# Artificial Dancing Intelligence: Neural Cellular Automata for Visual Performance of Music

**Anonymous** NULL

**Editors:** D. Herremans, K. Bhandari, A. Roy, S. Colton, M. Barthet

## Abstract

We present Artificial Dancing Intelligence (ADI), an interactive neural music visualizer that is accessed through a web app, but performs inference entirely on local devices. Our approach enables anyone to visually express music, while leveraging the expressive, and sometimes unpredictable dynamics of self-organized systems. ADI uses an audio stream's average energy (known as RMS) to modulate a neural cellular automata (NCA) to produce visual patterns that move and 'dance' along with the audio stream in real time. Through the web interface, users can adjust the relationship between the music's energy and the NCA system to create unique visual performances out of any music audio file. ADI achieves smooth, real-time responsiveness on modern consumer devices.

**Keywords:** neural cellular automata, interactive visualizations, music visualizations, real-time systems, web-based applications, generative media

## 1. Introduction

From dance—the human form embodying music (Carroll and Moore, 2008)—to the birth of early digital music visualizers (Whitney, 1980), music and moving visuals have had a long, intertwined, and ever-evolving history. Most recently, with the advent of AI, creative new ways to synthesize music visuals have emerged (Klemke, 2025; Liu et al., 2023; Ng et al., 2024). However, as arts and AI intersect, there is a reasonable public and academic concern of human contribution and connection to art being lost (Piskopani et al., 2023).

Despite their expressive potential, most AI models used for synthesizing music visualizations tend to be computationally intensive and therefore operate offline (Klemke, 2025; Liu et al., 2023; Ng et al., 2024; Revid.ai) or require specialized hardware (Kraasch and Pasquier, 2022). This first limitation restricts the opportunity for real-time experimentation and exploration between the AI and the human during artistic creation. The second restriction—requiring dedicated GPUs—limits the number of people who can interact with these creative systems. We argue that real-time interactivity and accessibility are of paramount importance for fostering *collaborative*, rather than *substitutive*, relationships between people and creative AI systems.

The system we present, Artificial Dancing Intelligence (ADI), creates interactive music visualizations while running locally on consumer devices, enabling constant artistic iteration and culminating in the capacity for live artistic performance. Therefore, we evaluate our system under the framework of Performance-Based Research (Skains, 2017). That is, we provide qualitative detail as to what the system responses are when collaborating and performing with it, rather than evaluating it with extensive numerical metrics which are not fit to capture nuanced notions like visual creativity and ease of expression. Additionally, in the *Methods*, and *Results and Evaluation* sections we present the technical reasoning behind the implementation of ADI along with web-rendering metrics (average fps, input delays, etc).

## 2. Related Works

### 2.1. (Neural) Cellular Automata and Music

Cellular Automata (CA) are computational systems composed of cells on a grid—sometimes called a substrate—where each cell in the grid has a state that is updated according to a common set of local rules (Wakefield)[1]. Interestingly, despite the locality of its rules, these systems exhibit globally organized behaviors, making them fall under the category of self-organized systems (Wolfram, 2002). The history of cellular automata and music is long and diverse. Since the late 1980s, many researchers have explored mapping CA dynamics to different musical properties (Beyls, 1989; Wolfram Research, 2005; McLaughlin and Tremblay, 2010; Zareei et al., 2015; Schaap and Hedblom, 2024; Didiot-Cook, 2025). However, while these efforts mostly use CA for sound synthesis and music composition, relatively little research has focused on CA-like systems purely as a medium to visualize music.

Neural Cellular Automata (NCA) are similar to CA, but instead of having rules be explicitly defined, they are learned by a neural network (Mordvintsev et al., 2020). NCAs have continuous rather than discrete states. However the fundamental idea of local rules driving global behavior still applies, as every cell is updated by the same neural network. Since their academic popularization in 2020, NCAs have proven useful in many fields and tasks such as morphing across images (Sudhakaran et al., 2022b), learning spatial-temporal patterns (Richardson et al., 2024), policy network learning for reinforcement learning tasks (Najarro et al., 2022), and even as potential models to achieve analog universal computation (Béna et al., 2025). In the musical visualization domain, NCAs have barely been explored within academic (Suk, 2024) and non-academic contexts (Baecker, 2024; Tension, 2023; u/PsyzygyMusic, 2023). However—similar to earlier research on classical CA—existing, NCA-based works have primarily focused either on audiovisual pieces, where sound and visuals are co-generated, or on music visualization processes that seem to operate off-line.

