovations are bound to happen; however, the identity of the inventor is largely a matter of chance. In other cases, there is not a singular inventor, but the design is the result of a multigenerational process that is analogous to natural evolution. Nia et al.[60], for instance, showed supporting evidence that the shape of sound holes in violins evolved through an evolutionary process that involved apprentices imitating their masters' designs while introducing random errors and variations—as in algorithmic design (Fig.4). It was observed that designs with louder sounds, resulting from the shape of the holes on the body of the violin, ultimately proved to be more successful over time (sold better), which introduced a selection pressure. The development of the violin's sound hole can be seen as a result of 'purely random mutations from craftsmanship limitations and subsequent selection.'



4. Figure Left: Sound hole shape evolution driven by maximization of efficient flow near outer perimeter, minimization of inactive sound-hole area and consequent maximization of acoustic conductance. Right: Illustration of a collection of design variation for a single task: lifting a computer monitor off a desk. Source: Matejka, J., Glueck, M., Bradner, E., Hashemi, A., Grossman, T., & Fitzmaurice, G. (2018, April). Dream lens: Exploration and visualization of large-scale generative design datasets. In Proceedings of the 2018 CHI conference on human factors in computing systems (pp. 1-12).

Creative agency in augmented design

Evolutionary theories of creativity question the egocentric view of creative agency by shifting the focus from the individual to the system-level interactions. This is in line with the cognitive theories of the mind, that view the subject as inherently distributed in the social, cultural, material environment. The 4E approach in cognitive science claims that cognition is embodied, extended, embedded, and enacted, therefore it cannot be entangled from its

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[58] A multiple discovery is said to take place whenever two or more scientists independently make the same contribution (Ibid.)

[59] (Ibid.)

[60] Nia, H. T., Jain, A. D., Liu, Y., Alam, M. R., Barnas, R., & Makris, N. C. (2015). The evolution of air resonance power efficiency in the violin and its ancestors. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 471(2175), 20140905.

environment and analysed separately.[61] The extended mind hypothesis refers to the idea that humans are inseparable from their technologies and agency is distributed in the material environment, because it is a relational property that emerges from the interaction[62]. As Bown points out 'The [blind] man does not see with the stick; the man+stick sees.'[63]

These notions shed a different light on the matter of agency because they question the so-called 'button press model' of the world, which assumes that agentive action originates in the singular subject.[64] In the button press perspective, subjects unilaterally control the world which is assumed to be independent of them. It can be contrasted with the 'handshake model' that posits that agency emerges from the interaction, therefore control is distributed. This is in line with Malafouries' theory of 'material agency'. He claims that as soon as we refer to internal causes, brain signals, etc. in the explanation of the creative process, we already fell in the trap of the 'I did it-stance.'[65] The term 'material agency' is introduced to explain the phenomena that 'agency and intentionality may not be properties of things, they are not properties of humans either: they are the properties of material engagement, that is, of the grey zone where brain, body and culture conflate.'[66] Bown formulates this mutual reciprocity between the individual and the environment in the following way: 'The potter is responsive to the clay, and in her adaptivity, allows causality to flow back in the opposite direction from clay to action.'[67]

Although the (im)materiality of AI systems is very different, it is still a relevant question, how the emergence of active AI tools can lead to new flows of causality in the design process. Using a metaphor: if we imagine traditional design like driving a car, then generative design is more like riding a horse, where the result emerges from the interaction between the rider and the animal. As the material responds to the creator's action, new affordances emerge that give ways to new actions in a reciprocal, cyclical process. Therefore, the responsivity of the material and the tool are necessary for creative making. Active tools are responsive in a unique way, and they introduce a special kind of randomness and complexity. Gero distinguishes 'routine designing' from 'creative designing' and shows that the latter is about 'perturbing the scheme to produce unexpected and incongruous results.'[68] Unexpectedness and emergence are characteristics of creative acts. Active, AI-infused, responsive tools can introduce *controlled* unexpectedness, therefore facilitate creativity more than their passive predecessors. As Celestino Soddu phrased it in his work on generative city design 'This field of possible randomness becomes the fertile

[61] Newen, A., De Bruin, L., & Gallagher, S. (Eds.). (2018). The Oxford handbook of 4E cognition. Oxford University Press.
[62] As Fred Cummins put it '…subject and world are brought forth through the self-creating, self-sustaining activities of the system.' Cummins, F. (2020). On vain repetitions: The enactment of collective subjectivities through speaking in unison. In Mediation and Immediacy (pp. 165–178). De Gruyter.
[63] Bown, O. (2015, June). Attributing Creative Agency: Are we doing it right?. In ICCC (pp. 17-22).
[64] Cummins, F. (2020). On vain repetitions: The enactment of collective subjectivities through speaking in unison. In Mediation and Immediacy (pp. 165–178). De Gruyter.
[65] Malafouris, L. (2008). At the Potter's Wheel: An Argument for Material Agency. In C. Knappett & L. Malafouris (Eds.), Material Agency: Towards a Non-Anthropocentric Approach (pp. 19–36). Springer US.
[66] (Ibid.)
[67] Bown, O. (2015, June). Attributing Creative Agency: Are we doing it right?. In ICCC (pp. 17-22).
[68] Gero, J. S. (1996). Creativity, emergence and evolution in design. Knowledge-Based Systems, 9(7), 435-448.

ground on which to graft the development of one's conceptual needs, one's subjective gestures, one's cultural references.'[69]

In this framework, we can argue that creative processes always have been distributed, encompassing individuals, tools, materials, and social environments. What is new in generative AI is that it makes visible this distributed feature of creative agency more than previous methods because it amplifies agentive input from the non-human side and introduces a unique source of randomness and serendipity. Due to the shared evolutionary principles beyond creativity, design and evolutionary algorithms, it is easy to see that algorithmic augmentation could support both divergent and convergent phases of the creative design process through idea generation and optimization. On the other hand, current AI models are just tools, lacking any kind of agency and creativity without human interaction, therefore we do not think AI will be able to replace human designers in the near future. Human and AI collaboration will likely outperform either one working independently. We believe that a co-creative design process sets the path to move forward.

