# Modeling Human Success and Social Mobility Through Incremental Development of a Multi-State Cellular Automaton

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March 21, 2025

**Abstract**

Cellular automata (CA) offer a simple yet powerful framework for modeling complex, emergent behavior based on local interactions and rule-based evolution. In this study, we explore the potential of multi-state cellular automata to simulate human generational success and social mobility. Building incrementally from a traditional 2-state elementary CA to a fully featured 3-state model through 6 phases of design, we introduce key mechanisms such as stochastic transitions, deterministic rule sets, inheritance, and social intervention. Each phase of development adds layers of realism that mirror socio-economic phenomena such as class emergence, systemic inequality, and the influence of environmental factors. In our final phase, we define contextually informed rule sets that reflect different societal worldviews—optimistic, balanced, and pessimistic—and analyze their impact on class distribution over time. The results show distinct structural patterns, including the natural rise of a middle class under certain models. This research demonstrates the capacity of CA to serve as both a theoretical and visual tool for studying the effects of societal conditions on long-term human outcomes, and lays the groundwork for future applications in policy modeling and socio-economic forecasting.

## 1 Introduction

Cellular automata (CA) have long fascinated researchers for their ability to generate complex global patterns from simple local rules. Originally developed in the mid-20th century, CA have since been used to explore phenomena in physics, computation, biology, and beyond. At their core, CA are discrete, rule-based systems where each cell in a grid updates its state based on a fixed set of rules that consider its immediate neighbors. Although simple in design, their capacity to exhibit rich, emergent behavior has positioned them as valuable tools in modeling systems that defy linear prediction.

In this paper, we investigate the use of CA to model one of the most intricate and nuanced systems of all: human development and social mobility. Inspired by the idea that generational success is influenced by a blend of environment, family foundation, and personal drive, we designed a multi-phase CA framework that incrementally builds toward this complexity.

Beginning with classic 2-state elementary CA, we progress through the introduction of a third state to represent different socio-economic statuses—struggling, stable, and thriving. We then explore the effects of randomness (stochastic success), complete deterministic rule sets, and ultimately the integration of societal mechanisms such as inheritance and intervention.

In the final phase of our model, we embed behavioral logic into the CA rules, allowing users to simulate society from various perspectives—optimistic, balanced, or pessimistic—each influencing the trajectory of individuals across generations. These simulations reveal not only visual complexity but also meaningful insights, such as the emergence of the middle class, the impact of societal rigidity or opportunity, and the ways structure or randomness shape human outcomes over time. Through this exploration, we position cellular automata as a novel and engaging tool for visualizing and analyzing socio-economic processes. The implications extend beyond theory, offering potential for application in education, policy development, and systems thinking for social equity.

# 2 Phase I: Elementary 2-State CA Behavior

Elementary cellular automata (CA) serve as the conceptual foundation for this model. These systems operate on binary rules where each cell has two possible states (0 or 1), and its future state is determined by itself and its two immediate neighbors. In this implementation, we initialize ten well-known elementary CA rules: 4, 22, 30, 45, 54, 73, 90, 110, 126, and 135. Each rule number corresponds to an 8-bit binary string that encodes the transition logic for all eight possible 3-cell neighborhood patterns. For instance:

- **Rule 30** is represented as 00011110
- **Rule 110** as 01101110
- **Rule 73** as 01001001

Each binary string is interpreted from left to right to define the outcome for the patterns from 111 to 000. These 8-bit representations result in a total of 256 unique rule sets, calculated as $2^8 = 256$.

Despite the simplicity, these rules generate surprisingly varied and often unpredictable patterns. Rule 110, for example, is Turing-complete, meaning it can theoretically perform any computation given sufficient time and space.

