REINTERPRETING CELLULAR AUTOMATA FOR ARCHITECTURAL DESIGN WITH AI

REINTERPRETANDO AUTÓMATAS CELULARES PARA EL DISEÑO ARQUITECTÓNICO CON IA

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How to cite:
Fernandez, A. (2025). Reinterpreting cellular automata for architectural design with AI. *Revista de Arquitectura, 30*(49), 96-109. https://doi.org/10.5354/0719-5427.2025.80849

Received: 2025-09-25
Accepted: 2025-11-24

ABSTRACT

This article explores the integration of Cellular Automata (CA) and Artificial Intelligence (AI), with a focus on Diffusion Models, to expand contemporary architectural design workflows. CA provide rule-based emergent patterns that serve as a foundation for computational exploration, while AI models—particularly diffusion-based systems—enable the translation of these discrete patterns into continuous spatial configurations. The proposed workflow unfolds in three stages: 1) the generation of CA datasets; 2) the incorporation of architectural drawings as contextual constraints; 3) and the reinterpretation of these enriched patterns through LoRA-enhanced diffusion models. Depth maps serve as a key intermediary, enabling the transition from 2D generative exploration to 3D architectural geometries suitable for digital fabrication and BIM integration. The study demonstrates how this CA+AI hybrid system can support adaptive, high-resolution form generation while maintaining architectural coherence. By articulating connections between abstract computational logics and material architectural design, the research proposes a methodological bridge between emergent rule-based processes and contemporary design practices.

Keywords

Architectural design, artificial intelligence, cellular automata, diffusion models, patterns

RESUMEN

Este artículo explora la integración entre autómatas celulares (AC) e inteligencia artificial (IA), con énfasis en los modelos de difusión, para ampliar los flujos de trabajo contemporáneos en arquitectura. Los AC generan patrones emergentes basados en reglas que funcionan como soporte para la exploración computacional, mientras que los modelos de IA —especialmente los basados en difusión— permiten traducir estas configuraciones discretas en geometrías continuas. El flujo metodológico propuesto se desarrolla en tres etapas: 1) la generación de conjuntos de datos provenientes de AC; 2) la incorporación de dibujos arquitectónicos como restricciones contextuales; y 3) la reinterpretación de estos patrones mediante modelos de difusión optimizados con LoRA. Los mapas de profundidad actúan como un mediador crucial, posibilitando el paso desde la exploración generativa en 2D hacia geometrías tridimensionales aptas para procesos de fabricación digital e integración BIM. El estudio demuestra cómo este sistema híbrido AC+IA puede producir geometrías adaptativas de alta resolución manteniendo coherencia arquitectónica. Al articular las conexiones entre lógicas computacionales abstractas y el diseño arquitectónico material, la investigación propone un puente metodológico entre los procesos emergentes basados en reglas y las prácticas de diseño contemporáneas.

PALABRAS CLAVE

Diseño arquitectónico, inteligencia artificial, autómatas celulares, modelos de difusión, patrones

