Innovation Diffusion Analysis of Digital Colonialism: An Agent-Based Approach to Modeling Cultural Resistance to Digital Colonialism

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Executive Summary

This model explores digital colonialism, where technological diffusion from dominant global actors (e.g., corporations or governments in the Global North) to receiving cultures (e.g., less digitally developed regions or post-colonial societies) leads to both advancement and cultural risks. It operationalizes how digital infrastructure, cultural resistance, and access inequality affect adoption, resistance, and long-term outcomes.

1. Introduction

Digital innovation increasingly operates as a mechanism of modern colonization. Michael Kwet defines the social mechanism, *digital colonialism,* as a structural form of domination enforced through centralized ownership of software, hardware, and network infrastructure (Kwet 2018).[1] This mechanism reproduces socio-political and economic power imbalances by entrenching technological dependencies, particularly in the Global South. In this project, I propose an agent-based model (ABM) to simulate this dynamic, drawing inspiration from existing models of innovation diffusion and augmenting them to reflect the cultural and infrastructural asymmetries that shape digital adoption and resistance, with an exploratory analysis of its effects on the digital divide. Building on this foundation, this model addresses the research question: *"How does cultural infrastructure, resistance, and the digital divide affect the adoption and long-term sustainability of digital technologies diffused by a dominant technological superpower?"*

2. Literature Review

South Africa is used as a conceptual case study to contextualize the power asymmetries between digital superpowers (such as U.S.-based tech corporations) and less-resourced recipient cultures. Kwet illustrates how digital infrastructure rollout by Big Tech corporations often leads to surveillance, dependency, and extractive profit flows, thus reinforcing neocolonial dynamics rather than promoting equitable development (Kwet, 2018). [1]

Digital colonialism presents a unique socio-technical dynamic in which the global diffusion of digital technologies reinforces existing hierarchies between technologically dominant nations and more culturally and infrastructurally vulnerable societies. This relational connection, between digital superpowers and digitally dependent nations, forms the foundation for exploring how agent-based modeling (ABM) can simulate the mechanisms of innovation diffusion within a digitally colonized world.

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[1] Kwet, M. (2018, August 15). '*Digital colonialism: US empire and the new imperialism in the Global South'* (SSRN Working Paper No. 3232297). https://ssrn.com/abstract=3232297

The proposed modeling approach draws from literature on innovation adoption in the Global South, particularly within agricultural and rural contexts, where disruptive technologies often fail due to misalignments with local culture, limited infrastructure, or resistance to imposed practices. [2] Studies of agricultural innovation adoption in developing areas, specifically in the paper *"Disruptive innovation in agriculture: Socio-cultural factors in technology adoption in the developing world"* (Curry et al., 2021) [2] emphasize that low adoption rates of technology are due to the incompatibility with "indigenous values, habits, socio-cultural institutions and ways of doing things that can make technology transfer challenging for farmers," (Curry et al., 2021).[2] This further echoes the correlation of cultural infrastructure alignment to the barriers of technology adoption, as well as the cultural risk and information gaps associated with adoption. Both Curry et al. and Kwet outline how tech products are deployed without regard to long-term cultural sustainability, instead reinforcing asymmetrical power relationships and undermining local autonomy.

Further reinforcing the relevance of the proposed model's cultural framing, recent digital transformation literature highlights how institutional narratives and power structures deeply shape the interpretation and perceived utility of technological value. The framing theory applied to digital adoption, as defined by Frida Ivarsson (2022) in *"Applying Framing Theory in Digital Transformation Research: Suggestions for Future Research,"* argues that technologies are not neutral objects but culturally coded interventions whose perceived benefits are contingent on alignment with local norms and values (Ivarsson, 2022). [3] This research gives merit to incorporating the attributes of *perceived utility* and *neighborhood influence* into the model of digital colonialism, emphasizing the additional powers that contribute to technological interpretation.