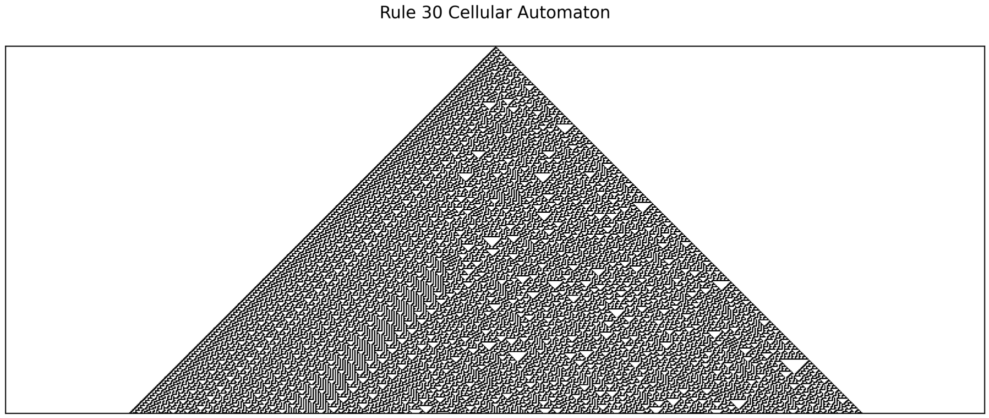


Figure 1: Rule 30 with 4000 steps

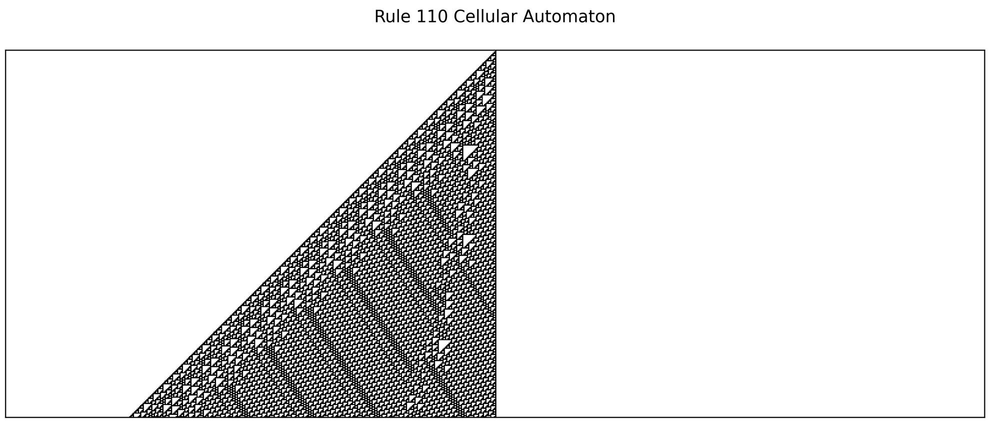


Figure 2: Rule 110 with 4000 steps

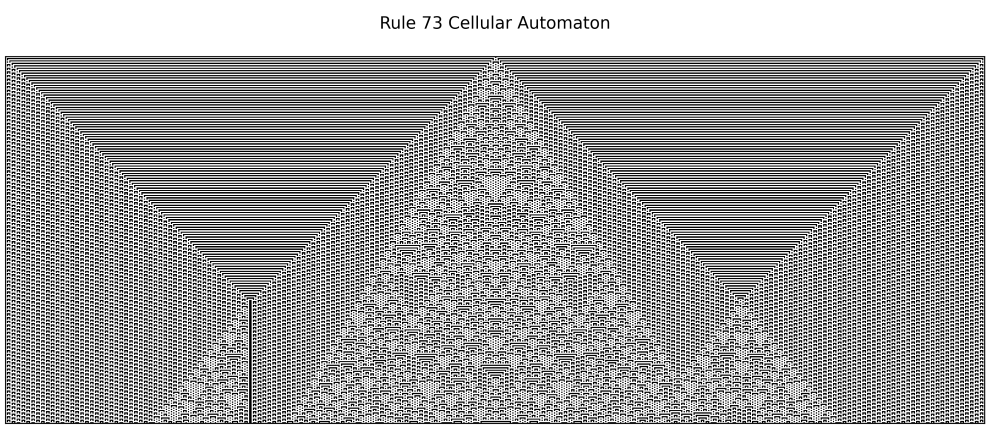


Figure 3: Rule 73 with 4000 steps

However, despite the computational power of some rules, the 2-state CA model is too limited to simulate complex human developmental outcomes. With only two possible states, it cannot adequately represent the nuanced dynamics of socioeconomic mobility or the multivariate influences that shape generational success. What this model demonstrates well is how localized rules can lead to emergent global patterns, a concept we will carry into more expressive models in subsequent phases.

# 3 Phase II: 3-State Symbolic Representation

To more accurately simulate a process as complex as human development shaped by socioeconomic factors, environmental influences, and personal decisions, we expand the state space from 2 to 3. Introducing a third state significantly increases the system's expressiveness and better reflects real-world variation. With three possible states per cell and three neighboring cells, there are neighborhood patterns. Each pattern can map to one of three outcomes, resulting in a sample space of possible rule sets. This is an exponential leap from the 256 rules of the 2-state model, unlocking over 7.6 trillion distinct behaviors. Each state in this 3-state implementation is interpreted as a level of socioeconomic status:

- 0 = **Struggling**: representing individuals below the poverty line or in sociologically disadvantaged situations.
- 1 = **Stable**: those with middle-class economic standing, often described as the American middle class.
- 2 = **Thriving**: individuals in the upper economic tier, capable of sustaining themselves and generational wealth, including the upper-middle class and ultra-wealthy.

This expanded model offers a much more diverse simulation landscape. As detailed in Chapter 3 of *Stephen Wolfram's A New Kind of Science*[3], even slight increases in the number of possible states can lead to profoundly more intricate and unpredictable behaviors. As shown below, the visual diagrams in that chapter showcase 3-state machines that showcase far more elaborate patterns than their 2-state machines, demonstrating symmetry and also unexpected bursts of randomness and self-organization. These examples inspired our transition to a 3-state framework, showing how adding a single layer of complexity can dramatically transform the system's expressive power. The additional state allows for more realistic modeling of individuals in transition, those on the edge of progress or decline. While the structure of society begins to emerge more clearly through the CA patterns, this model is still primarily deterministic and lacks the unpredictability inherent in real human experiences.

The diagrams generated from this phase, seen below, reflect a stronger resemblance to real societal structures than in Phase I, yet still fall short of capturing external, chance-driven events that heavily influence real-world outcomes. To model these unpredictable forces, both beneficial and detrimental, we transition into Phase III.