HTTPS://DOI.ORG/10.5354/0719-5427.2025.80849

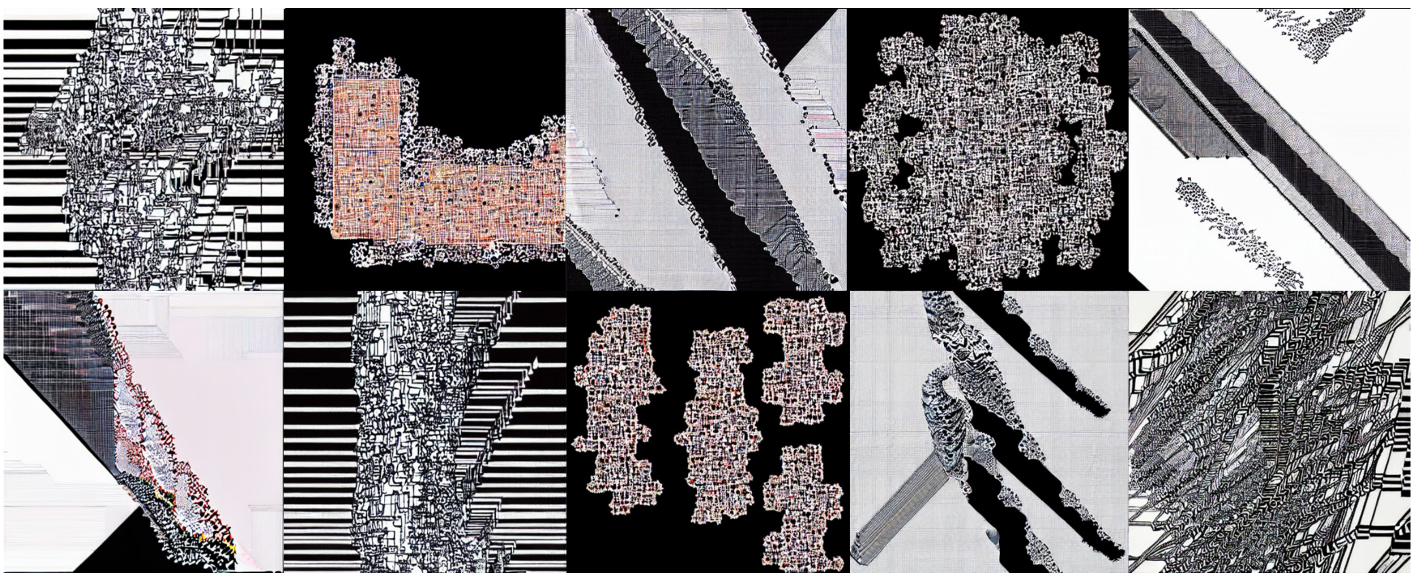
INTRODUCTION

The architectural discipline is undergoing rapid transformation as it seeks methods that enhance both design efficiency and creative potential. Traditional techniques, often reliant on manual drafting and fixed models, limit the exploration of complex geometries and adaptive frameworks (Ball, 2011; Batty, 2007). The integration of digital technologies has significantly reshaped this landscape, opening pathways for computational design strategies that deliver unprecedented accuracy, flexibility, and productivity (Carpo, 2020). Among the most influential developments is the rise of Artificial Intelligence (AI). Through neural networks and advanced computational processes, AI is redefining its role in architecture, offering tools that learn, adapt, and generate novel outcomes. In this context, Cellular Automata (CA) represent a compelling framework for architectural exploration. Rooted in natural logics of collective intelligence and artificial life (Fernandez Gonzalez, 2023a), CA operates on rule-based grid systems where local interactions give rise to complex patterns that resemble natural systems (Beigy & Meybodi, 2004; Ilachinski, 2001). By situating these processes within discrete spatial coordinates, CA provides a generative mechanism capable of producing emergent architectural configurations with potential for further modeling and application (Glover et al., 2021).

Parallel to this, AI methods—particularly machine learning and diffusion models—process large datasets to reconcile form and function, generating designs beyond the reach of conventional approaches (Gilpin, 2018). Diffusion models, inspired by physical phenomena such as particle dispersion, iteratively refine noisy or incomplete inputs into coherent outputs, whether images, videos, or spatial concepts (Beigy & Meybodi, 2007, 2008). Functioning almost as the inverse of a Gaussian blur (Mitchell, 2009), these models progressively reveal structured and meaningful representations, enabling new architectural possibilities (Betka et al., 2020).

This article explores the intersection of CA and AI diffusion models as complementary generative systems. Their integration fosters the creation of architectural forms that are both expressive and efficient, bridging the gap between speculative exploration and design implementation (Fernandez Gonzalez, 2023b). Depth map technologies extend this process further, translating 2D emergent patterns into 3D models, thus providing accurate spatial representations essential for construction-oriented workflows. As grayscale encodings of spatial depth, depth maps act as mediators between generative exploration and BIM-based applications, ensuring continuity from conceptual development to practical realization (Betka et al., 2020; Fernandez Gonzalez, 2023c) (Figure 1).

Figure 1
Set of CA-AI patters from the training LoRA process to be used later as information for 3D mesh model reinterpretation



Note. Images by the author.