### 2.2. Edge AI

Edge AI is an AI sub field concerned with AI systems that run computations and/or training on the device where data and input is collected. These systems are generally less powerful and less scalable than systems that run on centralized, super computers. However, Edge AI systems come with various advantages such as of operating without internet connection, reduced latency, increased privacy due to lack of centrality, and less reliance on expensive hardware (Gill et al., 2025). Since Artificial Dancing Intelligence generates visuals in response to audio and user inputs in real-time, the system's inference process should have as low latency as possible. Thus, framing the development of our system in the context of

1. This source has no year since it is from York University course DATT4950, taught by Assistant Professor Graham Wakefield, which has no visible date.

Edge AI aligns with our goal of exploring real-time, accessible, creative experiences with AI systems.

## 3. Methods

### 3.1. Technology Stack

Artificial Dancing Intelligence uses React (Stack Overflow, 2024) for its user interface, Tensorflow.js (TensorFlow Development Team, 2023) for conducting NCA computations, and the Web Audio API (World Wide Web Consortium (W3C), 2018) for audio stream feature extraction.

### 3.2. User Experience and User Interface

The user interface shown in Figure 1 is designed with the purpose of exposing inputs and outputs to the system on the same web page. The layout is divided into two sections, the *Controls* section which houses user inputs, and the *Viewer* section which displays the music visualization.


Figure 1: Artificial Dancing Intelligence Web Application UI with annotated sections.

### 3.3. Architecture

As shown in Figure 2, Artificial Dancing Intelligence builds upon a pre-trained Growing Neural Cellular Automata (GNCA) (Mordvintsev et al., 2020) architecture by modulating its update dynamics according to the audio stream's average amplitude energy (known as root mean square, RMS). The first half of this section summarizes the main components of the GNCA, while the second half describes the modifications introduced in ADI.

#### 3.3.1. Base Pre-trained Architecture

The GNCA architecture was chosen as the base for ADI for its small size, low computational cost, interesting growth dynamics and proven real-time, web portability (Mordvintsev et al., 2020). The GNCA is an NCA trained to grow a target image[2] from a single black pixel, also known as a *seed*. To do so, each pixel on the target image is represented in the GNCA with a 16 channel cell. Three of these channels represent the RGB channels present in images, the alpha channel A represent if a cell is alive ($A > 0.1$) or dead, while the remaining 12 channels are hidden channels.

The update process for the GNCA starts by extracting state representations of each cell and its neighbors. Then, a fully connected neural network is applied to each cell's state representation. The network then outputs $ds$, the incremental update of each cell. Finally only alive cells and cells next to alive cell are allowed to update (a process known as *alive masking*). Alive masking is necessary to induce the 'growing' process from single pixel to target image.