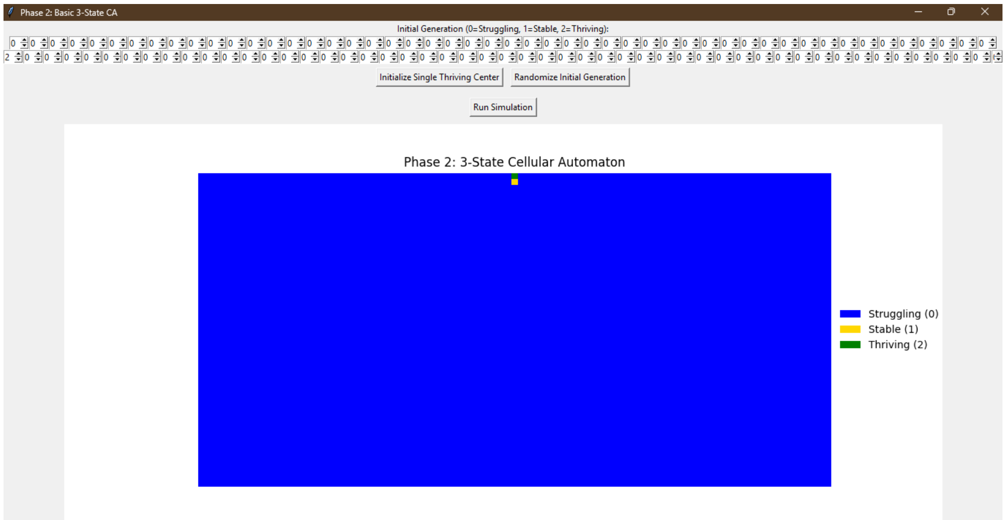


Figure 4: *A basic 3-state cellular automaton initialized with a single thriving (green) cell. This image demonstrates the early spreading patterns of success within a deterministic framework, highlighting the limited but organized expansion without any randomness or external influence.*

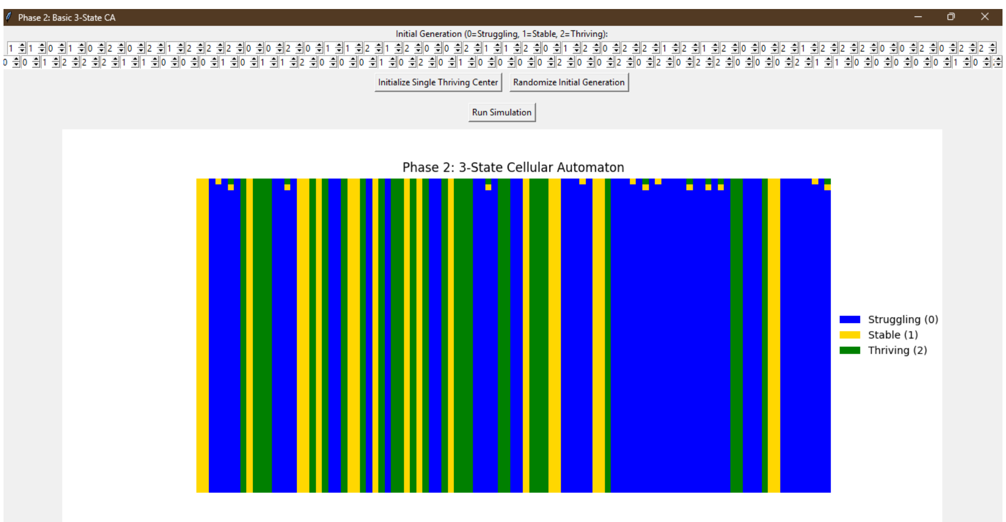


Figure 5: *A basic 3-state cellular automaton initialized with a randomized starting generation.*

# 4 Phase III: Stochastic Environmental Randomness

In Phase III, we introduce stochasticity to better simulate real-life unpredictability. Human success is not driven solely by deterministic factors; luck, timing, health, and social context all introduce randomness into an individual's life trajectory. This phase represents the "stochastic society, " one where outcomes may be heavily influenced by randomness, regardless of upbringing or initial conditions. To achieve this, we introduce a tunable randomness scale ranging from 0.0 to 1.0. At 0.0, the system behaves deterministically. As the slider increases, randomness becomes more dominant. For this phase, the randomness is fixed at a minimum of 0.1 to ensure a baseline level of uncertainty.

The ruleset in this phase still uses the same 3-state structure from Phase II, but only a limited subset of 8 neighborhood rules is explicitly defined. For the remaining 19 combinations, the model defaults to using the center cell's value, simulating a neutral or passive reproduction of the parent's socioeconomic condition. During simulation, each cell update has a defined probability of ignoring deterministic rules and instead being randomly assigned a new state (0, 1, or 2).

This design allows the simulation to express both upward and downward randomness in a society. Examples include:

- A prodigy child excelling despite being raised in poverty
- A spoiled child of a wealthy family falling short of expectations
- A random accident or stroke of fortune altering life paths dramatically (cancer, sporting incidents, car crashes)

While this randomness shown below better captures the chaotic nature of human experience, it also introduces limitations. The limited rule set and probabilistic overrides can produce erratic outcomes without strong structural patterns. To ground the model in predictable, policy-relevant scenarios, we expand into a deterministic design in the next phase.

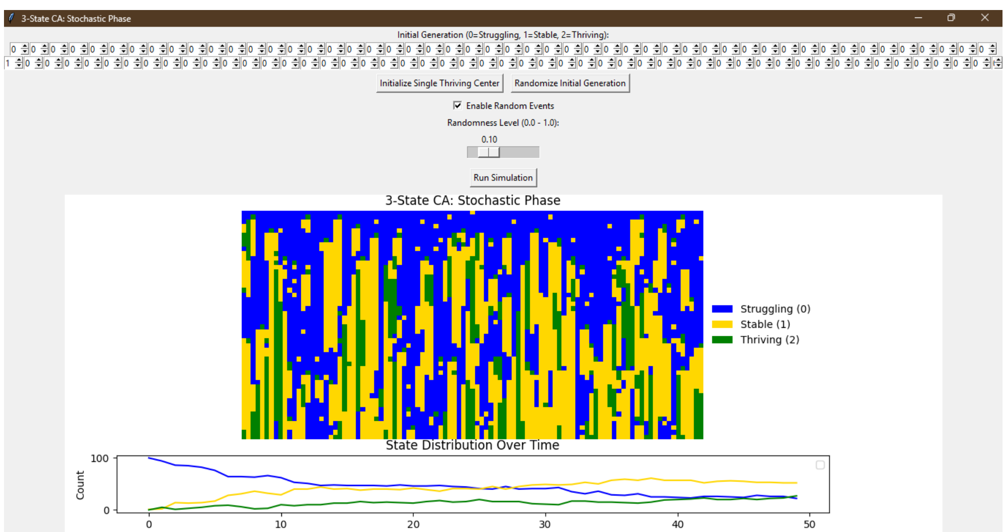


Figure 6: *A stochastic 3-state CA initialized with a single thriving center. With a moderate randomness level (10%), emergent patterns display the gradual rise of the stable middle class, mimicking real-world unpredictability in upward or downward mobility.*