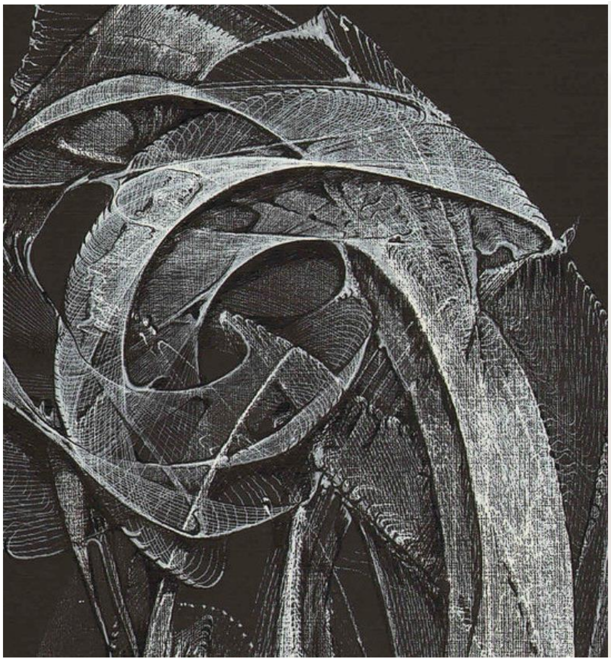
Forerunners of generative design in the 20th century

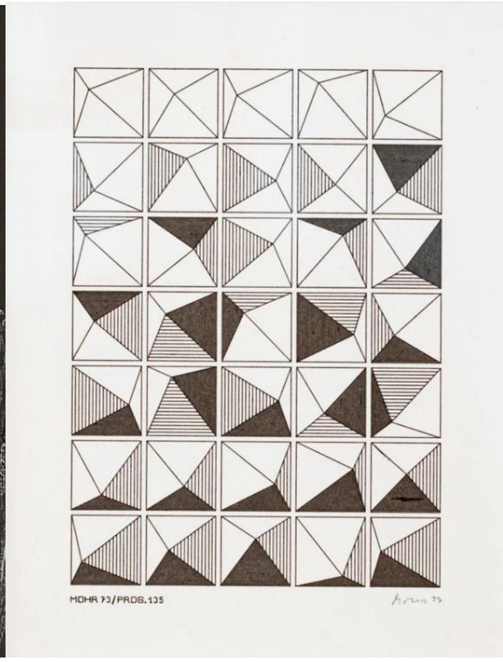
Algorithmic approaches to design—as repeated applications of simple rules that lead to complexity—has deep historical roots, and can be seen across cultures, from the tessellations of tiles at the Alhambra Palace, to the intricate patterns of Japanese Sashiko stitching. Algorithmic art and design are not new by any means, but computational tools helped to realize their true potential. Neo-constructivism, Kinetic Art, and other systematic approaches of the 1950s and 1960s had a 'tendency towards merging art and science and technology.'[70] As N. Katherine Hayles summarized fifty years later: 'The time was ripe for theories that reified information into a free-floating, decontextualized, quantifiable entity that could serve as the master key unlocking secrets of life and death.'[71] This radical belief in the power of information has been crystallized in the Information Aesthetics theory, created by Bense and Moles in the 1950s. Their concept of the 'aesthetic state' was a methodological approach to create a mathematical framework for art and beauty.[72] Bense's theories were inspired by the ideas from information theory, particularly those developed by Claude Shannon, and the field of semiotics, advanced by Charles Sanders Peirce. Despite the reductionist approach of Information Aesthetics, it has had a lasting influence on the philosophy of computer art and have sparked many discussions about the nature of aesthetic experience in the context of algorithmic and digital art forms.

Hungarian artist, Vera Molnár is considered one of the pioneers of computer art (Fig.7). She was familiar with Bense's ideas, and she started creating algorithmic paintings as early as the 1960s.[73] She used a plotter to execute her programmed geometric designs, which explored the visual complexity that could be generated from simple rules. In similar

