TOWARDS AI-ASSISTED DESIGN WORKFLOWS FOR AN EXPANDED DESIGN SPACE

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Abstract. The scope of this paper is to formulate and evaluate the structure of a viable design workflow that combines a variety of computational tools and uses artificial intelligence (AI) to enhance the designer's capacity to explore design options within an expanded design space. In light of the autonomous and progressively post-anthropocentric generative capability of recent AI strategies for architectural design, we are interested in investigating some of the challenges involved in the insertion of such AI strategies into a new generative design system, involving data curation and the placement of any AI-assisted model in the overall workflow, as well as its (AI's) reciprocity with other computational methods such as discrete assembly and agent-based modeling. The paper presents our interrogation of the proposed AI-assisted framework, demonstrated in experiments of formulating multiple design workflows following different strategies. The workflow strategies show that integrating AI networks into a framework with other computational tools affords a different kind of design exploration than other methods; the prospect of novel solutions is heavily dependent on the interconnectedness of such methods and the dataset curation process. Collectively, the work contributes to innovation in architectural education and practice through enhancing scientific research (in line with UN Sustainable Development Goal 9).

Keywords. Artificial Intelligence; Deep Learning; AI-assisted Design Workflows; Design Space Exploration; Generative Systems; SDG 9.

1. Introduction

Generative design systems (GDSs) have been implemented as powerful supportive schemes for designers' exploration. The first generation of GDSs involved rule-based and/or performance-driven algorithms that evolve design as a product of a parametric exploration, with specific parameters and constraints, often to satisfy a set of objective functions (Stocking, 2009). Such deterministic algorithms require designers to input a set of parameters and examine a feasible search space. Such an approach addresses design activity as a generalized reductive process, and the design space to be confined and limited to pre-programmed feasible solutions (Chen & Stouffs, 2021). Recent AI methods, (i.e. deep learning) are "learning systems" that do not require input-rules and

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learn directly from raw data to offer "unexpected" solutions (Hassabis, 2018). Benefitting from the widespread applications of AI, a recent second generation of GDSs is emerging, marking a shift in design, towards an unlimited exploration of the design space, which sometimes becomes a "hyper-dimensional" space, such as the latent space of StyleGAN models (Gui et al., 2020). AI models are now capable of autonomously defining their own parameters from information present in their input datasets (Chaillou, 2019a). Generative adversarial networks (GANs), which are sub-classes of DL models, can be incorporated to extend the lateral thinking constraints in current generative systems. Inserting AI into a generative approach expands the opportunities for exploring the complexity of a design problem within a larger, more representative search space where design decision-making based on a local examination, can determine how it contracts or expands (Bolojan, 2022).

This work addresses two research problems: (1) investigating new AI-assisted design workflows, and (2) researching methods of dataset acquisition-curation. Addressing Problem (1), we aim to interrogate methods and workflows for leveraging AI to coordinate other computational methods in the overall process. We examine how the "idea" of employing deep learning disrupts the "conventional" generative workflow and identifies possible combinations of methods and corresponding workflows to arrive at novel AI-assisted design systems. Such hybrid workflows require pre-design and intermediate tasks to be considered beforehand. Problem (2) addresses dataset acquisition-curation, a significant and time-consuming activity within AI approaches (Hasey et al., 2021). AI's performance is evidently contingent on the quality of data from which AI learns and extracts "knowledge". This investigation offers insight into the relevance of specific computational methods to produce custom datasets for AI processes. Proper dataset generation requires a prior clarification of the design intent so that the data reflects and supports the desired search direction. AI models seem to "learn" better from datasets that are explicitly designed for the training task relative to a specific design problem, compared to pre-existing data (i.e. available online). The "innovation" of AI-generated designs depends on the originality of the training datasets. Using AI to cross-pollinate architecture-specific domains with other types of references is analogous to architectural ideas' evolution through breeding different fields. The importance of this work lies in its research-driven pedagogy within an undergraduate architecture curriculum. Such work can act as a catalyst to attract funding towards advanced undergraduate research, a strategic goal in our institution, and create ties with the AI technology industry, (aligned with SDG 9) ensuring resiliency in the curriculum vis-à-vis future adoption of data-driven processes.