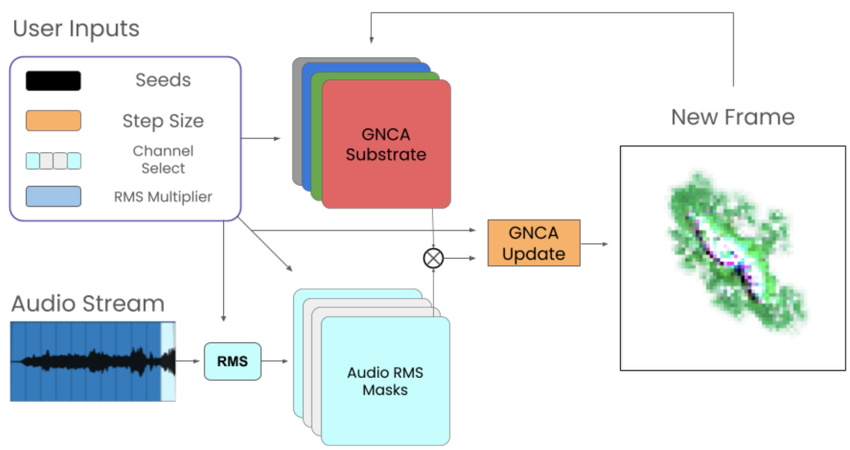



Figure 2: Artificial Dancing Intelligence Architecture

### 3.3.2. Audio Visual Architecture

The primary contribution of Artificial Dancing Intelligence is the real-time audio modulation architecture built on top of the pre-trained GNCA, shown in Figure 2. The update loop for this modulation system is outlined in Algorithm 1. After selecting an audio file in the Controls panel of ADI, we begin each frame rendering loop by extracting the audio stream's RMS since the last frame update of the web application. Then, this RMS value is multiplied by a user-adjustable floating-point scalar value —the *RMS Multiplier*. This multiplied scalar fills a tensor of size equal to the GNCA's grid. We refer to this tensor as the *Audio RMS Mask*, inspired by the goal-guided masks of Sudhakaran et al. (2022a), but here masks are computed on-the-fly from audio RMS rather than learned. The user selects which of the 16 channels of the GNCA's substrate to apply the Audio RMS Mask using the *Channel Select* user input. Finally, because the audio-NCA feedback loop introduced by our architecture occasionally causes the NCA substrate values explode in magnitude,

2. For this paper, we trained the base GNCA to grow a lizard emoji on a $64 \times 64 \times 16$ substrate.

**Algorithm 1:** Artificial Dancing Intelligence Update Loop

1. **While audio is playing:**
   (a) **Extract audio RMS** since last frame.
   (b) **Compute Audio RMS Masks:**
      i. Read user channel selection.
      ii. Apply RMS Multiplier to each selected channel.
   (c) **Apply modulation:**
      i. Perform element-wise multiplication between the NCA substrate and the Audio RMS Masks.
      ii. Apply `NaN_to_zero()` filter to clean invalid values.
   (d) **Update GNCA:** execute one GNCA step (Seed placement and Step Size parameters modulated by user inputs).
   (e) **Render output:** display the GNCA's RGBA channels for the user.

we add a `NaN_to_zero()` routine that converts NaN or Inf values into zero values before computing the GNCA's update and rendering it onto the Viewer.

Additionally, we introduce a user-controllable *Step Size* parameter. This input is a positive floating-point number that scales the GNCA's incremental cell update $ds$ described in the previous section. We introduce Step Size as a modification of the GNCA to explore how scaling incremental updates affects the system's growth dynamics. *Seed* is a user input that places a stream of seeds on the substrate based on where in the Viewer the user clicks and holds their cursor. Lastly, we introduce *Color Shift* a secondary input in ADI which shifts the colors of the rendered image to introduce color variety without affecting any of the GNCA substrate directly.

## 4. Results and Evaluation

### 4.1. Web Demo and Code Repository

The anonymized web demo can be accessed through https://adi2026.netlify.app. The anonymized repository with the website's code can accessed through https://github.com/adi-eaim-2026/adi_eaim2026_copy.

### 4.2. Web Application Metrics

To verify that Artificial Dancing Intelligence (ADI) operates in real time on consumer hardware, we profiled the deployed web version using Chrome DevTools (Lighthouse local metrics) on a 2023 MacBook Air (Apple M2, 8 GB RAM) running Google Chrome. The system achieved a Largest Contentful Paint (LCP) of 0.20 s, indicating rapid interface load, and an Interaction-to-Next-Paint (INP) latency of 32 ms, confirming immediate visual feedback to user inputs. Runtime analysis suggest an average render rate of 31.2 frames per second, maintaining smooth, perceptually real-time responsiveness. Together, these measurements substantiate that ADI performs well within standard browser environments in modern consumer hardware.

### 4.3. Performance-Based Research

Artificial Dancing Life is an instrument for the visual performance of music, which means creativity and exploration are at the center of its design. Therefore, we evaluate our system in the context of performance and artistic expression using Practice-Based Research (PBR), a methodology that generates new knowledge through the integration of creative practice and critical reflection (Skains, 2017). It typically involves formulating a research question, conducting contextual research, producing a series of artistic performances, and reflecting on their relationship to the initial inquiry and theoretical background. The value of this methodology emerges most clearly because the researcher also assumes the role of the performer, enabling a deep, embodied exploration of the system's capabilities and fostering the kind of serendipitous discovery described by Skains (2017). Accordingly, this section is organized around three research questions around the system's creative performance capabilities, followed by their corresponding artistic outcomes and discussions.