CA TO GENERATION OF AI MODELS AS LORA MODELS

Cellular Automata (CA) have long been recognized as a fertile framework for architectural experimentation. Originating in the mid-20th century as mathematical abstractions, CA offer rule-based systems in which simple local interactions accumulate to generate highly complex, often unexpected global geometries. This bottom-up approach resonates strongly with architectural design processes that seek to balance systemic logic with emergent creativity. Within computational design, CA not only serve as a model of natural processes—self-organization, growth, adaptation—but also as a generative engine capable of producing architectural forms that transcend the limitations of conventional top-down methods (Ilachinski, 2001).

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The behavior of CA is typically governed by the interplay of four core elements: neighborhood, discrete system, abstract rules, and dynamism. Together, these variables define the generative potential of the system, determining the complexity, variability, and adaptability of the patterns that emerge.

Neighborhood

In CA, the neighborhood refers to the surrounding cells that influence the state of any given cell. These local interactions define the rules of change and establish the system's capacity to evolve over time. The scale and configuration of a neighborhood directly affect the richness of the emergent outcomes: small neighborhoods yield highly constrained patterns, while larger or irregular neighborhoods allow for more diverse, layered interactions. In this study, six neighbors along the 3D axis were employed to intensify spatial interactions and explore higher-order emergent behaviors (Beigy & Meybodi, 2006). This expanded neighborhood not only increased the complexity of the resulting patterns but also served as a testing ground for translating local relationships into architectural logics.

Discrete System

The discrete system provides the structural framework of CA, establishing a quantized lattice in which cells operate. Each cell inhabits one of a finite number of states, and the system evolves through discrete time steps. This quantization is essential, as it distinguishes CA from continuous mathematical models and makes it particularly suitable for computational design. In this research, the discrete system was structured as a 1024 × 1024 grid, with cells limited to binary states of "on" or "off." This clear binary framework allowed for both computational efficiency and the generation of high-contrast patterns, which later formed the basis for translation into image datasets. By fixing both spatial and temporal dimensions, the discrete system provides a robust environment in which emergent behavior can be systematically studied.

Abstract Rules

Rules are the core drivers of CA. They determine how cells update their states based on their own condition and that of their neighbors. While rules can be extremely simple—such as binary transitions—they can also encode complex logics capable of generating intricate global patterns. For this experiment, Langton's Ant rules were adapted into a three-dimensional framework. This reinterpretation introduced additional degrees of freedom into the conventional rule set, allowing the system to exhibit novel behaviors not achievable in a strictly 2D context (Ilachinski, 2001;

Mitchell, 2009). The introduction of dynamic rule variation added an additional layer of unpredictability and richness, demonstrating how abstract computational rules could be pushed toward architectural generativity.

Dynamism

The final element, dynamism, refers to the temporal unfolding of CA systems. Starting from a simple or even uniform initial condition, CA evolve iteratively, producing forms of increasing complexity across time steps. In this experiment, the system was observed across 3,000 iterations, capturing its gradual transformation from order to complexity. The results illustrated hallmark features of CA: self-organization, emergent order, and adaptive pattern formation (Fernandez Gonzalez, 2023b; Glover et al., 2021). Importantly, dynamism highlights the generative richness of CA—not as static outcomes but as processes in constant evolution, opening possibilities for architecture conceived as time-sensitive and adaptive rather than fixed and finite.

Taken together, these four elements—neighborhood, discrete system, abstract rules, and dynamism—formed the methodological foundation for creating datasets that could bridge CA with AI diffusion models. Using Processing, CA-generated image datasets were first created to capture the diversity of emergent patterns. These datasets were then enriched by a machine vision process that provided semantic approximations of each pattern's meaning, enhancing the interpretive layer necessary for integration into AI workflows.

To leverage this material, Low-Rank Adaptation (LoRA) was introduced as a key mechanism. LoRA enables large pre-trained models, such as transformer-based architectures, to be fine-tuned for specific tasks without requiring full retraining. This approach drastically reduces computational costs while maintaining high performance. In this study, LoRA was applied to fine-tune Stable Diffusion 1.5 and SDXL 1.0 models. The resulting hybrid models became capable of generating outputs that remained consistent with CA principles while incorporating the flexibility, adaptability, and representational richness of AI-driven systems.