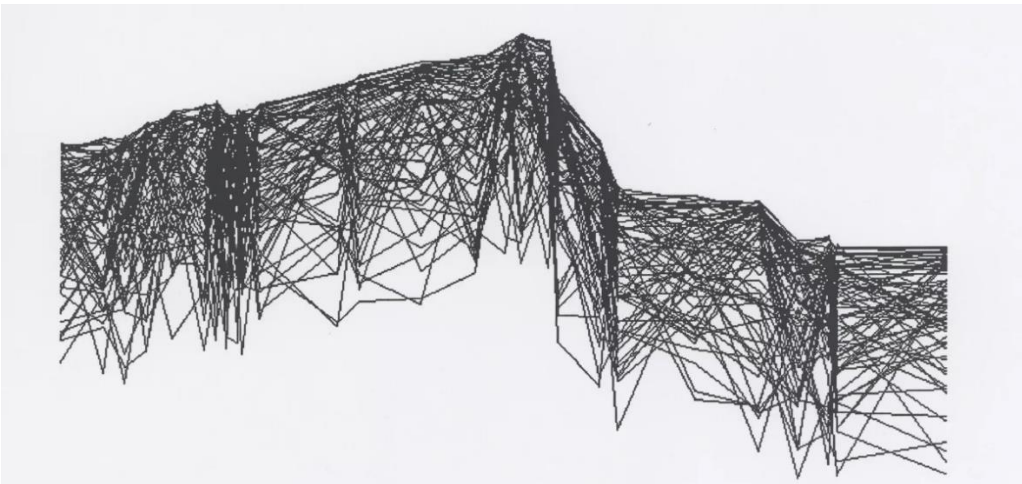
[69] Soddu, C. (1989). Generative City Design, Aleatority and Urban Species, Unique, Unrepeatable and Recognizable Identity, like in Nature. pp. 21
[70] Fritz, D. (2011). Mapping the Beginnings of Computer-generated Art in the Netherlands.
[71] Hayles, N. K. (2000). How we became posthuman: Virtual bodies in cybernetics, literature, and informatics. pp. 19
[72] Guillermet, A. (2020). Vera Molnar's computer paintings.
[73] (Ibid.)

vein, in the late 1960s, Manfred Mohr[74] started creating computer-generated artwork with analogue equipment. His work focused on the cube and its higher-dimensional analogues, exploring the logical rigor and variations within strict geometric frameworks (Fig 6). Desmond Paul Henry is another famous figure of the field. He served as a navigator and bomb-aimer in WWII, and later he constructed a drawing apparatus inspired by the bombsight equipment he used in the war.[75] The machine moved a pen across a drawing surface in intricate patterns determined by its settings. These settings could be adjusted to create variations in the designs, resulting in a unique piece of art every time. (Fig 5)





5. Figure Desmond Paul Henry, #096, 1965Kate Vass Galerie 6. Figure Manfred Mohr | P-135small (1973)



7. Figure Vera Molnar, Variations St. Victoire, 29,7 x 42 cm, Laser Print, Edition of 4, 1989-1996

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[74] Mohr, M. (2002). 9 Generative Art. Explorations in Art and Technology, 111.
[75] "Desmond Paul Henry." Wikipedia: The Free Encyclopedia. Wikimedia Foundation, 26 November 2023. Web. Accessed 15 December 2023.

The 1968 Cybernetic Serendipity exhibition curated by Jasia Reichardt at the Institute of Contemporary Arts in London can be viewed as a landmark in the history of algorithmic art and design. Among many others, it featured John Whitney's computer-generated movies, Peter Zinovieff's generative musical equipment, and Margaret Masterman's generated haikus. [76] The exhibition had more than 40 thousand visitors and it helped to spread ideas of computer art in the 1960s and led to the establishment of the Computer Arts Society in Britain which quickly gained global reach.

Generative methods also influenced architecture, and the first contemporary uses of GD appeared in the 1980s and 1990s. Architects like Peter Eisenman and Greg Lynn have experimented with techniques of scaling, fractals, overlay and superposition, inspired by Derrida's Deconstruction theory[77] and Deleuze's 'The Fold: Leibniz and the Baroque'[78]. The works of Eisenman can be considered as the first contemporary generative design attempts. His approach is reflected for instance in the Biocentrum in Frankfurt (1987, the Groningen Music-Video Pavilion (1990), and in the Nunotani Corporation headquarters in Tokyo (1992). Greg Lynn is another early contributor to GD. His biomorphic designs often utilize 'blobs' and he coined the term 'blobitecture' in which buildings have an organic, amorphous form. Lynn discovered the idea by playing with organic-looking multi-dimensional isosurfaces (meatballs) in computer graphics software.[79] John Frazer's book 'An Evolutionary Architecture', published in 1995, outlines his vision of an architecture that mimics natural evolutionary processes. The text delves into themes of AI, genetic algorithms, and the potential of architecture to self-organize and adapt to its environment over time. Frazer championed the idea that designs should not be static end-products but rather evolving entities that can respond to changing conditions and user needs. He explored the potential of creating design systems that could generate a multitude of solutions rather than a single fixed form. One of Frazer's significant contributions is his emphasis on the adaptability of structures to their environments, promoting the concept of a symbiotic relationship between architecture and nature. His idea of the 'Universal Constructor'[80] was an early project to generate form autonomously. It was based on the concept of cellular automata and could theoretically extend infinitely in all directions.

Since the 1990s, GD has seen significant advancements propelled by rapid developments in computational power and software, but we are still at the beginning of this paradigm shift. The integration of AI has enabled more complex, adaptive, and efficient design processes, and collaborative tools have allowed cross-disciplinary interactions, while the rise of digital fabrication technologies like 3D printing has enabled the realization of intricate generative designs. While GD has been successfully applied in many areas, due to

[76] Reichardt, J. (1968) Cybernetic Serendipity. In Compart Center of Excellence Digital Art archive. Retrieved from http://dada.compart-bremen.de/item/exhibition/3
[77] Agkathidis, A. (2016). Generative design. Hachette UK.
[78] Torres, N. R. (2017). Computational Matters.
[79] Schumacher, P. (2010). Patrik Schumacher on parametricism, 'let the style wars begin'. Architects' Journal, 6.
[80] Frazer, J. H. (1993). The architectural relevance of cybernetics. Systems research, 10(3), 43-48.