**Question 1: How do user inputs in isolation affect the system?**

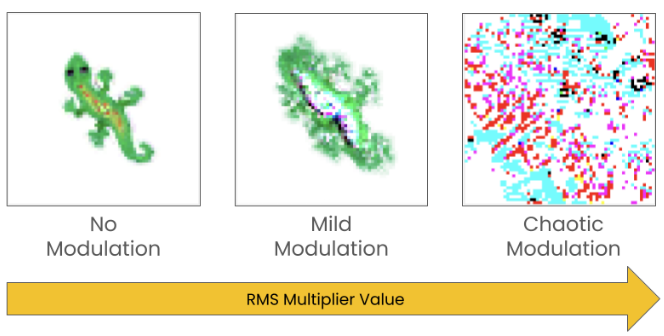



Figure 3: System evolution as RMS Multiplier increases.

**RMS Multiplier:** This parameter can be modulated during performance via a slider input in the ADI UI. When this input is set to zero, the GNCA behaves normally by growing the target image from a seed. However, as the RMS Multiplier increases, as shown in Figure 3, audio-reactive color changes, and emergent[3] growth dynamics start transforming the target image. As the RMS Multiplier is further increased, the rate of this growth is not always predictable. If the product of the RMS Multiplier and audio source's RMS exceed a certain threshold, the system's growth explodes, leading to clipping of colors and chaotic dynamics. In other words, the choice of music audio file plays an important role in shaping the visual outputs of ADI.

3. The growth dynamics observed have a structured nature, yet they were not explicitly coded.

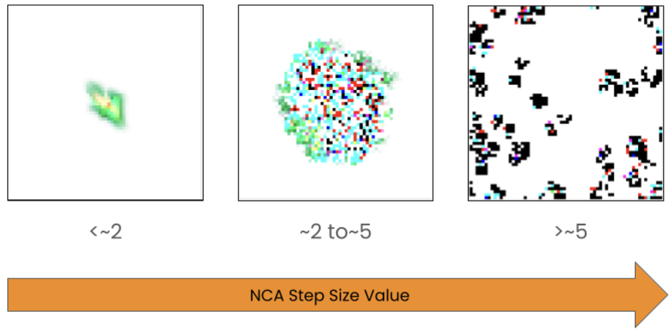
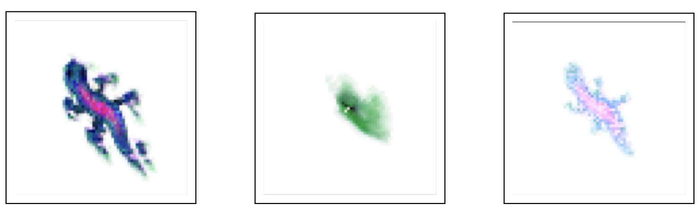



Figure 4: System evolution as Step Size increases.

**Step Size:** This parameter is adjusted during performance via a slider input. When Step Size is set to zero, the GNCA dynamics freeze because the incremental update *ds* of each cell is zero. As Step Size increases to approximately[4] 2.0, as shown in Figure 4, the system dynamics gradually speed up to reach the target image. As the Step Size continues to increase, the target image suddenly grows into clipped colors with seemingly random dynamics. As the Step Size is further increased, these random noise-like dynamics start organizing into small gliding shapes reminiscent of "glider" patterns in Conway's Game of Life[5] (Gardner, 1970).

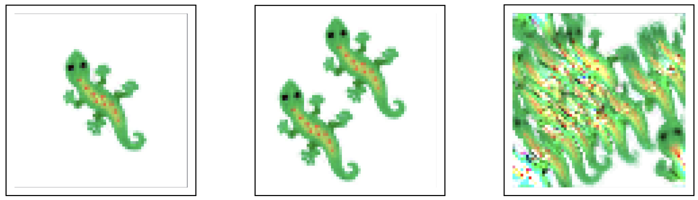


($a$) Green ($b$) Hidden ($c$) Alpha

Figure 5: Different visual outputs from audio modulating different GNCA channels.

**Channel Select:** These parameters are changed via toggles in the ADI UI. Selecting the red, green, or blue channel has an immediate impact on the colors of the system. As shown in Figure 5($a$), if the Green channel is selected, any cell that contains green in the target image will start pulsing and changing color along with the music. By contrast, audio modulation of hidden channels generally does not affect the colors of the system; rather, it induces unpredictable distortions to the growth dynamics of the GNCA as shown in Figure 5($b$). Since the alpha channel regulates the GNCA's growth, modulating this channel causes the target image to change in opacity. If the audio modulation is too strong, the system goes blank (every cell turning dead). However, at lower modulation strengths, the target image grows and shrinks along with the music audio stream, as shown in Figure 5($c$).