The convergence of CA and LoRA-based diffusion models thus marks a critical step in rethinking architectural design workflows. By embedding rule-based generativity into adaptive AI frameworks, the process demonstrates how emergent computational logics can be transformed into tools for both speculative exploration and practical design application.

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DIFFUSION MODELS AS A CA REINTERPRETATION

The integration of diffusion models with Cellular Automata (CA) offers a renewed perspective on how CA can be understood and applied within artificial intelligence and computational design. Traditionally, CA systems rely on fixed rules and neighborhood logics that, while powerful in producing emergent complexity, remain constrained by their deterministic structure and rigid grid frameworks. The incorporation of diffusion models, particularly through LoRA-enhanced fine-tuning, introduces a new layer of flexibility, allowing CA to evolve into adaptive systems capable of producing outcomes that exceed the limits of conventional approaches (Beigy & Meybodi, 2007; Fernandez Gonzalez, 2023a). In this hybrid framework, CA patterns are no longer restricted to static iterations but are dynamically reinterpreted through AI processes that embed learning, variability, and contextual responsiveness.

One of the most significant reinterpretations occurs in the treatment of neighborhoods. In classical CA, neighborhoods are defined exclusively by the adjacent cells surrounding a given unit, with rules governing how their interactions determine state transitions. Within the CA+AI model, however, neighborhoods are no longer limited to local adjacency. Instead, they are reformulated as abstract constraints that can be informed by contextual, spatial, or even visual data. Tools such as ControlNet Edges or Depth Maps function as expanded definitions of neighborhood conditions, enabling the system to incorporate external cues into its generative logic. This transformation dramatically broadens the scope of interactions, allowing the emergence of patterns that are responsive not only to internal logics but also to external architectural and environmental inputs.

Similarly, the reliance on explicit rules is redefined within the diffusion-enhanced framework. While conventional CA depend on pre-coded transition rules that govern state evolution, in the hybrid model rules become embedded behaviors, learned and adapted by the AI during the training process. This enables the system to infer, adjust, and reinterpret rule sets in real time. Rather than following a fixed pathway, the CA+AI model can evolve with the dataset, producing more nuanced and contextually appropriate outcomes. The capacity to embed rules within the AI significantly enhances generative flexibility, positioning the system closer to adaptive natural processes rather than rigid mathematical constructs (Gilpin, 2018).

The grid system of CA is also reimagined. Conventional CA operate on a fixed lattice of cells, most commonly represented in two or three dimensions. By contrast, diffusion models introduce diffusion grids, where resolution levels—such as SD or XL—act as constraints guiding pattern exploration. These grids are not static but dynamic environments, capable of encoding features such as texture, depth, and material complexity. In doing so, they extend the expressive potential of CA, transforming abstract, pixel-based interactions into richly detailed generative structures. The grid, once a limitation of CA, becomes an adaptive framework that allows for multi-scalar and multi-dimensional exploration of form.

The role of randomness further differentiates this reinterpretation. In traditional CA, dynamism arises from the sequential unfolding of state transitions across iterations. The CA+AI model introduces random seeds to initiate diffusion processes, embedding stochasticity directly into the generative cycle. These seeds inject variability into initial conditions, creating iterative loops of evolving complexity. As the AI continuously reassesses and refines outputs, patterns emerge that are organic, unpredictable, and aligned with the principles of self-organization, growth, and adaptation observed in natural systems (Fernandez Gonzalez, 2023b; Glover et al., 2021). This stochastic dimension elevates the generative process, allowing it to mirror biological and ecological processes more closely than traditional CA frameworks.

The final stage of this workflow involves translating these enriched generative behaviors into architectural contexts. By embedding architectural assets—such as facade photographs or depth maps—into the process, the abstract logic of CA is grounded in material and spatial reality. The CA-specific LoRA models become capable of producing architectural outcomes that are both conceptually compelling and practically relevant. This bridging of speculative generativity with real-world application ensures that the methodology does not remain a theoretical experiment but evolves into a workflow capable of informing tangible design practice (Figure 2). In this sense, the reinterpretation of CA through diffusion models contributes to a broader discourse on how artificial intelligence can expand architectural vocabulary while simultaneously maintaining ties to material construction and spatial coherence.