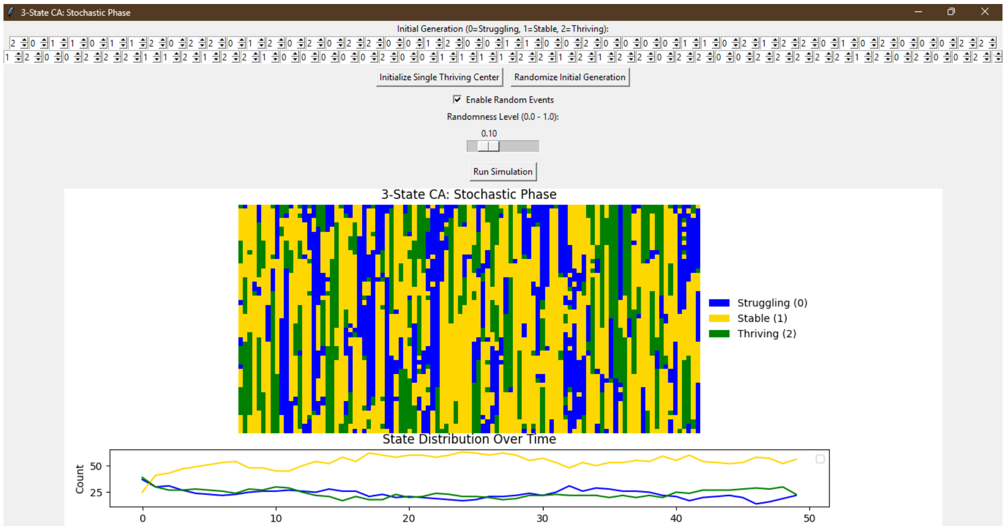


Figure 7: *A stochastic 3-state CA initialized with a random distribution of struggling, stable, and thriving individuals. With a moderate randomness level (10%).*

# 5 Phase IV: Deterministic Rule Expansion (27 Total Rules)

In Phase IV, the model matures into a fully deterministic system by defining all 27 possible 3-cell neighborhood rules. This allows the automaton to operate without reliance on default or fallback behaviors. Every potential state transition is now specified, enabling systematic analysis of outcomes based on specific configurations.

The goal here is not to eliminate randomness entirely, but to explore the effects of structure, rules, and institutional systems in shaping generational success. This phase reflects the presence of rigid, predictable systems in society. Some systems include public education, economic frameworks, zoning laws, and access to healthcare — which shape large-scale outcomes despite individual variation. Importantly, randomness remains an optional toggle for comparative analysis. By turning it off, we can examine how purely deterministic systems evolve. When enabled, it serves as a noise layer on top of a structured foundation.

Visualizations from this phase show chaotic emergent behavior. Particularly, they demonstrate the rise of a dominant "middle class" under certain rule configurations, where thriving and struggling states exert balancing forces, leading to a stable, self-replicating band of moderate success. This mimics the economic equilibrium many developed societies aim for, where upward mobility is possible but constrained by systemic forces.

Despite its strengths, the model shown below in this phase lacks the ability to simulate one of the most critical social dynamics: the inter-generational transfer of wealth and the impact of one's environment on upward or downward mobility. This is addressed in the final phase.

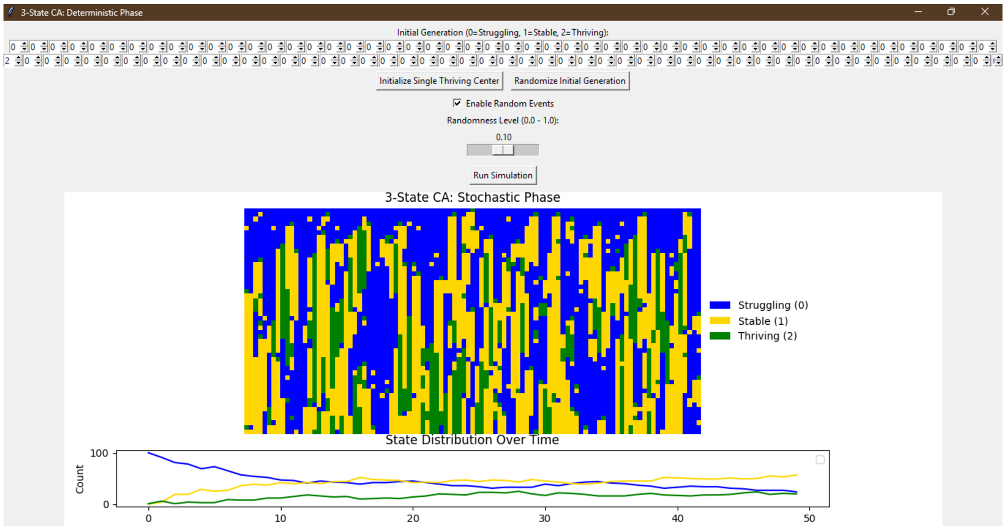


Figure 8: *In a fully deterministic 3-state system with all 27 rules defined, a single stable center cell expands in an ordered fashion. The rules favor state preservation and mild upward movement, leading to a highly structured pattern of middle-class emergence.*