4. The actual range depends on the pre-trained image and the current growth stage of the GNCA.
5. Conway's Game of Life is arguably the most famous two-dimensional cellular automaton.



($a$) Single Seed ($b$) Independent Seeds ($c$) Overlapping Seeds

Figure 6: Different growth dynamics based on seed placement

($a$) Step Size = 0 ($b$) Step Size= 0.06 after 0.2 s ($c$) Step Size= 0.06 after 1.0 s

Figure 7: Progression observed with drawing functionality.

**Seeds**: The user can place seeds by clicking and dragging on the ADI Viewer component. When a single seed is placed, a single pretrained target image grows, as shown in Figure 6($a$). If two or more seeds are placed far apart, they each independently grow a target image, as shown in Figure 6($b$). However, when seeds are placed close enough, their independent growth processes overlap and interfere with each other causing distorted target image formations, as shown in Figure 6($c$). If Step Size is set to zero while the system is playing, as shown in Figure 7($a$), the click and drag gesture enables users to draw shapes. When the Step Size is then increased above zero, as show in in Figure 7($b$) and 7($c$), the drawn pattern will grow and react to music.

**Question 2: How predictable are the system's visual outputs?**

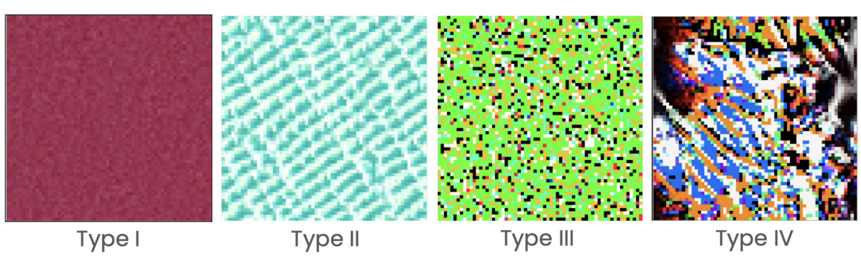



Figure 8: ADI outputs reminiscent of the Wolfram Four Type classification of Cellular Automata

When varying input parameters and songs, we found that the visual outputs of ADI tend to fall into Wolfram classes of CA behavior, as seen in Figure 8. In his book *A New Kind of Science* (Wolfram, 2002), Wolfram classifies cellular automata behavior into four types. Type I is constant, where the automata is in a uniform state. Type II is a repetitive state. Type III is seemingly chaotic or random behavior. Type IV is when the automata shows emergent behaviors. While we observe Type IV patterns in ADI with beautiful shape and color distortions, they also tend to rapidly break down into one of the other three types of patterns.

**Question 3: How expressive is the system?**


Figure 9: Four examples of emergent ADI Visual Outputs. The named labels are the authors' own interpretation.

PBR encourages the researcher-practitioner to "remain open to [the] serendipitous connections" they may come across. In Figure 9, we present notable and unexpected visual result that emerged from freely performing with ADI using a wide variety of songs. These compositions are a testament to the ease of exploration and expressive power of Artificial Dancing Intelligence, especially considering that only one pre-trained GNCA model was used for all the work shown in this paper.

## 5. Discussion and Future Work

The system we present in our research is able to harness self-organization to produce varied, unexpected, and musically informed visuals, while running in real-time on modern consumer devices. However, this same self-organized nature of Artificial Dancing Intelligence can make it difficult to control (Kelly, 1995). More specifically, we note that the neural cellular automata feedback loop is very sensitive to the music's dynamic variations and the various user inputs. A focused study on varying the audio signal's nature while monitoring the NCA's substrate in real-time could shed light into the origin of (and potential control over) the chaotic tendencies of the system.

Currently, the system we present has a user interface that enable easy exploration of the system's parameters. Future work will involve conducting user-testing to align the user interface, and user experience of ADI for live and casual performances. Additionally, we plan to optimize the system's performance by moving away from TensorFlow.js to a direct

"WebGL API and GLSL shader language" (Mordvintsev et al., 2020)[6] implementation of the GNCA in order to increase the resolution and frame rate of the visualizations.