When compared with established generative design methods such as parametric modeling or evolutionary algorithms, the CA+AI diffusion approach introduces a fundamentally different paradigm. Parametric systems rely on deterministic relationships between predefined variables, producing controlled yet limited variations. Evolutionary algorithms, while capable of generating diverse solutions, are often constrained by fitness functions that reduce design potential to optimization problems. In contrast, the CA+AI workflow thrives on emergence, adaptability, and contextual responsiveness. By embedding rule-based generativity

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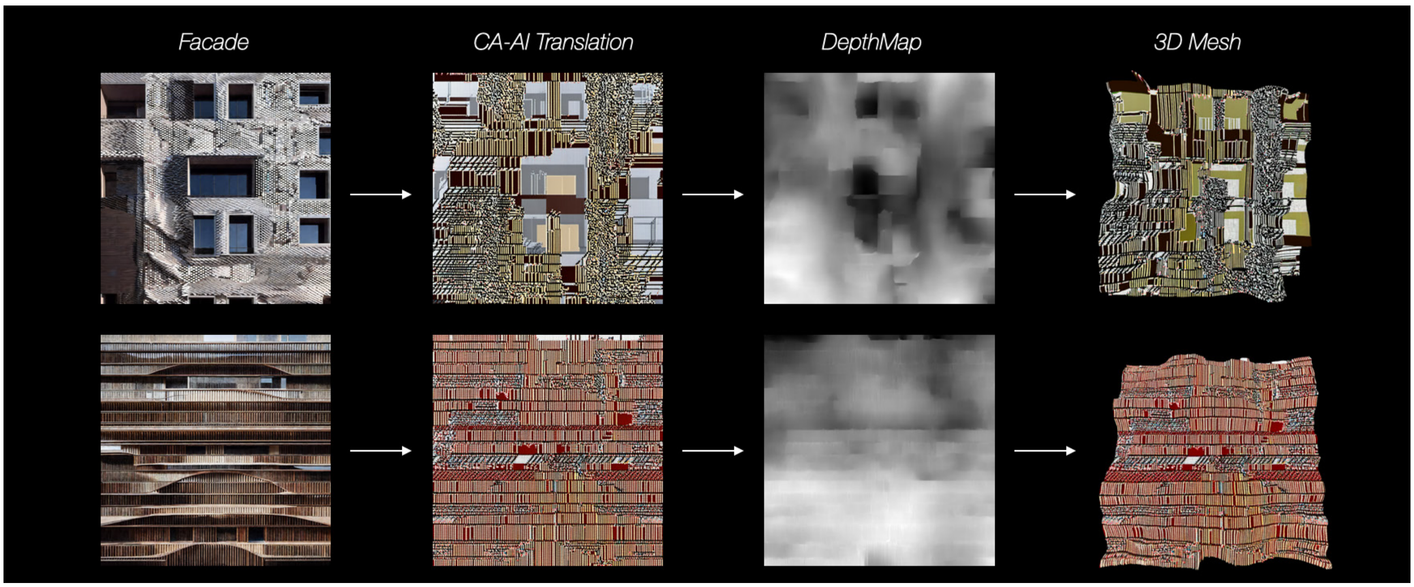
within diffusion models, this method resists over-determination and embraces stochasticity, producing outcomes that are less about optimization and more about exploration. This situates the approach as a valuable complement to existing computational design frameworks, expanding the range of architectural possibilities by foregrounding unpredictability, self-organization, and hybrid logics of order and randomness.

Figure 2
The transition of Facades as CA-AI obtaining their DepthMap information for 3D mesh reinterpretation