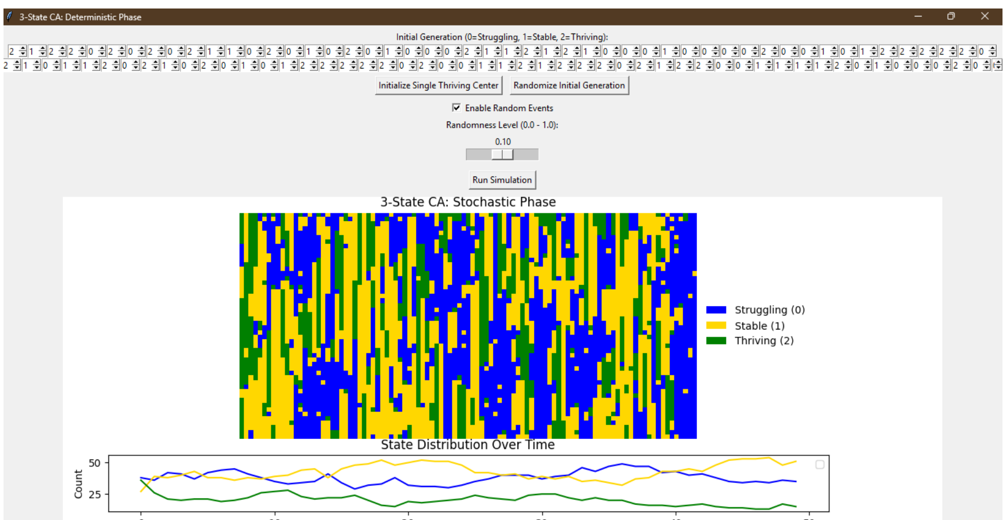


Figure 9: *With a randomized starting population but deterministic rule logic, the system rapidly converges toward a structured balance, reinforcing stability and favoring the emergence of a dominant middle-class block, despite the initial randomization.*

# 6 Phase V: Inheritance and Systemic Intervention Logic

Phase V introduces two powerful new mechanisms that significantly enhance the social realism of the model: inheritance and intervention. These dynamics help simulate the effects of generational support and systemic disadvantage, factors that are often decisive in human success. Inheritance is implemented by checking the states of a cell's left and right neighbors. If both are thriving (state 2), the center cell is promoted one level (if not already thriving). This models the effects of supportive families and communities where wealth, education, mentorship, and cultural capital are passed down and elevate the next generation. Real-world data supports this, with sources like Oxfam[1] reporting that 36% of billionaires inherited their wealth, and financial institutions like Ramsey Solutions[2] estimating that around 20% of millionaires do as well.

Social intervention, in contrast, models the pull of adversity. If a cell is surrounded by struggling neighbors (state 0), it is demoted one level (if not already at the bottom). This represents environments of persistent disadvantage, where even capable individuals are dragged down by circumstances. Ranging from economic hardship to peer influence and lack of opportunity. Examples include children unable to attend college due to financial burdens or high-achieving youth burdened with caregiving roles in unstable households.

These mechanisms are layered on top of the deterministic foundation of Phase IV and still interact with stochastic noise from Phase III. The result is a dynamic, responsive model that incorporates structural rules, chance, and social feedback. A transition-tracking visualization shows how many state changes were caused by randomness, inheritance, intervention, or rule-based logic. This addition creates a valuable diagnostic tool for analyzing the forces shaping societal outcomes. With this semi-final addition, the model shown below becomes not only a simulation tool but also a lens through which to examine class mobility, generational inequality, and the emergent properties of structured society. The visual emergence of the middle class, now less dominant and more volatile, reflects the fragility of upward mobility in today's world. This is not only a computational model, it is a conceptual framework for social insight. With Phase V's versatile approach, we can now bridge the gap between different societal outlooks that are weighted on social factors and not purely on luck and environment, as implemented by Phase IV.

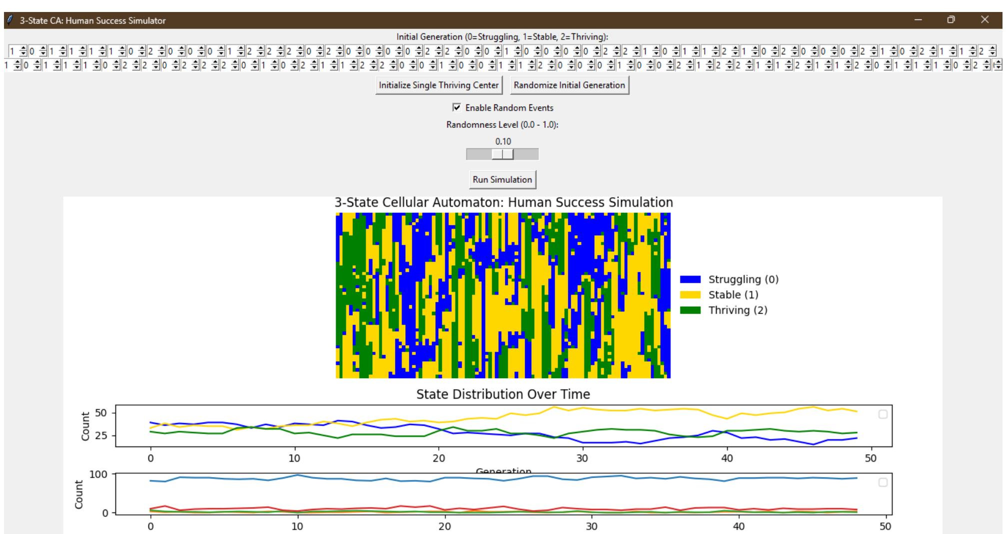


Figure 10: *This simulation demonstrates the effects of inheritance and social intervention on generational success. Cells surrounded by thriving neighbors are more likely to rise, while those surrounded by struggle may drop a level. Despite initial randomness, these added mechanisms produce stronger class stratification over time.*

# 7 Phase VI: Contextual Behavioral Logic for Deterministic Society Modeling

In this final refinement, we introduce a more socially grounded behavioral logic into the rule definition itself. Rather than manually defining all 27 outcomes or relying on a uniform fallback, the simulation now supports contextual interpretations of each individual's neighborhood, mapping local social context into probabilistically guided behavior.