Our initial goal was to conduct an exploration of a music energy modulated NCA to produce interactive music visualizations. Similar investigations could be conducted using other audio features—frequency spectra, pitch contours, onsets, etc.—and NCA architectures other than the GNCA. In other words, the possibilities for using Neural Cellular Automata for music visualizations are vast, and ready for continued exploration.

## References


Ralf Baecker. Cellular performance: Audiovisual performance / instrument. https://rlfbckr.io/project/cellular-performance/, 2024. Generative software using elementary, advanced and neural cellular automata; sonic layer rendered by sonifying pixel data in real time.

Gabriel Béna, Maxence Faldor, Dan Goodman, and Antoine Cully. A path to universal neural cellular automata. In *Proceedings of the Genetic and Evolutionary Computation Conference Companion*, pages 2099–2107, 2025.

Peter Beyls. The musical universe of cellular automata. pages 21–24, 1989. URL https://quod.lib.umich.edu/cgi/p/pod/dod-idx/musical-universe-of-cellular-automata.pdf?c=icmc;idno=bbp2372.1989.009;format=pdf. Accessed: 2025-09-09.

Noël Carroll and Margaret Moore. Feeling movement: Music and dance. *Revue Internationale de Philosophie*, 62(246):413–435, December 2008. doi: 23961196.

Thomas Didiot-Cook. Cellular au–tonnetz: A unified audio–visual midi generator using tonnetz, cellular automata, and iot. In Penousal Machado, Colin Johnson, and Igor Santos, editors, *Artificial Intelligence in Music, Sound, Art and Design. EvoMUSART 2025*, volume 15611 of *Lecture Notes in Computer Science*. Springer, Cham, 2025. ISBN 978-3-031-90166-9. doi: 10.1007/978-3-031-90167-6_4. URL https://doi.org/10.1007/978-3-031-90167-6_4.

Martin Gardner. Mathematical games. *Scientific American*, 223(4):120–123, 1970. ISSN 00368733, 19467087. URL http://www.jstor.org/stable/24927642.

Sukhpal Singh Gill, Marcin Golec, Jianmin Hu, et al. Edge ai: A taxonomy, systematic review and future directions. *Cluster Computing*, 28(18), 2025. doi: 10.1007/s10586-024-04686-y. URL https://doi.org/10.1007/s10586-024-04686-y.

Kevin Kelly. *Out of control: the new biology of machines, social systems, and the economic world*. Addison-Wesley Longman Publishing Co., Inc., USA, 1995. ISBN 0201483408. See page 8, section titled "Learning to surrender our creations.".


6. The "Implementation Details" section of the paper mentions how their web demo was coded directly using WebGL API and GLSL shader language to see how much they could push the system's performance.

Nicolai Klemke. The music video revolution musicians have been waiting for, 2025. URL https://www.neuralframes.com/product.

Jonas Kraasch and Philippe Pasquier. Autolume-live: Turning gans into a live vjing tool. In *Proceedings of the 10th Conference on Computation, Communication, Aesthetics X (xCoAx 2022)*, 2022. URL https://2022.xcoax.org/pdf/xcoax2022-kraasch.pdf. Accessed: 2025-09-09.

Vivian Liu, Tao Long, Nathan Raw, and Lydia Chilton. Generative disco: Text-to-video generation for music visualization. *ArXiv e-prints*, 2023.

Scott McLaughlin and Pierre Alexandre Tremblay. Spectralconway: Cellular automata off the grid. In *Proceedings of the International Computer Music Conference (ICMC)*, pages 68–71, 2010.

Alexander Mordvintsev, Ettore Randazzo, Eyvind Niklasson, and Michael Levin. Growing neural cellular automata. *Distill*, 2020. doi: 10.23915/distill.00023. https://distill.pub/2020/growing-ca.

Elias Najarro, Shyam Sudhakaran, Claire Glanois, and Sebastian Risi. Hypernca: Growing developmental networks with neural cellular automata. *ArXiv*, abs/2204.11674, 2022. URL https://api.semanticscholar.org/CorpusID:248376835.

Brian Man-Kit Ng, Samantha Rose Sudhoff, Haichang Li, Joshua Kamphuis, Tim Nadolsky, Yingjie Chen, Kristen Yeon-Ji Yun, and Yung-Hsiang Lu. Visualize music using generative arts. In *2024 IEEE Conference on Artificial Intelligence (CAI)*, pages 1516–1521, 2024. doi: 10.1109/CAI59869.2024.00273.