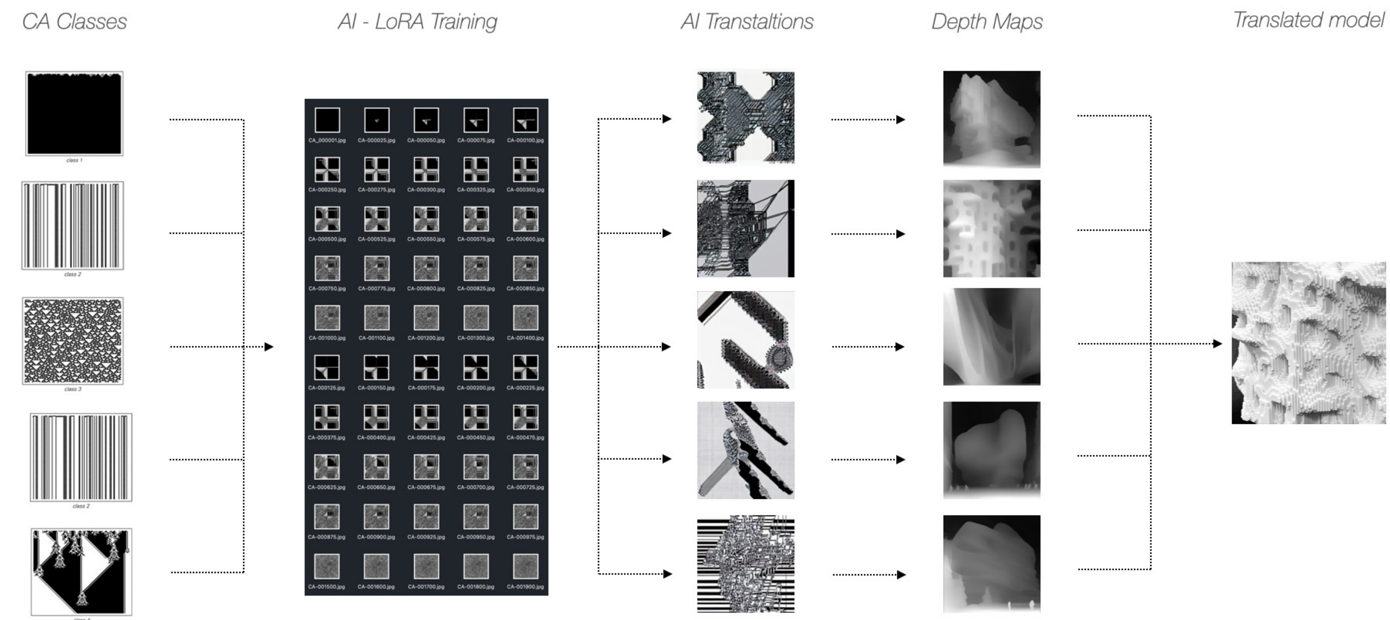
Note. Images by the author.

Integration of Architectural Assets: from CA Patterns to Architectural Facades

A key step in connecting abstract computational models with practical design is the integration of architectural assets into the generative workflow. In this research, facade photographs were introduced as input samplers, enabling the CA+AI model to work with real-world references and architectural contexts. By anchoring the generative process in recognizable building elements, the system moves beyond purely speculative pattern generation and begins to suggest design proposals that can inform concrete architectural interventions. This integration ensures that the translation from Cellular Automata (CA) to diffusion-based models remains relevant to practice, providing a direct bridge from emergent computational logic to facade articulation (Figure 3).

At the center of this process lies the construction of depth maps, which serve as the translation layer between two-dimensional CA+AI outputs and three-dimensional architectural reinterpretations. Depth maps encode spatial differentiation through grayscale gradients, where darker values correspond to greater distance and lighter values to proximity. This method enables the system to move from surface-level abstraction into volumetric expression, ensuring that the emergent logics of CA can be embedded into architectural form. In this workflow, Stable Diffusion was combined with a custom Processing-based depth translator, which extracted and structured depth information directly from facade regeneration images. To maintain precision, the resulting depth maps adhered to strict spatial constraints, operating at a resolution of 1024 × 1024 pixels arranged within a mesh grid of equal XY values.

Figure 3
The final proposed workflow from CA to AI, Depthmap and a 3d model



Note. Images by the author.

Once generated, the depth information was imported into Rhino, where it guided the creation of precise architectural geometries. Rhino's computational environment, known for its ability to handle complex parametric data, served as the platform for translating pixel-based information into spatially coherent forms. A custom mesh and point cloud reloaderwas implemented to ensure that the structural constraints embedded in the depth maps were preserved throughout the modeling process. This stage is critical, as it guarantees that emergent patterns do not lose coherence when translated from algorithmic abstraction to material geometry.