To reflect real-world social dynamics, the three-cell neighborhood of the automaton is reinterpreted as follows:

- Left Neighbor → **Environment**: including peers, mentors, and geographic surroundings
- Center Cell → **Family Foundation**: including socioeconomic status, household stability, and generational support
- Right Neighbor → **Personal Drive**: encompassing motivation, ambition, and resilience

These components are evaluated using one of three behavioral outlook models, each representing a distinct sociological worldview:

- **Pessimistic Society**: downward mobility is common, and thriving is rare.
- → Struggling = 0.45, Stable = 0.45, Thriving = 0.10
- **Balanced Society**: moderate stability with a mix of success and hardship.
- → Struggling = 0.3, Stable = 0.5, Thriving = 0.2
- **Optimistic Society**: upward mobility and success are more accessible.
- → Struggling = 0.15, Stable = 0.5, Thriving = 0.35

This phase retains the inheritance and intervention logic introduced in Phase V, but significantly expands the model's flexibility and realism. The ability to simulate different behavioral outlooks allows us to better model regional disparities, cultural differences, and policy-driven environments. For instance, a "stable" (state 1) upbringing in San Diego, CA may provide vastly different opportunities compared to a "stable" upbringing in Jefferson City, MO, despite being classified under the same state label.

By allowing the user to simulate these distinctions, Phase VI transforms the model into a powerful tool for exploring class dynamics, opportunity distributions, and structural inequality within varying social ecosystems. It reflects the reality that societies are not always deterministic, nor uniformly fair, some environments reward effort, while others trap individuals in cycles of struggle, regardless of potential.

With these enhancements, we begin to see the emergence of complex and beautiful structures that cellular automata are known for. Much like the fractal triangles of Elementary

Rule 90, the chaotic edges of Rule 30, or the gliding interactions in Rule 73, our model now exhibits layered and nuanced dynamics, highlighting how even simple local rules can create rich macro-level behavior when grounded in a human-like context.

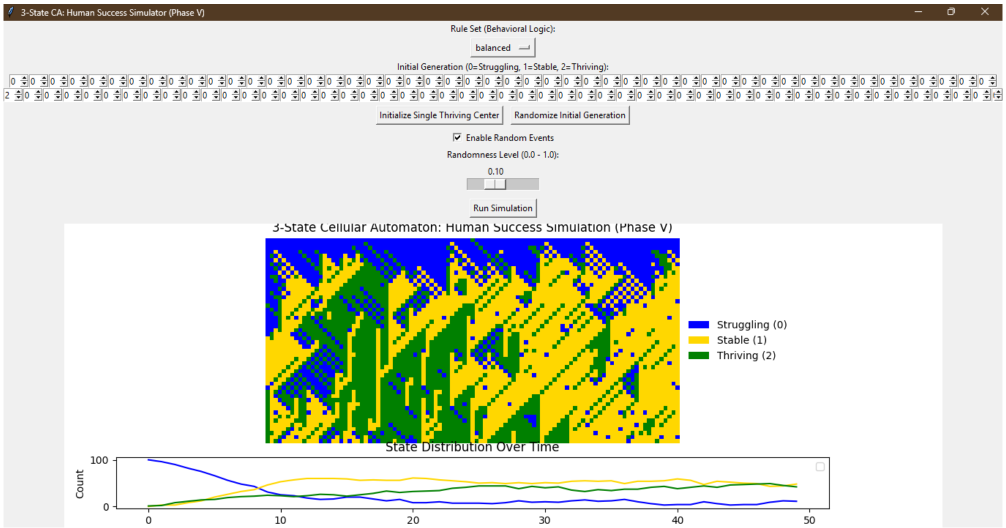


Figure 11: *Single thriving center within a balanced society, rules promote stability and preserve the middle class. These simulations demonstrate a society that encourages moderate upward mobility while maintaining structural equilibrium.*

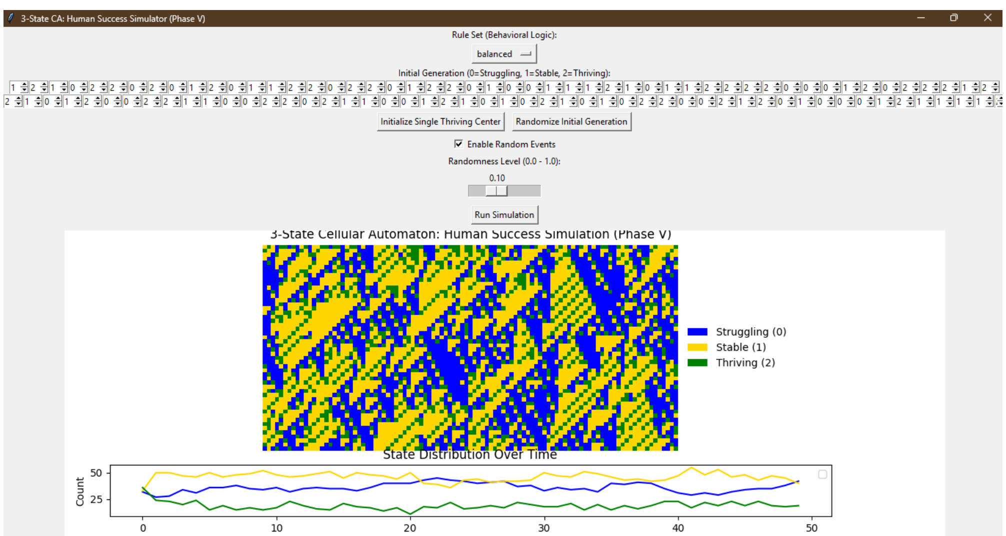


Figure 12: *Randomized first generation within a balanced society, rules promote stability and preserve the middle class.*