Anna Maria Piskopani, Alan Chamberlain, and Carolyn Ten Holter. Responsible ai and the arts: The ethical and legal implications of ai in the arts and creative industries. In *Proceedings of the First International Symposium on Trustworthy Autonomous Systems*, TAS '23, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400707346. doi: 10.1145/3597512.3597528. URL https://doi.org/10.1145/3597512.3597528.

Revid.ai. Revid.ai – ai-powered video creation platform. https://www.revid.ai/. Creates viral short videos from ideas using AI scripts, voices, templates; supports TikTok, Instagram, YouTube (accessed 2025-09-09).

A. D. Richardson, T. Antal, R. A. Blythe, and L. J. Schumacher. Learning spatio-temporal patterns with neural cellular automata. *PLOS Computational Biology*, 20(4):e1011589, 2024. doi: 10.1371/journal.pcbi.1011589. URL https://doi.org/10.1371/journal.pcbi.1011589.

Garrit Schaap and Maria M. Hedblom. Discussing the creativity of automatone: an interactive music generator based on conway's game of life. In *Proceedings of the 15th International Conference on Computational Creativity (ICCC'24)*, pages 456–460, Jönköping, Sweden, 2024. Association for Computational Creativity (ACC). URL https://hj.diva-portal.org/smash/record.jsf?pid=diva2:1921715. Accessed: 2025-09-09.

Lyle Skains. Creative practice as research: Discourse on methodology. *Journal of Media Practice*, 19, 01 2017. doi: 10.1080/14682753.2017.1362175.

Stack Overflow. Stack overflow developer survey 2024: Technology. https://survey.stackoverflow.co/2024/technology, 2024. Accessed: 2025-09-10.

Shyam Sudhakaran, Elias Najarro, and Sebastian Risi. Goal-guided neural cellular automata: Learning to control self-organising systems. *arXiv preprint arXiv:2205.06806*, 2022a.

Shyam Sudhakaran, Elias Najarro, and Sebastian Risi. Goal-guided neural cellular automata: Learning to control self-organising systems, 2022b. URL https://arxiv.org/abs/2205.06806.

Hyewon Suk. Audiovisual morphogenesis. In *Speculative Sound Synthesis Symposium 2024 Proceedings*, Graz, Austria, 2024. URL https://speculativesoundsynthesis.iem.sh/symposium/docs/proceedings/suk/. Performance / generative audiovisual project using neural cellular automata.

Mark Tension. spectrogramnca. https://github.com/MarkTension/spectrogramNCA/tree/main, 2023. Last commit 2 years ago.

TensorFlow Development Team. Tensorflow.js guide. https://www.tensorflow.org/js/guide, 2023. Last updated: 2 June 2023; accessed: 2025-09-10.

u/PsyzygyMusic. Unique audio-reactive visualization technique i programmed based on neural cellular automata. https://www.reddit.com/r/generative/comments/1c2nkec/unique_audioreactive_visualization_technique_i/, 2023. Reddit post; source of neural CA audio-visual demo.

Graham Wakefield. Cellular automata (and related lattice models). https://artificialnature.net/courses/datt4950/cellular.html. Accessed: 2025-09-09. Course material from DATT4950: Artificial Life, Generative Art, York University.

John Whitney. *Digital Harmony*. McGraw-Hill, Peterborough New Hampshire, 1 edition, 1980. URL https://archive.org/details/DigitalHarmony_201611/page/n1/mode/2up.

Stephen Wolfram. A new kind of science (online edition). https://www.wolframscience.com/nks/, 2002. Accessed: 2025-09-09.

Wolfram Research. How it works – wolframtones. https://tones.wolfram.com/about/how-it-works, 2005. Accessed: 2025-09-09.

World Wide Web Consortium (W3C). Web audio api. https://www.w3.org/TR/webaudio/, 2018. Latest published version as of 2025-09-10; W3C Candidate Recommendation occurred on 18 September 2018.

Mo H. Zareei, Dale A. Carnegie, and Ajay Kapur. Noise square: Physical sonification of cellular automata through mechatronic sound-sculpture. In *Proceedings of the 21st International Symposium on Electronic Art (ISEA 2015)*, Vancouver, Canada, 2015. URL https://www.isea-archives.org/docs/2015/proceedings/ISEA2015_proceedings.pdf. Paper presented in Sculpture session; accessed via ISEA Symposium Archives.