2. Theoretical Framework & State-of-the-Art

Reviewing state-of-the-art literature, Makoto Watanabe pioneered the use of AI within architectural design through an "inductive design approach". His method generated unpredicted "magic-like" aesthetics without a preconceived notion of "what good is". The process entailed an inter-exchange between the designer and the machine, where the computer inferred the design purpose based on designer's sketches, offering further ideas, followed by review until the design is satisfied (Watanabe, 2004). In interactive media art, Refik Anadol's process represents an excellent example for controlling the data curation to produce a creative artistic expression (Forbes, 2020). Chaillou's

(2019b) work represents early research of AI and architecture. His method, ArchiGAN, is a Pix2Pix-based GAN model that employs deep learning models at multiple scales to generate floor plans automatically. The model is trained with a database of annotated plans, starting with building footprints and moving to interior spatial distributions. Another research project employed CycleGAN to perform a heuristic search, cross-pollinating domains of Sagrada Familia with forests, hinting at ways that the network can learn structures and morphology (Bolojan & Vermisso, 2020). Daniel Bolojan and the work of Deep-Himmelb(l)au offer new possibilities for 3D-based GAN models (2022). In a different approach to 3D, Immanuel Koh (2021) uses discrete sampling to produce 3-dimensional representations for AI learning, in a hybrid workflow of computational and AI tools. Speculating on AI's role in architecture, Leach (2021) speaks of a future dominant "architectural intelligence". AI-assisted design is still experimental without yet leveraging AI's full capabilities in system-driven approaches. This work examines AI's potential for multiple design tasks across different phases.

We adopt here Christopher Alexander's systems thinking and his theory of "systems generating systems" (1968). In this sense, "a generating system is not a view of a single thing, it is a kit of parts, with rules about the way these parts may be combined" (Menges & Ahlquist 2011, p. 64). We consider the complex design problem as a process that involves multiple tasks (activities), and that AI models and computational methods can be connected in a sequential logic to achieve an "augmented" generative system. The significance of this work lies in demonstrating how DL models can be integrated into architectural design pedagogy, and their explicit support towards various aspects of design like concept, design development, etc. Emphasis is placed on the benefits and limitations of these hybrid workflows instead of the design outcomes because we believe the strategies are not project-specific and can be extrapolated to design studios in general. In order to expand the design space to include reference datasets (architectural, inspirational), computationally generated and behavior simulation-driven approaches can be incorporated, operating as dataset generation tools for the AI models. We herewith propose a hybrid prototype, that involves interlacing deep learning models and computational methods to control (guide) a generative system. To achieve that, the prototype involves developing multiple design workflow strategies (Section 4) to address: (i) identification of possible structures for integrating AI within different phases of the design cycle, (ii) identification of methods for dataset generation-curation, and (iii) evaluation of the AI-assisted generative workflows. The objective is to experiment with developing possible AI-assisted design workflows and offer insight into the potential and disadvantages of specific combinations of AI and computational methods for creative exploration.

3. Methodology

Our discussion addresses the importance of crafting custom design workflows that synthesize a variety of computational tools, as we place gravity on the impact of "process" for creativity. Indeed, neuroscience accepts several approaches for assessing creativity, focusing on "product" and "process" (Abraham, 2018). We believe that examining the advantages of the overall workflow and calibration of computational tools involved can provide a better intuition on their potential for novelty, than an independent evaluation of the design results. It is important to note that the creative potential of this hybrid process is contingent on its degree of flexibility; predetermined parameters and objectives do not necessarily support creative exploration. In fact, in computational design processes, design objectives and evaluation criteria often co-evolve with the development of the project. Researching how designers can intervene within GDSs becomes important to achieve an adaptable, mediated, and guided design process (Harding & Brandt-Olsen, 2018). Moving beyond rule-based systems and allowing machines' self-learning and creative exploration to occur necessitates a thorough investigation of the design steps and their continuity within the overall cycle. This way, designers engage in non-deterministic methods through ideas and reflections that resemble their creative thinking within an open-ended search space, without being constrained to a predetermined end. The research methods used in this study comprised literature study, experimentation, prototyping, testing, and evaluation. To represent and test the proposed design process, a system's framework (a prototype) has been developed. Three essential components were pursued in developing the computational system: generating mechanisms, testing mechanisms, and a control approach (Mitchell, 1990). Within generating mechanisms, methods of discrete assembly, in particular the wave function collapse (WFC) method, agent-based modeling (ABM), and GANs were connected to evaluate possible scenarios of those methods; AI was used as a control mechanism for guiding the general framework (Fig.1).