Abdullah Alsaleh contributes literature that frames the impacts of technological advancements through the lenses of technological determinism, the digital divide, and the role technological advancements play in cultural development. Specifically, Alsaleh explores the dual nature of technology in both its to be a "catalyst for cultural change" and a driver to cultural homogenization, defined as "the loss of unique local traditions in favor of mainstream, globalized norms" (Alsaleh, 2024).[4] Drawing on the *Actor-Network Theory (ANT), Media Archaeology, and Digital Cultural Semiotics*, Alsaleh emphasizes the risk of cultural erosion of technology deployed without regard for local context (Alsaleh, 2024).[4] Collectively, this literature motivates the development of an ABM that does more than measure adoption rates—it simulates the lived tensions between adoption, resistance, and cultural survival under the conditions of digital colonialism.

Currently, AMBs exist around simulating technological adoption within innovation contexts, utilizing a utility function approach. The foundation mechanism underlying these models stems from Everett Rogers' seminal *Diffusion of Innovation Theory* (1962-2003).[5] Within Rogers' framework, there are defined and delineated phases of adoption that purpose when and why individuals adopt innovations. The application of this theory manifests in the proposed ABM decision-making process through the considerations of perceived benefits, peer pressures, and personal characteristics, where Rogers states that peer influences matter most when making an adoption decision. *(See Figure 1)*

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[2] Curry, G. N., Nake, S., Koczberski, G., Oswald, M., Rafflegeau, S., Lummani, J., Peter, E., & Nailina, R. (2021). *'Disruptive innovation in agriculture: Socio-cultural factors in technology adoption in the developing world'*. *Journal of Rural Studies*, *88*, 422-431. https://doi.org/10.1016/j.jrurstud.2021.08.011

[3] Ivarsson, F. M. (2022). *'Applying framing theory in digital transformation research: Suggestions for future research'*. In *Proceedings of the 55th Hawaii International Conference on System Sciences* (pp. 6207-6216). University of Hawaii at Manoa. https://doi.org/10.24251/HICSS.2022.773

[4] Alsaleh, A. (2024). *'The impact of technological advancement on culture and society'*. *Scientific Reports*, *14*, 32140. https://doi.org/10.1038/s41598-024-83995-z

[5] Rogers, E. M. (2003). '*Diffusion of innovations'* (5th ed.). Free Press.

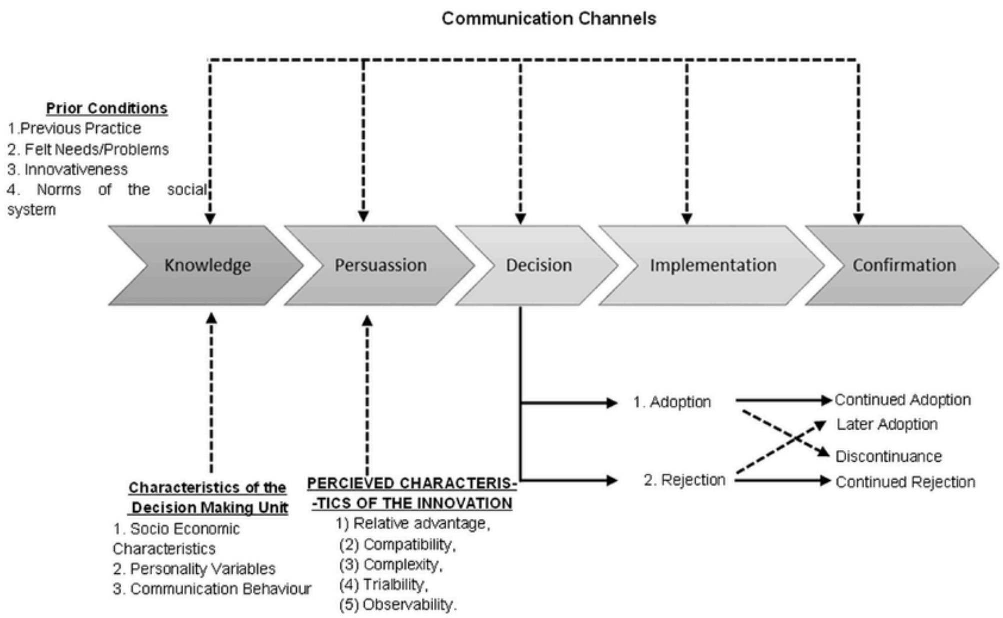

Figure 1. Phases of Adoption - Communication Channels, Everett Rogers (1962,2003)