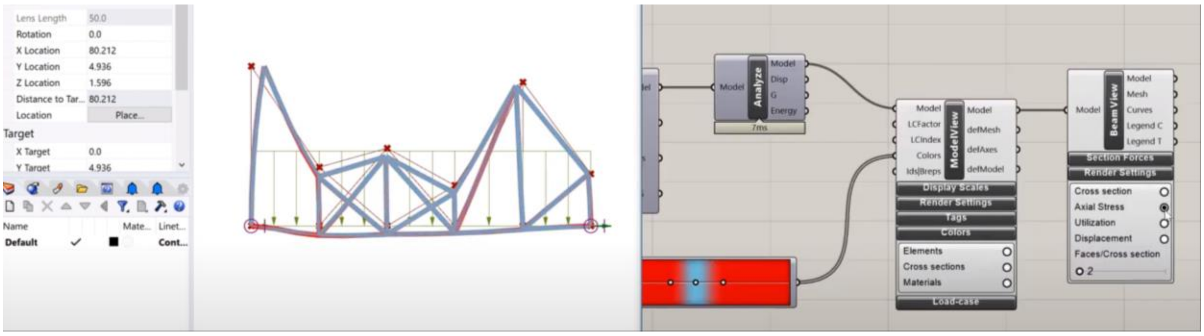
the limitations of current manufacturing techniques, the large-scale breakthrough it promises is still ahead of us.

Generative design today

The terms ‘generative design’ (GD), ‘parametric design’, and ‘algorithmic design’ are often used interchangeably to describe the same design approach that focuses on the generation of design solutions based on rules or algorithms[81]. We can distinguish between the old-fashioned generative design (GD) and the broader use of GenAI, which stems from more recent advancements in GANs and convolutional networks. GD, in its traditional sense, is an established method that utilizes algorithms for form-finding and optimization. GD is most applicable in tackling problems that can be expressed mathematically, as it is a parameter-based technique. The first generative attempts in design date back to the 1950s, and over the past few decades, GD has been employed across various fields, including architecture, engineering, additive manufacturing, product design and urban design.[82] Topology optimization, which is a subtractive method to remove material, and generative design solutions, which are additive methods to 'grow' structures, are the two main approaches.[83]

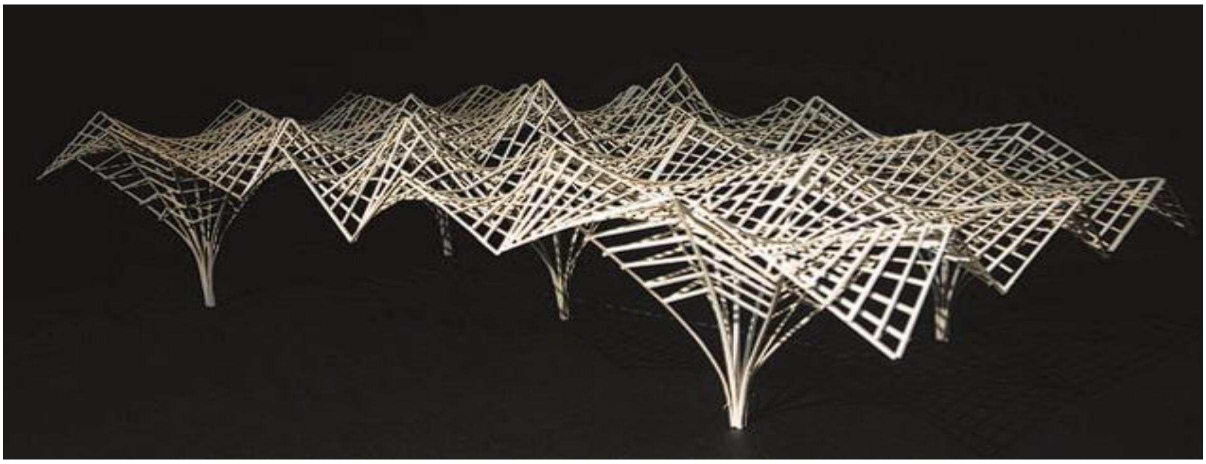
These techniques rely primarily on evolutionary algorithms, not ANNs. To carry out a GD study, the designer needs (1) a parametric model that is able to explore the design space, (2) a set of design goals to evaluate the solutions (3) and an optimization engine to evolve the best solutions. In iterative steps, the model can find optimal solutions for complex design problems. The job of the designer is to properly set up the computational environment and guide the ‘evolution’ of the solutions (e.g. with a script in Grasshopper[84] Fig.8). Modern GD is based on computational tools implemented in software like Rhinoceros 3D, Autodesk Fusion 360, or nTop among others. In this context, GD is essentially an explorative process that quickly generates design alternatives within the constraints set by the user. It allows for the exploration and optimization of large design spaces. According to Buonamici, GD ‘refers to a series of tools, implementing artificial intelligence methods and algorithms, applied to solve design problems. … [T]his often results in an iterative optimization process that tries to minimize an objective function.’[85] Iteration and optimalization are central to generative methods.