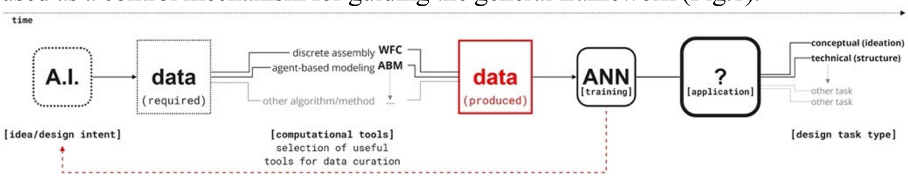


Figure 1. Proposed AI-assisted design framework: AI guides the initial activities, informing the subsequent processes. Multiple methods are used to generate datasets for AI training and several ANNs are applied to tackle different design scales at variant phases.

4. Testing and Implementation

The proposed prototype was a pilot study within a graduate design studio setting. The design brief addressed the concept of a post-pandemic, high-density, mixed-use residential township. One of the project objectives was to generate speculative, resilient futuristic design propositions, additionally inspired by natural systems. Different groups addressed the same design problem through different combinations of computational approaches (WFC, ABM, GANs), for the three targeted phases (Fig.2), resulting in three workflow strategies (4.1., 4.2., 4.3.). Experiments of the WFC method were performed using a C# program embedded into a Rhino/Grasshopper® algorithmic definition. Studies of agent-based modeling were conducted using the Culebra tool (developed by Complicit-Matter group). PyTorch® and Tensorflow® deep learning packages were used within the PyCharm environment for training the neural networks. A number of Python algorithms were written specifically for management of datasets.

4.1. WORKFLOW STRATEGY 1: DL-WFC-ABM

This workflow strategy applied an AI model first, followed by the WFC algorithm and ABM simulations, for the aforementioned design stages, respectively (Fig.2). (1)

Explore-Conceptualize: AI (CycleGAN) was used as an inspirational and suggestive approach to establish a new design concept by cross-pollinating different domains: natural structural patterns (Domain A) and architectural sections (Domain B). Thereby new spatial configurations and relationships were retrieved. The CycleGAN model trained for 200 epochs (# of iterations to process the whole dataset), using a dataset of 2000 images for each domain and 500 images for testing at 512x512 resolution. The new AI-generated sections informed massing strategies. (2) *Generate-Revise*: The WFC generated design iterations of discrete assemblages to occur within the massing generated in the previous step that served as an input for the spatial distribution and design generation (floor plans). (3) Develop-Qualify: Behavior simulation was used to "qualify" successful design iterations and progress to design development. ABM simulations (tracking behavior) informed building circulation, revising the discrete aggregations. Although this strategy yielded inspirational and suggestive designs from the AI model, there were certain shortcomings. Starting with AI excluded the possibility of using our own computationally generated datasets and relied exclusively on existing online data. Furthermore, the AI-synthesized images were manually post-processed as projection templates to acquire volumetric sculpting, leading to abstraction and loss of certain features of the original AI designs. Consequently the AI step was diluted overall, relinquishing control to the other methods (WFC, ABM).