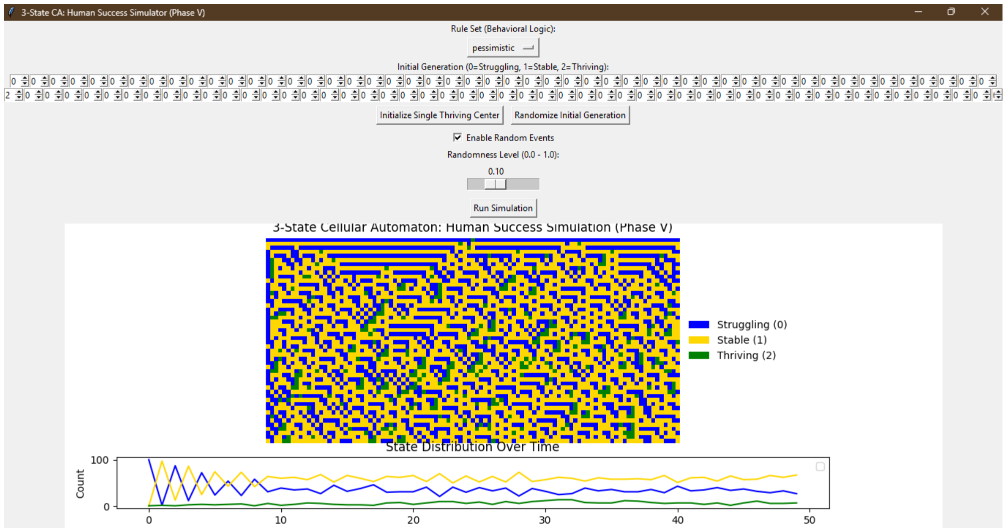


Figure 13: *With a single thriving center, simulations in a pessimistic society demonstrate difficulty in rising to thrive status. Struggling cells dominate, and small successes tend to erode over generations. These patterns mimic systemic drag and downward pressures found in under-resourced regions. This same structure is seen in Figure 14.*

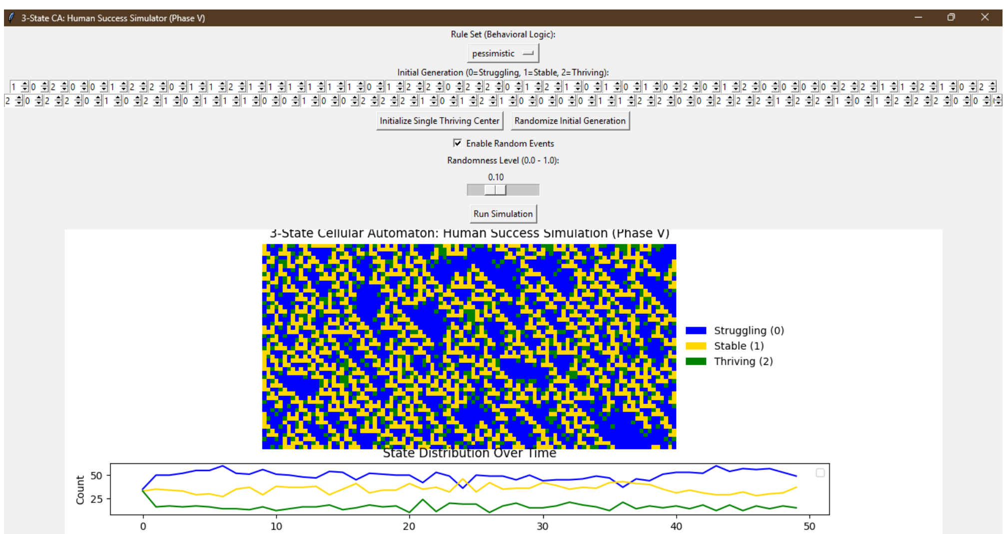


Figure 14: *Randomized first generation within a pessimistic society.*

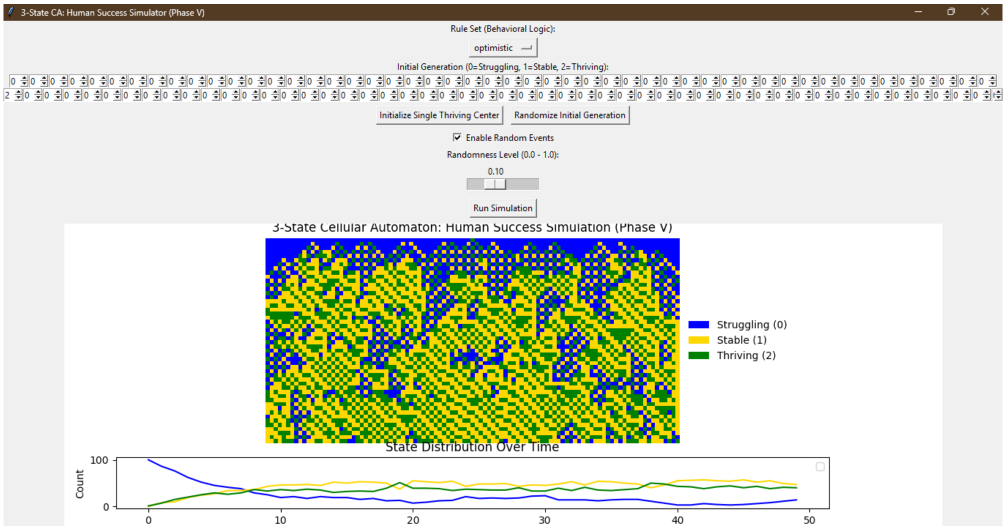


Figure 15: *Under an optimistic rule set, the system is biased toward upward mobility. Even with a single thriving center, thriving outcomes are more probable even in mixed environments. These two simulations show how opportunity-rich societies promote success and generate widespread green zones over time.*