[81] Agkathidis, A. (2016). Generative design. Hachette UK.
[82] Soddu, C. (1989). Generative City Design, Aleatority and Urban Species, Unique, Unrepeatable and Recognizable Identity, like in Nature.
[83] Miller, E. (2019, Aug 28) Topology Optimization vs. Generative Design. Youtube. Retrieved from https://www.youtube.com/watch?v=QLA92V_85_I&ab_channel=AdditiveManufacturingMedia
[84] Grasshopper is a visual programming language integrated within Rhinoceros 3-D application. It allows designers to create form-generating algorithms without the need for traditional programming knowledge.
[85] Buonamici, F., Carfagni, M., Furferi, R., Volpe, Y., & Governi, L. (2020). Generative Design: An Explorative Study. Computer-Aided Design and Applications, 18(1), 144–155.



8. Figure. Grasshopper UI. Source: Nagy, D. https://www.youtube.com/watch?v=mrXOuiudzQA&ab_channel=DanilNagy

A synonym for GD in the architectural discourse is "digital morphogenesis" which refers to the synthetic approach of generating complex architectural components with computational tools. It is associated with the concepts of emergence, self-organization, and form-finding.[86]-[87] To emphasize its similarity to biological and evolutionary processes, Hensel defines morphogenesis as a 'self-organization process, underlying the growth of living organisms, from which architects can learn.'[88] While algorithmic design approaches can be goal-oriented, they also support explorative form-finding practices, as seen in architectural studies[89], for instance explorations with bendable timber meshes[90] ; concrete shell primitives[91]; paraboloid surfaces[92]; digital twisting techniques.[93] (Fig.9)



9. Figure Paraboloid structure, double-curved surface model.

[86] Roudavski, S. (2009). Towards Morphogenesis in Architecture. International Journal of Architectural Computing, 7(3), 345–374.
[87] Liu, J., Guan, Z., Chen, X., & Chun-yi, X. (2018). Digital morphogenesis: a synthetic approach to generate architectural elaborate components. Proceedings of the 2017 3rd International Forum on Energy, Environment Science and Materials (IFEESM 2017). https://doi.org/10.2991/ifeesm-17.2018.253
[88] Hensel, M. (2006). Computing self-organisation: environmentally sensitive growth modelling. Architectural Design, 76(2), 12-17.
[89] Agkathidis, A. (2016). Generative design. Hachette UK.
[90] (Ibid.) pp. 25
[91] (Ibid.) pp. 30
[92] (Ibid.) pp. 38
[93] (Ibid.) pp. 72

An iconic example of GD in architecture is The Water Cube of the 2008 Beijing Olympics what was inspired by the structure of soap bubbles and then modelled with algorithmic tools.[94] (Fig 10.)

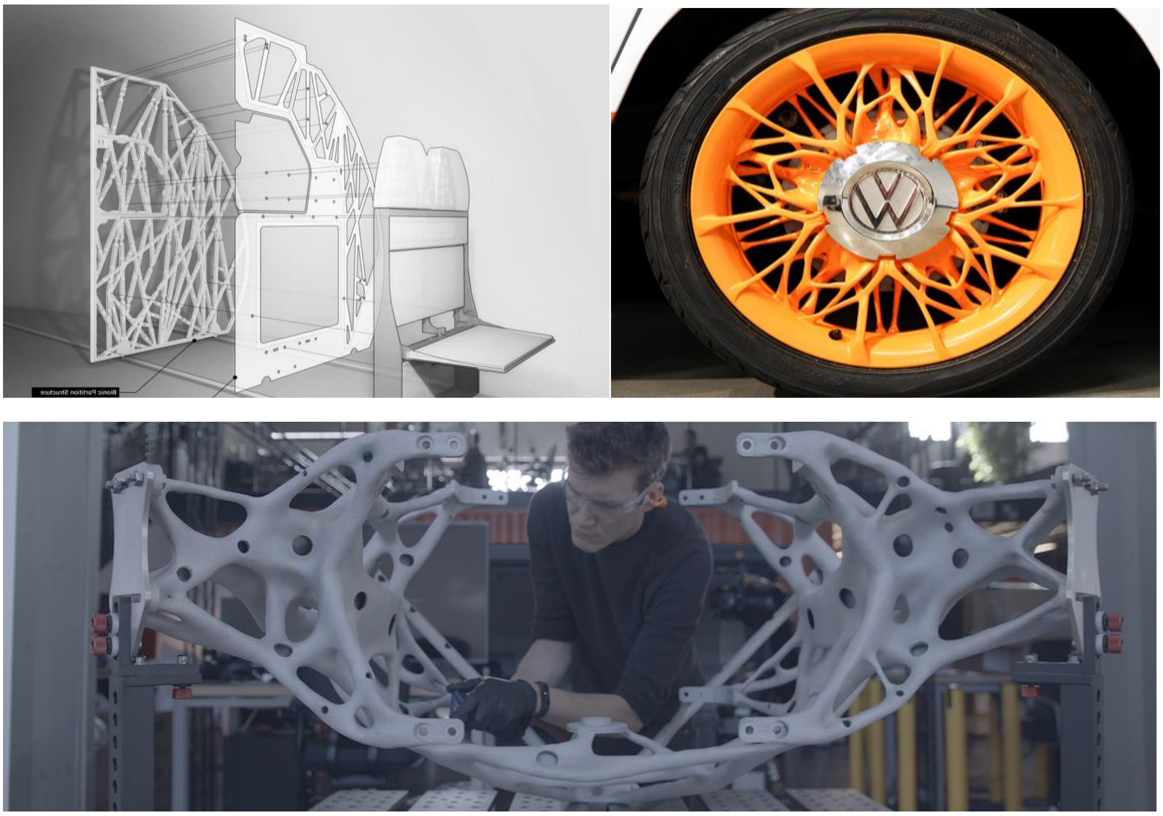
10. Figure The Water Cube, 2008, Beijing