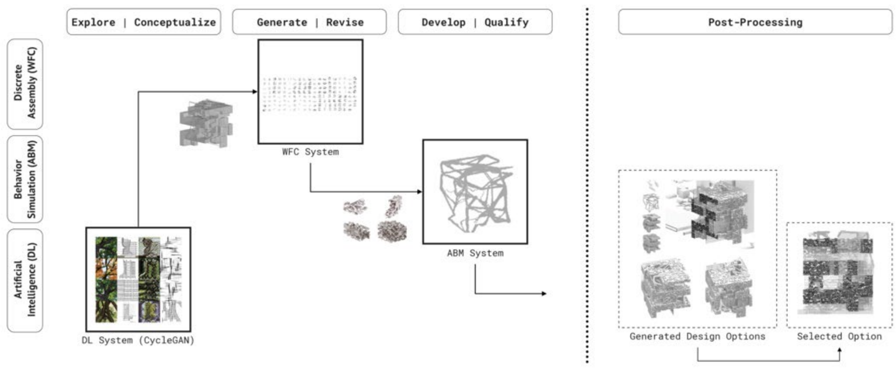


Figure 2. Workflow strategy 1 curates combined methods (DL, WFC, ABM) for three design phases.

4.2. WORKFLOW STRATEGY 2: ABM-WFC-DL

This experiment was conducted in a different order of methods. To begin with, the ABM system was used as a starting point for exploration, followed by the discrete assembly, and then AI, as explained next (Fig.3). (1) *Explore-Conceptualize:* Starting with the context variables, a behavior simulation method was employed, establishing a generative system that informed initial conceptualization. The trails of the ABM simulation (stigmergy) were converted into a topological mesh, serving as an initial volumetric exploration. (2) *Generate-Revise:* For this phase, the WFC method was utilized to produce design options contained within the massing suggested in the previous step, leading to variations and iterations of spatial distributions. Intentionally, the system produces a large dataset of "computationally-generated" design options, to be used for the later AI process. (3) *Develop-Qualify:* In the third phase, this exploration examined the possibilities of disrupting the orthogonal rule-based logic of the WCF-generated floorplans and their spatial qualities by breeding that dataset with a more organic system (termite nest structure). The CycleGAN model was used to train two domains (Domain A: WFC-based floorplans; Domain B: Natural system of termite-nest pattern). The model was trained for 200 epochs, using 2500 images (512x512 pixels) for each domain, and 500 images for testing.

This experiment has led to new, algorithmically-generated, architectural datasets, bred with natural patterns in the AI training as a further exploration task to modify the architectural language (Fig.4). Overall, the pseudo-random qualities of the termite nest pattern redefined the spatial relationships in the floorplans.

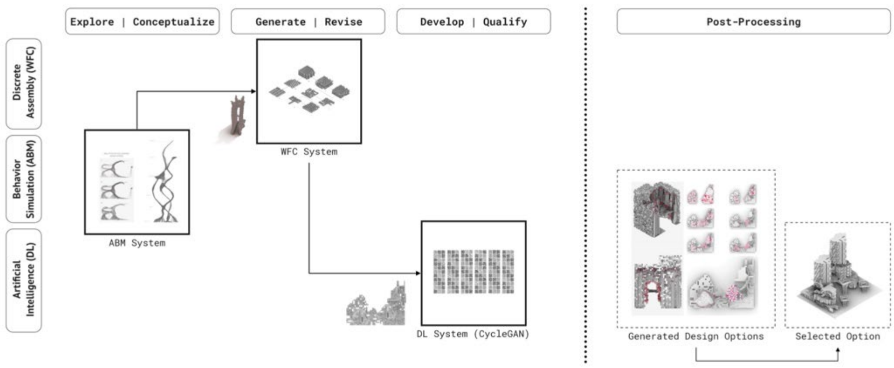


Figure 3. Workflow strategy 2 curates combined methods (ABM,WFC,DL) for three design phases.

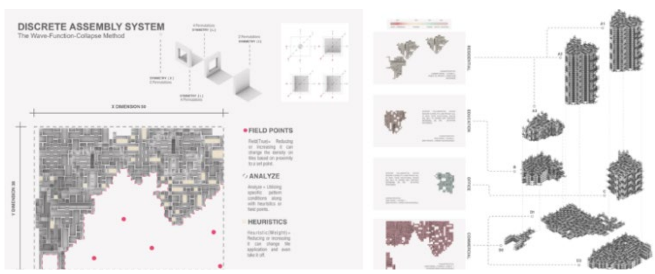


Figure 4. The Wave-function-collapse method to generate datasets.