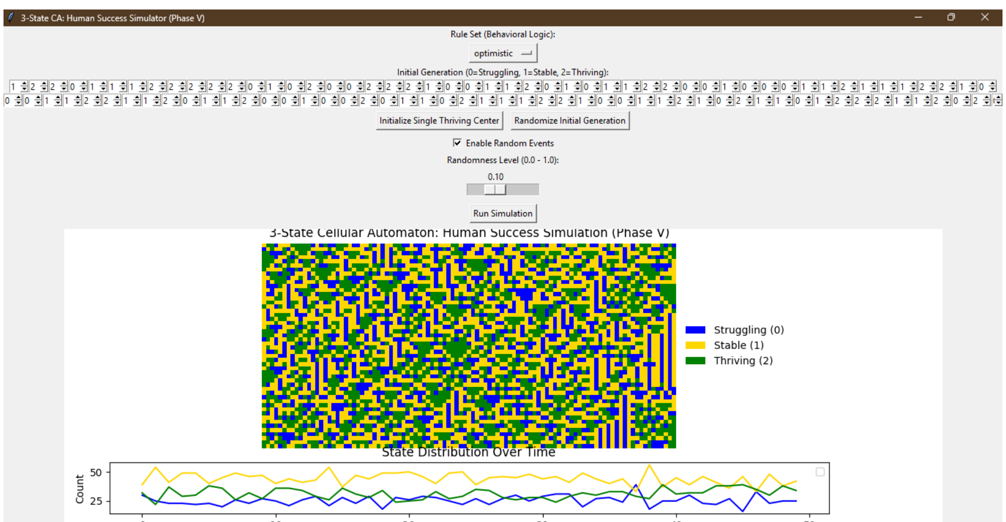


Figure 16: *Randomized starting generation under an optimistic rule set.*

# 8 Future Work

The implementation presented in this study demonstrates the viability of using a multi-state cellular automaton to model complex human and societal behaviors, including generational success, social mobility, and systemic intervention. However, the real-world complexity of socioeconomic systems offers multiple avenues for expansion.

A key direction for future work is the integration of policy-driven dynamics. By allowing targeted rule modifications based on simulated interventions, such as tax policy, education funding, housing subsidies, or healthcare access, the model can begin to simulate how specific governmental or institutional actions ripple through society over generations. For example, the introduction of a universal basic income policy could be reflected by modifying the transition logic for low-state neighborhoods, while a reduction in public education funding might disproportionately affect stability or upward mobility in struggling regions.

Another powerful direction lies in modeling the impact of economic variables, such as price shocks or inflation, especially for items or services disproportionately consumed by a specific class or demographic. For instance, a sudden increase in housing costs or essential goods could be translated into changes in neighborhood dynamics, shifting more families from a stable to a struggling state. By creating a mapping between external shocks and CA rules, the model can serve as a sandbox for socioeconomic forecasting and impact analysis.

Additionally, given that 3-state cellular automata have a rule space of over 7.6 trillion possibilities $3^27$ , there is potential for representing a vast array of regional cultures, historical scenarios, and policy regimes. Future versions of the model could leverage rule search and optimization techniques, including genetic algorithms or reinforcement learning, to automatically identify rules that best represent real-world datasets, census results, or economic surveys.

Finally, the platform could evolve to include multi-dimensional cellular automata, network-based neighborhoods, or time-varying rules, allowing for even richer structural analysis. Such extensions could allow for the simulation of mass migration, segregation, social contagion, or innovation diffusion, all critical elements in the study of modern complex societies.

# 9 Conclusion

Elementary Cellular Automata have proven to be a powerful and elegant foundation for modeling complex systems. What begins as a simple set of binary reproduction rules, eight deterministic outcomes based on local neighborhoods can evolve into a dynamic, extensible framework capable of simulating sophisticated social and economic behavior. The notion that such a minimalistic system can mimic intricate societal patterns such as generational mobility, class emergence, and systemic inequality is both profound and inspiring.

This study demonstrates that the gap between simple computational models and complex real-world systems is not as vast as it might seem. The key lies in abstracting fundamental rules and embedding contextual meaning into those abstractions. By interpreting neighbors as environment, family structure, and personal drive, the system becomes not just a simulation engine, but a meaningful reflection of human development.

The incremental design, moving from basic 2-state elementary automata to a 3-state model incorporating randomness, deterministic logic, inheritance, and now contextual societal logic, shows how powerful complexity can emerge from structured simplicity. This work is not a conclusion but a foundation. Phase IV and Phase V represent stable stepping stones for further evolution, with the potential to scale up to n-state cellular automata, policy-driven simulations, or even machine learning-enhanced rule discovery.

Ultimately, this study serves as a glimpse into how local, discrete, and rule-based systems like cellular automata can serve as mirrors of society, offering insight, clarity, and creative exploration into the mechanics of success, struggle, and societal change.

# References

[1] Oxfam America. Top 5 ways billionaires are bad for the economy, 2023. Accessed: 2025-03-19.

[2] Ramsey Solutions. How many millionaires actually inherited their wealth, 2023. Accessed: 2025-03-19.

[3] Stephen Wolfram. *A New Kind of Science*. Wolfram Media, 2002.