In fashion and sportswear, GD is often used to design custom products, such as the Nike 2016 Olympic footwear which was algorithmically optimized for each athlete and helped to win 45 medals (Fig.11 a). Under Armour's 3D printed footwear is optimized for weight and stability (Fig.11 b) while Ica & Kostika's 3D printed mycelium shoe plays with weird AI-generated forms that showcases GD aesthetics (Fig.11 c). GD excels in creating complex, organic-looking structures that are lightweight and still very strong. It is interesting that optimized forms often look organic for the human eye, which underlies the similarities in evolutionary and algorithmic form-finding. GD simply look organic, because the forms are 'evolved' through an iterative selection process, similar to natural selection—they are closer to optimal than traditional human designs.

11. Figure Shoes made with GD. Source: a) https://designisso.com/2022/10/25/co-creating-with-machine-intelligence-an-interview-with-lysandre-follet b) https://medium.com/@autodesk/how-generative-design-helped-under-armour-make-its-first-3d-printed-training-shoe-975fad6573a6 c) https://design-milk.com/ica-kostika-launch-3d-printed-footwear-collection-called-exobiology/

[94] Carfrae, T. (2006). Engineering the water cube [The engineering factors which led to the Beijing Olympic Swimming Centre by PTW, China State Construction and Engineering Co and Arup.]. Architecture Australia, 95(4), 103-105.

With the slow but steady advances in additive manufacturing (3D printing), mass production of generatively designed solutions may be possible in a decade.[95] The benefits of additive manufacturing are ‘design liberty, bulk customization, unwanted minimization, and the capacity to build complicated assemblies, as well as rapid prototyping.’[96] Airbus’ 3D printed cabin component that weights 45% less than current designs[97] (Fig.12 a) or Volkswagen GD-enhanced hippie bus[98] (Fig.12 b) that showcases the aesthetics of GD, are only proof of concepts, because we are still quite far from the scalability of these products. But where scalability is not an issue, GD solutions can yield great results. The collaboration between Autodesk and NASA’s Jet Propulsion Laboratory aims to find out how to incorporate GD into the design of landers.[99] (Fig. 12 c)



12. Figure a) Boeings cabin partition element b) VW’s concept design of a generated wheel c) NASA’s GD lander

[95] Jandyal, A., Chaturvedi, I., Wazir, I., Raina, A., & Haq, M. I. U. (2022). 3D printing–A review of processes, materials and applications in industry 4.0. Sustainable Operations and Computers, 3, 33-42.
[96] Praveena, B. A., Lokesh, N., Buradi, A., Santhosh, N., Praveena, B. L., & Vignesh, R. (2022). A comprehensive review of emerging additive manufacturing (3D printing technology): Methods, materials, applications, challenges, trends and future potential. Materials Today: Proceedings, 52, 1309-1313.
[97] "Pioneering bionic 3D printing." (2016). Airbus. Retrieved from https://www.airbus.com/en/newsroom/news/2016-03-pioneering-bionic-3d-printing
[98] Deplazes, R. (2019). Autodesk Collaborates With Volkswagen Group on Generative Design in Electric Showcase Vehicle. Autodesk. Autodesk Collaborates With Volkswagen Group on Generative Design in Electric Showcase Vehicle
[99] Collins, C. (2018). Autodesk Teams Up with NASA’s Jet Propulsion Laboratory to Explore New Approaches to Designing an Interplanetary Lander. Autodesk. https://adsknews.autodesk.com/en/news/nasas-jet-propulsion-lab-teams-autodesk-explore-new-approaches-designing-interplanetary-lander/

Generative AI in the creative industries

In its broader sense, GD also includes a new branch of GenAI applications that can be used in design as well. Most of these tools rely on the new wave of foundation models, such as GPT-4, DALL-E, Midjourney, Stable Diffusion Synesthesia, etc.[100] Apps using these models represent a different class of tools, that are more accessible without programming knowledge, and often more customizable than the large models own interface but still limited in many aspects.[101] Opensource models like LLaMA 2 or BERT offer a more customizable alternative, and they do not lag behind significantly in performance.[102]