3. Model Description

The proposed model features two types of agents: the Tech Superpower Agent (TSA) and the Receiving Culture Agent (RCA). These agents represent a simplified abstraction of global dynamics in digital colonialism, where powerful entities (cultural, companies, or countries) disseminate technology and culturally distinct communities respond in varied ways. The model employs a two-agent architecture within a small-world network topology to capture both decision-making and collective social influence processes between the RCA, where the TSA acts as a broadcast actor.

3.1 Agent Architecture

Receiving Culture Agents (Communities/Regions/Companies)

Receiving agents represent heterogeneous communities, regions, and companies that are targets for technology diffusion and are influenced by TSA technology. Each agent is characterized and initialized by several attributes that capture digital colonialism factors:

Cultural Resilience (Range: 0.05-0.8): This parameter represents the resistance to culture change by technological distribution. The lower bound of 0.05 reflects a community without cultural identity and/or resistance to cultural identity or change. The upper bound of 0.8 reflects an unrealistic state of complete cultural impermeability in a globalized space. The range is calibrated based on heterogeneous stratification of culture and also realistic ranges to maintain computational stability.

Infrastructure Strength (Range: 2- 12): Represents communities/agents' capacity to implement and sustain digital technologies. The range represents the spectrum from basic developing structure

(2-4), moderate capacity (5-8), to advanced technological capacity (9-12), making outcomes based on infrastructural readiness.

Adoption Threshold (Range: 0.1-1.0): This threshold represents a random heterogeneous value to represent the minimum value needed for the community to consider adopting the technology. The lower bound, of not 0, ensures that adoption is always possible (preventing model stagnation), and the upper bound is maximum resistance, making adoption less likely.

Digital Access Score (Range: 0.2-1.0): This quantifies and simplifies the agent's position within the digital divide, where 0.2 reflects digital isolation and 1.0 is full tech infrastructure integration, implicitly, including digital literacy, access to technology before the model, and internet/bandwidth.

Boolean States:

- *Was Targeted:* Reflects if the TSA's deployment policy targets agents to trigger adoption decision rules
- *Adopted:* reflects if the agent decided to adopt the technology after targeted deployment
- *Banned*: reflects if the agent decided to ban the technology or not after adoption or neighbor observation
- *Collapse*: reflects if the agent's well-being due to adoption went below 65, making them an inactive agent node in the social network graph

3.1.1 Community Stratification - Receiving Culture Agents

The model implements a realistic economic stratification where 30% (0.3) represents "privilege community" or "digital natives" with high Infrastructure Strength (8-12) and Digital Access Score (0.7-1.0), while 70% (0.7) represent "average communities" or "digital adapters" with lower capabilities for Infrastructure Strength (2-8) and Digital Access Score (0.2-0.7) ensuring heterogeneous adoption dynamics.

Technological Superpower Agent

The Technological Superpower agent represents dominant technological entities such as nations, corporations/companions, or alliances attempting to diffuse their digital technologies. Parameters include:

Tech Dominances (Range: 1-5): Represents the suprepowers' technological influence capability and relative power projection capacity, where 1 is minimal influence and 5 is maximum technological hegemony. This parameter dynamically changes based on adoption and collapse feedback outcomes of the Receiving Culture Agents.