4.3. WORKFLOW STRATEGY 3: WFC-DL-DL

This strategy included the WFC method for conceptualization and two DL models for subsequent phases (Fig.5). (1) *Explore-Conceptualize:* The WFC system was customized to generate initial design configurations involving massing or "global variables" and unit assembly options of "local" qualities. This rule-based generative system yielded a specific language of stacking and orthogonal spatial configurations due to the use of orthogonal tiles. It is important to note that the WFC can produce curved and rounded geometry, yet the aggregation was constrained by the 3D voxel-based field, leading to a specific DA language. (2) *Generate-Revise:* Here, a DL model (CycleGAN) was used to modify and revise the WFC-generated system, by cross-pollinating two domains: WFC-produced section designs (Domain A) and forests and tree structures (Domain B) in an elevation view. The model trained for 200 epochs with 2000 images (training) and 500 images (testing) at a 512 resolution. The results suggested altered section designs (Fig.8). (3) *Develop -Qualify:* Synthetic sections from the CycleGAN training were combined with architectural building designs of green roofs and terraces using a StyleGAN (50% for each domain). The StyleGAN trained for 18 hours (stopped at Network snapshot 131). The image size was 1024x1024 pixels. Synthetic images generated by the StyleGAN model re-designed the WFC-based designs, incorporating greenery into the building. Multiple interpolation walks through the StyleGAN's latent space were examined, offering design ideas to transition from "brutalist" to "green" design options. This strategy demonstrated reciprocity between AI-assisted steps, where AI-generated images from the second phase (CycleGAN) informed an AI model (StyleGAN) in the final phase.

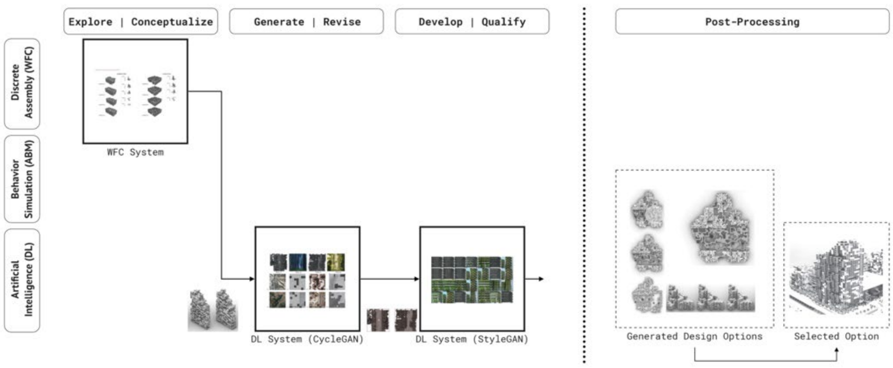
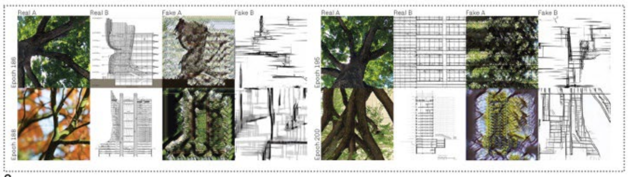


Figure 5. Workflow strategy 3 curates combined methods (WFC, DL, DL) for three design phases.

5. Results and Discussion

Strategy 1 Results: The AI-synthesized images (Fig.6) offered possibilities for new approaches to design spaces with unexpected sections that suggested initial design concepts and defined new spatial relationships. The process did not fully benefit from AI stage, since starting with CycleGANs remained vaguely suggestive for design initiation, i.e., later phases and tasks did not involve other AI models. Such an approach has also been found in existing research where AI is primarily used for representation and applied to one design aspect (floor plans, sections, facades). *Strategy 2 Results:* The AI exploration, with breeding computational and natural systems has led to the definition of a new language, a modified discrete assembly with higher complexity, which offers inspirational concepts of unpredicted spatial configurations and relationships (Fig.7). This workflow offered a new application of AI, to be integrated as an intermediate process for design revision of the computationally produced designs. AI intervened in the rule-based generated design process and allowed for parallel exploration, expanding the design search space. In this case, AI has allowed a translation from a strictly modular vocabulary to a more geometrically fluid system, using a CycleGAN network. *Strategy 3 Results:* The CycleGAN synthetic designs offered design revision concepts, suggesting an update in the section design, moving away from the stacking effect resulting from the WFC algorithm to non-Euclidean possibilities that allow reciprocal visual connectivities in space (Fig.8). The StyleGAN model's hyper-dimensional latent space allowed review and exploration of other design alternatives, behaving like an additional parametric environment where unlimited design alternatives can be examined. This experimental outcome offered insight into the necessity of considering connecting multiple AI models so that one model's output can intentionally encode design intent into another model.