Foundation models are 'frozen in time' which refers to the fact that their parameters can only be tweaked by costly retraining, and although they can handle new data through APIs and other tricks, the models are fixed which means users do not have direct control over the internal parameters of the model like in traditional GD. But this does not mean they are useless in the design process—which is reflected in the proliferation applications (based on foundation models) designed for the creative industries. The capabilities of foundational models like GPT-4 are not fully understood yet, and researchers work on different tactics to reveal it—such as connecting AIs in a social simulation to see what emerges.[103] This points to an interesting aspects to these models. ChatGPT for example can be 'coded' to do things in natural language, without any programming skills. For instance, in the mentioned social-AI study, researchers gave instructions to the models in form of English sentences to inform them who they are and how to handle the simulation. This type of human-computer interaction is only made possible by the recent appearance of large language models, and it allows users with limited programming skills to set up multi-agent environments or to build apps.[104] Ever since APIs have been released for the large models, applications can integrate their functionality much better, which has opened new options, such as unique editing tools that give much more control over the generation process. For instance, InvokeAI[105] is an implementation of the open-source model Stabel Diffusion and it provides a streamlined toolkit to aid the image generation process. It runs on personal computers with GPU cards with as little as 4 GB of RAM. It is a good example of what already existing technology can achieve if connected in smart ways. Training one's own neural network to generate data is also an option and allows for more artistic, unique tools that designers can develop for themselves. Research has showed that Pytorch implementations of different GAN algorithms (trained with a single GPU on ten thousand

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[100] For a review of 42 unique AI tools, see Hwang, A. H.-C. (2022). Too Late to be Creative? AI-Empowered Tools in Creative Processes. Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems, Article Article 38.

[101] Interactive machine learning is an attempt to solve this, since it gives users access to model parameters. Fails, J. A., & Olsen Jr, D. R. (2003, January). Interactive machine learning. In Proceedings of the 8th international conference on Intelligent user interfaces (pp. 39-45).

[102]https://www.youtube.com/watch?v=TlThruDJcrQ&list=PLL0Y5BskqF2pnfNl_JmifSl3MREs_AbVg&index=3&ab_channel=WesRoth

[103] Park, J. S., O'Brien, J., Cai, C. J., Morris, M. R., Liang, P., & Bernstein, M. S. (2023, October). Generative agents: Interactive simulacra of human behavior. In Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (pp. 1-22).

[104]Benson, T. (2023, May 1). GPT-4 - How does it work, and how do I build apps with it? - CS50 Tech Talk. Youtube. Retrieved from https://www.youtube.com/watch?v=vw-KWfKwvTQ&ab_channel=CS50

[105] https://invoke-ai.github.io/InvokeAI/

images of character silhouettes) yielded good results in generating new silhouettes that could serve as a starting point for ideas.[106] (Fig.13) This paper also demonstrates that training an AI model on a custom database using a personal computer is possible with current tools.

13. Figure Silhouettes for character design Source: Lataifeh, M., Carrasco, X., Elnagar, A., & Ahmed, N. (2023, June). Augmenting Character Designers' Creativity Using Generative Adversarial Networks. In International Conference on Interactive Collaborative Robotic

A notable example in the field of UX design is Uizard[107], an AI-powered design tool that is tailored to help convert UI ideas into mock-ups with ease. It can transform hand-drawn sketches into interactive, digital formats. The platform is designed to accelerate and simplify the creation process, making it more accessible for people without in-depth knowledge of complex design software to bring their digital ideas to life.

Although the raw output of image generators like DALL-E or Midjourney are not suitable for professional work (even if it could win a prize at the Colorado State Fair[108]), they could serve as inspiration pumps. AIs cannot extrapolate well from the dataset, but by remixing the billons of images they were trained on –which represents large portion of visual culture— novelty can emerge. As we have discussed above, combination and mutation of ideas is essential in invention, therefore the common view that novelty cannot emerge from existing things is not supported by the evolutionary accounts of creativity. Generating different textures[109], 3D models[110], seamless patterns[111], backgrounds[112], characters[113] by combining different visual styles, themes and prompting techniques, can serve as a source for new ideas. GenAI can supports ideation also by the speed it generates content.

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[106] Lataifeh, M., Carrasco, X., Elnagar, A., & Ahmed, N. (2023, June). Augmenting Character Designers' Creativity Using Generative Adversarial Networks. In International Conference on Interactive Collaborative Robotics (pp. 80-92). Cham: Springer Nature Switzerland.
[107] Uizard. https://uizard.io/
[108] Roose, K. (2022, Sept 2) An AI-generated picture won an art prize. Artists aren't happy. Thw New York Times. Retrieved from https://www.nytimes.com/2022/09/02/technology/ai-artificial-intelligence-artists.html
[109] https://poly.cam/tools/ai-texture-generator
[110] https://www.alpha3d.io/ai-3d-model-generator/
[111] https://www.patterned.ai/gallery
[112] https://hotpot.ai/background-generator
[113] https://perchance.org/ai-character-generator

Hwang[114] has tested 42 unique creative AI apps and categorized them into the following four categories:

Editors streamline various tasks, making it easy for users to modify content (e.g. changing the background of an image)

Transformers modify content from one form to another (e.g. turning hand-drawn sketches into digital images or translating UI templates into executable front-end code).

Blenders merge multiple creative elements to forge new concepts and creations (e.g. restyling an image).

Generators create ready-made creative content based on user-provided guidelines or constraints (e.g. image generators).

The future of generative design

At last, we would like to give a few predictions concerning the future of GenAI and GD, informed by current trends.