Deployment Policies:

- *All:* Universal deployment to all RCA
- *Random:* Targets 50% of available communities, splitting randomly between the high-access (Digital Access Score >= 0.6) agents and low-access (Digital Access Score < 0.4) agents
- *Filtered:* Selective targeting of only high-access agents (Digital Access Score >= .6)

3.2 Decision-Making Mechanisms

I. **Deployment Policy Choice by the TSA** *(detailed and referenced above)*

II. **Adoption Decisions Process by the RCA**

Each targeted receiving agent by the TSA deployment policy criteria follows a utility maximization framework with individual attributes, social network factors, and problem contextualization factors:

a. *Adoption Score = Perceived Utility + Peer Influence - (Cultural Resistance*0.5) + Bias Randomness*

The 0.5 multiplier on cultural resistance reflects that cultural factors influence but do not completely determine adoption decisions. Bias Randomness (range: -0.2 to +0.3) adds realistic unpredictability to the positive bias of the technology based on the TSA's influence through power and pressure.

b. <u>Utility Calculation:</u> *Perceived Utility = max(Infrastructure Strength/Implementation Cost) * Cultural Fit * Digital Access Score * Tech Dominance Boost*

The minimum utility floor of 0.3 prevents the complete adoption from being impossible. The tech dominance boot (1.1x to 1.5x multiplier) captures the TSA's influence on perceived benefits based on their Tech Dominance values. Also within this calculation is the Implementation Cost of the technology and Cultural Fit of the technology, which are exogenous values determined within the GUI.

c. <u>Peer Influence Mechanism</u>

Social influence is determined through the social network modeling Watts-Strogatz small-world network (k=4 neighbor connections, p=0.3 rewiring probability), chosen to balance local clustering and distance connections.

III. **Wellbeing Dynamics and Attribute Update**

a. <u>Wellbeing Evolution of RCA</u>

For adopter: *Wellbeing change = (Infrastructure Strength -5) * 4*

The baseline of 5 represents the turning point where technology goes from being a hindrance to being beneficial. The 4x multiplier amplifies the outcomes for visualization and captures technological dependence. Technological wear is actualized as a 0.4 deduction from Infrastructure Strength at each model step.

IV. **Banning Mechanisms and Collapse Condition**

The model implements two banning pathways:

a. <u>Post Adoption Banning:</u> Upon observing/monitoring their (RCAs) wellbeing over a 3-step window, they ban the technology if their average wellbeing falls below 65, the point where cost outweighs the benefits of adoption.

b. Network-Based Banning: Agents observe a neighbor suffering (wellbeing < 70) or collapse through the social network, and will preemptively ban technology to capture risk-averse behaviors.
    i. Collapse Condition: Wellbeing < 35 (survival threshold)

V. Dynamic Feedback Mechanisms

a. Tech Dominance Adjustment: reflects how tech superpower influence is based on long-term diffusion success, where failed technology pushes reduce future influence capacity.
    - Decreases when the failure rate (bans+collapse) exceeds 30%
    - Increases when the success rate (stable adoption) exceeds 40%
    - Gradual recovery toward the baseline of 3.0

3.3 Network Topology

The Watts-Strogatz small-world network (k=4, p=0.3) between the RCA, reflecting realistic social influence patterns where communities are primarily influenced by their immediate neighbors, who are usually their strongest cultural connections. The use of this network topology (top-down approach for diffusion) is inspired by John Goldenberg's Network Theory for how the structure of social networks affects innovation diffusion, which he concluded that the Watts-Strogatz graph captures realistic social networks for peer-to-peer influence. [6]

3.4 Model Validation

The models' temporal dynamics operate on abstract time steps representing periods that allow for adoption decisions, their effects on wellbeing to manifest, and effect immediate and long-term changes and analysis. Additionally, Technology is represented by attributes (Implementation Cost, Technological Wear, and Cultural Fit) rather than an agent itself to simplify the complex social dynamics of the three agents.

3.5 The GUI

The Graphical User Interface allows for analysis variance the Number of Receiving Agents (range: 10-200; default= 50), Implementation Cost of the technology (range:1.0-10 ** *arbitrary values not to reflect actual monetary values* **; default =5), Cultural Fit of the technology (range:0.1-1.0; default =.8), Tech Dominance (range: 1-5; default = 3), and the TSA's Deployment Policy (all, random, or filtered). The Watts-Strogatz small-world network is visualized with a legend of the Not Adopted (light blue), Adopted (green), Banned (red), and Collapsed (black) boolean states of the RCAs. Two dynamic graphs are shown to show the relationship between Technology Adoption Over Time Steps and the Average Community Wellbeing Over Time Steps.