The combined use of Stable Diffusion, depth mapping, and Rhino's modeling capabilities establishes a workflow in which CA-inspired abstractions can be systematically transformed into facade interventions. The results are forms that are both visually expressive and structurally coherent, balancing computational exploration with architectural feasibility. This bridging function is particularly important in the field of design computation, where

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speculative generative outputs often fail to reach the stage of material translation. By embedding depth maps as a mediating protocol, this research ensures continuity between conceptual exploration and real-world application.

The implications of this approach extend beyond facade design. By proving that CA-derived abstractions can be successfully adapted into architectural contexts, the workflow demonstrates the potential for integrating emergent computational processes into BIM frameworks, fabrication pipelines, and construction workflows. Facades, in this sense, act as a testbed for broader architectural applications, highlighting how abstract logics rooted in collective intelligence and artificial life can be materialized in built form. Ultimately, the integration of architectural assets situates CA+AI systems not only as speculative tools for design but also as pragmatic instruments for shaping the architectural environment.

DISCUSSION

The results of this study highlight the potential of combining Cellular Automata (CA) with AI-driven diffusion models to extend the architectural design toolkit. While conventional CA frameworks have long been valued for their ability to generate emergent spatial logics through simple local rules (Ilachinski, 2001), their translation into architectural applications has often been constrained by their abstraction and reliance on fixed grids. By integrating LoRA-enhanced diffusion models, the experiments presented here demonstrate a critical shift: the generative capacity of CA is not only preserved but enriched through AI's ability to embed, reinterpret, and dynamically adapt rules in real time.

This approach resonates with recent international discussions on computational design, where the focus has shifted from deterministic rule sets toward adaptive, non-linear processes (Carpo, 2020). The reinterpretation of neighborhoods as constraints, rules as embedded behaviors, and grids as flexible diffusion environments illustrates how CA can evolve when placed in dialogue with AI methodologies. The introduction of random seeds as drivers of dynamism further amplifies this adaptability, producing outcomes that are organic, unpredictable, and more closely aligned with natural systems than with the rigid logics of conventional CA.

At the same time, the integration of architectural assets—specifically through facade photography and depth maps—ensures that these abstract processes remain grounded in practice. This methodological step bridges speculative generative exploration with the material demands of construction. The workflow developed here demonstrates how CA-inspired patterns can be processed into depth maps, translated through Stable Diffusion, and ultimately modeled with precision in Rhino. In this way, the system aligns with international literature on the role of BIM and computational pipelines in translating digital speculation into buildable reality.

From a local perspective, this research also contributes to emerging debates on the use of artificial intelligence in architecture within Latin America, where questions of adaptability, resource efficiency, and cultural expression are pressing. By embedding CA within AI workflows, the study suggests a pathway toward design practices that are not only formally innovative but also capable of engaging with contextual constraints in ways that traditional top-down methodologies cannot. In particular, the incorporation of local image data—such as facade photographs or site-specific visual references—opens new opportunities for developing design processes rooted in local perspectives and identities. This allows computational systems to learn directly from the architectural language of their immediate cultural and urban environments, reinforcing regional distinctiveness while aligning with broader global discourses on AI-driven design.

Nevertheless, several limitations must be acknowledged. First, the computational costs of training LoRA-enhanced diffusion models remain significant, raising questions about scalability and accessibility for wider practice. Second, dataset biases in the training phase can influence the outputs, potentially narrowing the range of architectural solutions if not carefully curated. Finally, while the method demonstrates strong potential at the facade scale, further research is required to assess its applicability to larger, more complex architectural systems, including whole-building envelopes and urban configurations. Future studies should therefore focus on optimizing computational efficiency, diversifying training datasets, and expanding the scope of application, ensuring that CA-AI hybrid frameworks can operate robustly across multiple architectural scales.

ARCHITECTURAL RELEVANCE AND SCOPE FOR CONTEMPORARY DESIGN

The integration of Cellular Automata (CA) and AI-based diffusion models represents not only a technical advance within computational design methodologies but also opens a valuable field of reflection for architectural culture at large. In a disciplinary context faced with challenges related to material efficiency, spatial adaptability, and formal exploration, these hybrid systems enable new ways of conceptualizing architectural design through behaviour, evolution, and emergence (Carpo, 2020; del Campo, 2024). Unlike traditional parametric methods—where the relationship between parameters and form is explicitly defined—CA operate

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through simple local rules that, when iterated, generate unexpected global results (Mitchell, 2009). This emergent logic offers an alternative model for understanding how structures, facades, or material systems might behave and transform over time. In this sense, CA function as an operative metaphor for imagining architectures that are dynamic, responsive to external conditions, and capable of self-regulation (Fernandez Gonzalez, 2023b).