We anticipate that AI will become increasingly integrated into workflows across creative industries. AI assistants and features supported by AI are expected to be implemented in every major piece of software so seamlessly that their presence goes unnoticed.[115] Automating routine tasks will be the norm, and designers will commonly use AI tools to help brainstorm and create basic design elements. For example, video game artists might use AI to quickly create different textured 3D models of environments and then pick the one they prefer.[116] In this context the designer steps up as a conductor or a curator who guides the generation process and picks the best solutions based on his/her intuition, and the rest of the work is automated. Extrapolating this trend shows a paradigm shift where creative professionals focus on high-level, strategic decisions, while automated AI systems would be making granular decisions and carrying out routine tasks.

Another important aspect is GenAI's contribution to enhanced customization and personalization. As generative design tools become more accessible, products and designs could be customized completely to individual preferences or specific sites without increases in cost or time. Imagine a scenario where an individual's biometric data, style preferences, and usage patterns are fed into a GD system. In industries like fashion or furniture design, such data can give rise to products that are not just tailored to the individual’s size and shape but also to their aesthetic preferences and functional requirements. This approach could also encourage customers to share their personal data, thereby incentivizing data collection from their perspective. Additionally, it would promote further deployment of environmental sensors, thereby expanding the Internet of Things (IoT) infrastructure even more. The need for data may also influence design decision in favour for solutions that can collect data from the user.

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[114] Hwang, A. H.-C. (2022). Too Late to be Creative? AI-Empowered Tools in Creative Processes. Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems, Article Article 38.

[115] As seen in products like Adobe Firefly generative AI in Photoshop https://www.adobe.com/products/photoshop/ai.html

[116] https://auctoria.ai/

In product design, engineering and architecture, GD algorithms will be part of the primary toolkit soon. GD will enable the rapid prototyping of products and accelerating development. In engineering these tools can help in simulating real-world scenarios, testing how designs perform under different conditions without the need for costly physical prototypes. GD can also contribute to more efficient use of materials, benefiting both the environment and cutting costs. It can also streamline the design and manufacturing processes by optimizing for factors such as durability, material distribution, waste minimization, and environmental impact. The main challenge the industry is facing now is with manufacturing these products on large-scale. GD is progressing rapidly, but the additive manufacturing needed to mass-produce GD is not advancing as fast. This gap slows down the full application of GD in production, and advancements in additive manufacturing are needed to realize the complex designs that algorithms can create.

The trend of shortening development periods is likely to continue and may be further accelerated by the integration of GD and additive manufacturing techniques. With the advancement of these technologies, traditional notions of development cycles could become obsolete. Instead, product development might shift towards a continuous, real-time process that is highly responsive to immediate user feedback. The growing capacity for customization made possible through these methods could potentially signal the end of standardized product development cycles. This would represent a shift from a discrete, step-by-step approach to an iterative and flexible model of production, where the lines between product development stages become increasingly blurred. This design paradigm could be characterized by a model that is open-ended and dynamic, consistently self-optimizing, and highly customizable. This approach would be a departure from static, predetermined designs, moving towards a system that evolves and improves continuously.

As we see, GD will become a major disruptor in design and manufacturing industries, potentially revolutionizing how we create, build, and use everything from consumer products to buildings to infrastructure systems. The key to its future will be in how well it is integrated with other evolving technologies and the extent to which industries are ready to adopt these new methods.

Conclusions and further research

In this article, we have reviewed the fundamental questions of generative artificial intelligence and sought its connections to contemporary design. The investigation primarily took place from the perspective of design theory, emphasizing the changes in design methodology and the designer's toolkit.

Through the overview of generative AI techniques, we have found that for contemporary generative design, evolutionary algorithmic systems are the most influential. While design can be defined in many ways, here we primarily described it as a problem-solving process, involving a series of optimization and iterative steps. This aligns with numerous contemporary design definitions, and allows us to connect design processes to the theory of evolutionary creativity. Thus, highlighting a clear connection between design thinking and the mechanisms of generative AI. However, as we explore the relationship between AI and design in the future, it may be worthwhile to incorporate other nuanced definitions of design into the research and open up to the historical contexts of modern design and human-machine interaction.

The analysis of the questions of agency in the augmented AI environment has allowed us to start developing the theory of generative design towards the concepts of shared agency and co-creation. This necessitates further elaboration and research, placing even greater emphasis on the diversity of various contemporary design practices. Furthermore, shared agency can expand thinking not only in the context of AI but also in other directions, such as towards biomimicry or biodesign, and enable the development of a broader design framework.

The mapping of current generative techniques in the creative industries has enabled the extrapolation of future trends, such as the strengthening of designers as curators, the expansion of the world of customizable products, the reduction of product development cycles, the proliferation of the Internet of Things (IoT), and the emergence of non-static designs. Examining the AI-influenced design space has made it clear that designers must increasingly move away from the conceptualization of standalone objects and experiences towards thinking in systems if they want to meaningfully describe and control the augmented design process.

As a continuation of this research, it is important to move beyond design methodologies. We need to open up to broader historical and cultural contexts of generative design, as well as its contemporary sociotechnical systems, to grasp the radical changes that the rise of AI could bring to design culture. In this pursuit, we will draw upon critical AI studies—an emerging field that does not describe developments in AI solely through narrow technical histories or speculative narratives related to technological singularity. Instead, it investigates the social and historical embedment of AI.[117]

Our goal is to start blending the extensive critical discourses related to GenAI with the relevant aspects of design culture studies. The initial steps towards this were taken in this article. In the future, we will draw on the results of contemporary social theory and science and technology studies to provide a more precise description of the generative turn in the field of design culture.

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