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[6] Goldenberg, J., Libai, B., & Muller, E. (2001). *'Talk of the network: A complex systems look at the underlying process of word-of-mouth'. Marketing Letters*, *12*(3), 211-223. https://doi.org/10.1023/A:1011122126881

4. Parameter Sweeps

I. Dynamics Sensitivity Analysis: Technological Dominance Effects on Adoption Patterns

To examine the relationship between technological superpower influence in terms of their technological dominance and digital diffusion outcomes. I conducted a parameter sweep across all five labels of technological dominance (TD = 1-5) while maintaining all other parameters at default values and a random deployment policy. Each simulation was executed for 10 steps to look at short-term outcomes across identical initial conditions for comparability across dominance levels.

Methodology: I analysed two primary dimensions: 1) network state evolution showing spatial patterns of adoption, resistance, and collapse, and 2) temporal dynamics tracking adoption rates, ban rates, collapse rates, and community (average) wellbeing over time. Key metrics that were calculated and analyzed were adoption-ban line crossing points, convergence timing, average wellbeing final state, and TD final state.

Convergence Analysis: I measured when adoption and ban trajectories interested as an indicator of system tipping points. Average convergence across all dominance levels occurred at Step 4. This reveals nonlinear threshold effects in technological dominance :

Average Convergence = 3 steps(TD=1) + 7 steps(TD=2)+4 steps(TD=3)+6 steps(TD=4)+0(TD=5; Never Crossed)/5 = 4

A. Tech Dominance Level 1 (TD =1)

Figure 2.1 - Network State Analysis

Spatial Distribution: Large clustering of banned agents (red) with the single collapsed agent (black) towards the center of the red cluster. Adopted Agents (green) are pretty isolated, but each is attached to at least one or two banned agents (red), implying they are the turning point of state changes from adopted to banned upon more simulated steps based on the neighbor influence of the model.

Network Effects:

- 8/50 (16%) Adoption Success Rate at End State
- 1/50 (2%) Collapse Rate at End State
- 25/50 (50%) Ban Rate at End State
- Final Tech Dominance State: 1.0 (+- 0 Difference from Initial Tech Dominance State)

Figure 2.2 - Temporal Dynamic Analysis

Crossing Point Analysis: Crossing event of ban and adoption trajectories occurred at a point approximately at steps 5 and 15 in agents in both groups.

Wellbeing Impact: Observed a 22.5 unit decrease from the initial 100 value to 77.5 by the final state