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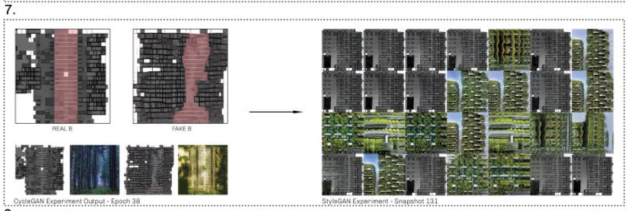

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Figure 6. Strategy 1 CycleGAN model outputs. Design: K. Schilling, Y. Etiliens
Figure 7. Strategy 2 CycleGAN output, breeding the WFC patterns (Domain A) and natural patterns (Domain B). Design: T. Taylor, C. Candelier
Figure 8. Left: output of the CycleGAN model of Strategy 3 breeding the WFC patterns (Domain A) and natural patterns (Domain B); Real and synthetic images of the trained StyleGAN model, in the latent space (Network Snapshot 131). Design: A. Milani, E. Alawadi

The students used a variety of tools and methods to investigate AI-assisted design workflows that support explorative search and design space expansion. Although different groups addressed the same design problem, they employed various computational approaches, using the same tools for different reasons (i.e., geometry module distribution/propagation; pattern application) and in a different order. Some used AI before the WFC algorithm, and others began with ABM simulations. Overall, three distinct strategies were identified (S1: DL-WFC-ABM, S2: ABM-WFC-DL, S3: WFC-DL-DL, Fig.9). The relevance of the order of a given method depends on the reciprocity between these specific approaches and their usefulness for each other (input-output connection). It is especially important to outline the efficiency of certain methods only in relation to this order of execution. The exploration of all strategies tried to overcome the constraints imposed by generative design systems and their own rules and algorithms and expand the search space of possible solutions. Sometimes, if an exploration occurs in a local area of the design space, we may misinterpret neighbouring solutions as optimal (the most successful design candidate, aesthetically or performatively). Finding different ways to explore design space is important, to avoid getting stuck with locally optimal solutions and missing the global maxima/minima that may be located elsewhere in the design space.

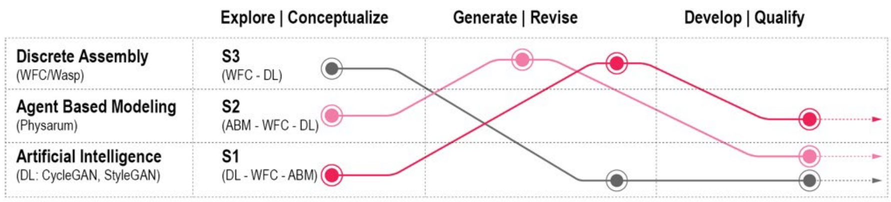

Figure 9. Workflow Strategies: Three main strategies were used by the students, each one combining computational tools in various order during the early, middle, and final stages of the design project. All strategies used at least one deep learning model for some part of the design.