The incorporation of diffusion models amplifies this potential by introducing the ability to reinterpret CA-generated patterns into continuous, coherent geometries aligned with recognizable architectural languages. Recent advances in AI generative processes—particularly diffusion models—demonstrate how noisy or incomplete inputs can be transformed into high-resolution architectural outputs. Through such reinterpretation, CA-based systems move from mathematical abstraction toward concrete tools for designing envelopes, structural surfaces, or interior components.

Practically, this methodology can be applied to a wide range of architectural scenarios. For example, in the design of adaptive facades, emergent patterns may translate into modulations of shade, ventilation, or natural lighting—areas where rule-based formation logics have shown significant potential (Oxman, 2017). In experimental pavilions, such as those developed by ICD/ITKE in Stuttgart, growth logics inspired by self-organizing systems resonate strongly with CA principles, suggesting pathways for lightweight, biomimetic structures. By connecting CA and diffusion models with digital fabrication pipelines, these systems support the development of fabricable prototypes that translate generative patterns into buildable physical assemblies. Even at the urban scale, CA have been used to simulate densification, clustering, or mobility patterns, supporting new models of urban evolution (Batty, 2007).

By connecting these processes with digital fabrication tools and BIM workflows, a direct bridge is established between conceptual exploration and material realization. Thus, CA and diffusion models not only enrich the architectural imagination but also contribute tangible solutions to contemporary demands for sustainability, efficiency, and spatial complexity (Carpo, 2023; Fernandez Gonzalez, 2023c; Leach, 2021).

CONCLUSIONS

This study demonstrates the innovative and transformative potential of combining Cellular Automata (CA) with Artificial Intelligence (AI), particularly through diffusion models and LoRA fine-tuning. By loosening the deterministic constraints traditionally associated with CA, the integration creates new opportunities for generating, analyzing, and translating emergent patterns into architectural contexts.

The fusion of CA principles with AI diffusion models establishes a system that balances structured rule-based logic with creative flexibility. Prompts, depth maps, and random seeds together enable stochastic and adaptive processes that counteract the rigidity of conventional CA. Each iteration becomes a dynamic reinterpretation of initial conditions, generating evolving complexity that parallels natural processes of growth, adaptation, and emergence.

This approach expands the scope of adaptive design by enabling the creation of intricate and contextually responsive geometries that would be difficult to achieve with CA alone. The introduction of LoRA models trained on CA patterns further strengthens this potential, offering new avenues for integrating emergent generative logic into architectural workflows.

A key contribution of this framework lies in the role of depth map technologies. By accurately translating 2D CA+AI patterns into coherent 3D structures, depth maps ensure spatial precision, structural integrity, and seamless integration into design-to-construction pipelines. This positions depth maps not only as a technical tool but also as a conceptual bridge between abstract computational processes and practical implementation.

Looking ahead, this research lays the foundation for future work in optimizing depth map translation and expanding its role as a testing environment for emergent geometries. Promising directions include voxel-based reinterpretations of architectural assets and alternative 3D translation methods such as Gaussian splatting. These innovations could enhance the resolution, coherence, and scalability of generative outputs, ultimately pushing the boundaries of how CA and AI can inform architectural design at multiple scales.

FUNDING
This research has been funded by ANID PhD Scholarships and UCL.

CONFLICT OF INTEREST
The author declares no conflicts of interest.

AUTHORSHIP STATEMENT
Alberto Fernandez Gonzalez: Conceptualization, Fund Acquisition, Research, Methodology, Writing - review and editing, Visualization, AI image generation.

STATEMENT ON AI USE
In the course of developing this work, the author used Grammarly for Proofreading Grammar. Following use of this tool/service, the author carefully reviewed and revised the content and assume full responsibility for the content of the publication.

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