6. Conclusions and Future Work

The incorporation of artificial intelligence into design in recent years foreshadows substantial impact on the overall design process, yet it is usually assessed as a singular tool/method. This paper examined the opportunities of innovative AI-assisted design workflows and their promise for refining current research-based pedagogy (SDG 9). This is an initial phase in a larger project about the efficient combination of AI with other computational tools based on their input requirements and degree of automation. Hybrid frameworks using generative adversarial networks (GANs) can augment design thinking, reaching into an expanded search space. The strategies discussed herewith allow reciprocal exchange between parametric models and AI models. Moving between rule-based generative algorithms and unsupervised deep learning models (CycleGAN, StyleGAN), designers can connect multiple computational models to search for "unexpected" design propositions. Our comparison of three strategies (Fig.9), has identified shortcomings and opportunities in specific combinations of neural networks before or after other tools, like ABM or WFC, depending on user experience and design intentionality. The evaluation of the resulting latent space (solution space) in StyleGAN using more than one domain, depends on understanding how the percentage of different domain samples in the dataset affects the domain "breeding" process, unlike CycleGAN, where equal domain input is used. CycleGAN is considered a good strategy for pursuing extrapolative creativity -finding new ways beyond how human designers think, but still within the same general context/field (Hassabis, 2018). CycleGAN best serves scenarios where design intentions are already defined; in Strategy 1, CycleGAN was used early on-before certain parameters had been set, bringing forward limitations in dataset preparation (also due to students' inexperience with such tools). On the other hand, the StyleGAN network can be used as a heuristic tool at any stage, perfect for exploration that is a priori undetermined. Its architecture is suitable for interpolation (average or merging) between existing datasets (Hassabis, 2018), so this could serve as a starting point for inspiration within a design studio.

References

Abraham, A. (2018). *The neuroscience of creativity:* Cambridge University Press.
Alexander, C. (1968). Systems generating systems. *Architectural Design, 38* (Dec.), 605-610.
Bolojan, D. (2022). From Artificial to Architectural Intelligence. In N. Leach & M. del Campo (Eds.), *Machine Hallucinations: Architecture and Artificial Intelligence:* Wiley.
Bolojan, D., & Vermisso, E. (2020). Deep Learning as heuristic approach for architectural concept generation. Paper presented at the *ICCC*.
Chaillou, S. (2019a). *The advent of architectural AI.* Retrieved from towards data science https://towardsdatascience. com/the-advent-of-architectural-ai-706046960140.
Chaillou, S. (2019b). *AI+ Architecture: Towards a New Approach*. Harvard University.
Chen, J., & Stouffs, R. (2021). From Exploration to Interpretation-Adopting Deep Representation Learning Models to Latent Space Interpretation of Architectural Design Alternatives.
Forbes, A. (2020). *Creative AI: From Expressive Mimicry to Critical Inquiry. Artnodes,* 26, 1-10.
Gui, J., Sun, Z., Wen, Y., Tao, D., & Ye, J. (2020). A review on generative adversarial networks: Algorithms, theory, and applications. *arXiv preprint arXiv:2001.06937*.
Harding, J., & Brandt-Olsen, C. (2018). Biomorpher: Interactive evolution for parametric design. *International Journal of Architectural Computing,* 16(2), 144-163.
Hasey, M., Elliott, S., & Rhee, J. (2021). Archi_Base: Automated Dataset Construction of Architectural Imagery for Deep Neural Networks. Paper presented at *the CAADFutures 2021*. https://github.com/michaelhasey/Archi_Base
Hassabis, D. (Producer). (2018). Creativity and AI. *The Rothschild Foundation Lecture.*
Koh, I. (2021). *AI Sampling*. Retrieved from https://www.digitalfutures.world/workshops/91.html
Leach, N. (2021). *Architecture in the Age of Artificial Intelligence: An Introduction to AI for Architects:* Bloomsbury Visual Arts.
Menges, A., & Ahlquist, S. (2011). *Computational design thinking: computation design thinking:* John Wiley & Sons.
Mintrone, A., & Erioli, A. (2020). Cognizant Architecture - What If Buildings Could Think? Paper presented at *the eCAADe 2020, Anthropologic - Architecture and Fabrication in the cognitive age.*
Mitchell, W. J. (1990). *The logic of architecture: Design, computation & cognition:* MIT press.
Stocking, A. W. (2009). *Generative design is Changing the face of architecture.* Building Design. Retrieved from https://www.cadalyst.com/cad/building-design/generative-design-is-changing-face-architecture-12948
Watanabe, M. (2004). *ALGORITHMIC DESIGN / INDUCTION DESIGN, Three Kinds of Flow / Three Stations. AI / AD / ID.* Retrieved from https://www.makoto-architect.com/kashiwanohaCSt.htmlreferences.