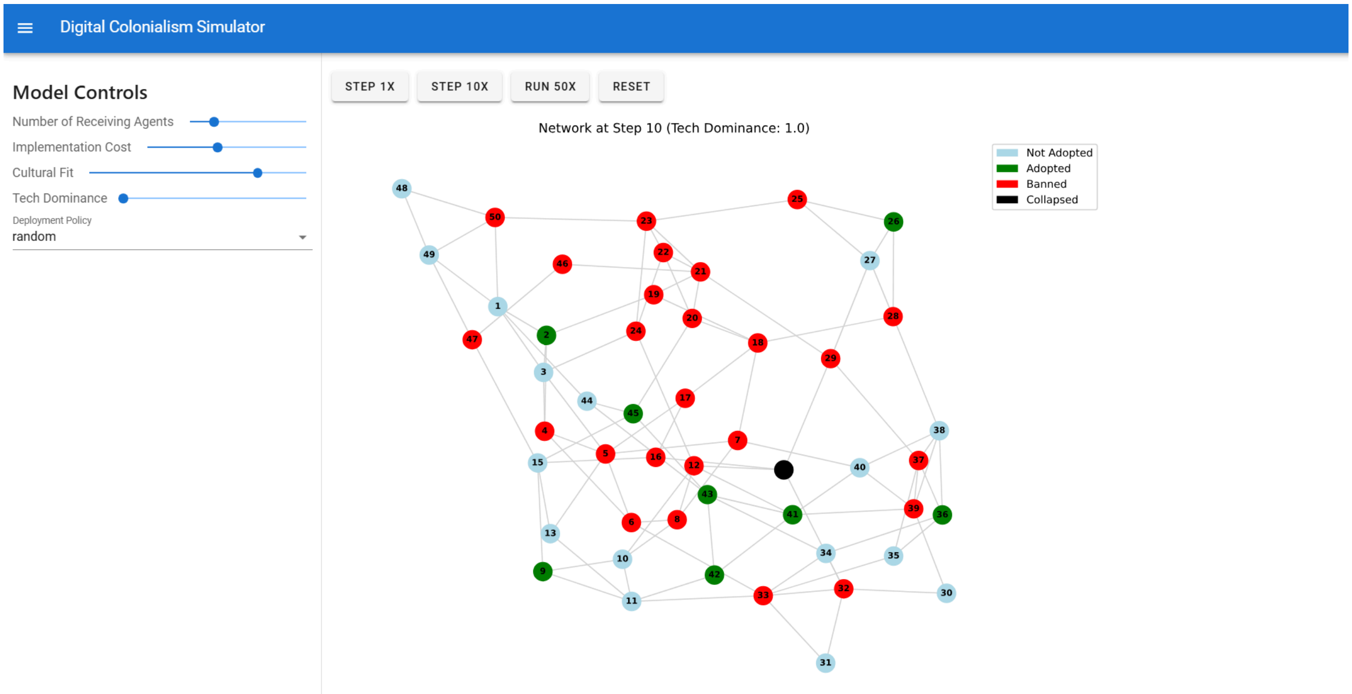


Figure 2.1: Agent Network State After 10 Simulation Steps (Tech Dominance = 1, Default Parameters)

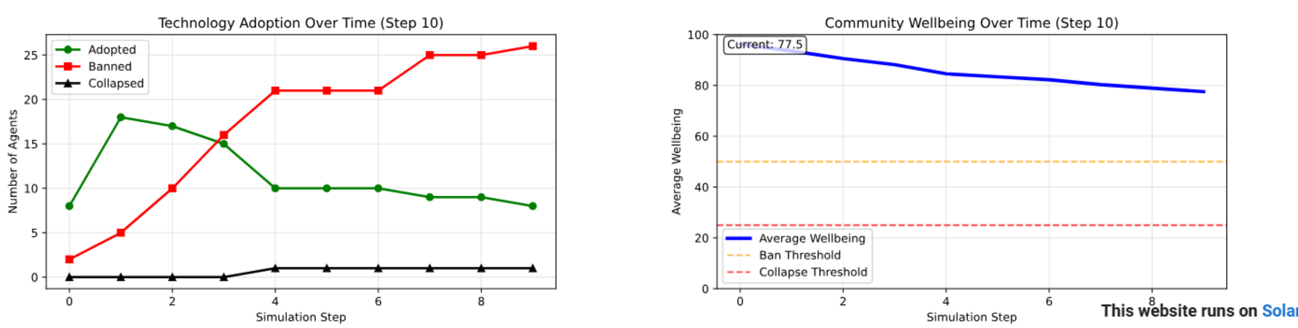


Figure 2.2: Time Series Analysis of Technology Adoption and Community Wellbeing Over 10 Steps (Tech Dominance = 1, Default Parameters)

B. Tech Dominance Level 2 (TD =2)

Figure 3.1 - Network State Analysis

Spatial Distribution: Small clustering of banned agents (red) with the single collapsed agent (black) positionally centered in a red cluster. Adopted Agents (green) are pretty sporadic throughout the red clusters (with attached banned=red neighbors), however, there is an isolated cluster without any direct connection to red neighbor agents, suggesting these are agents that will sustain adoption for a longer period, thus having a longer resistance to banning.

Network Effects:

- 13/50 (26%) Adoption Success Rate at End State
- 1/50 (2%) Collapse Rate at End State
- 23/50 (46%) Ban Rate at End State
- Final Tech Dominance State: 2.6 (+ .6 Difference from Initial Tech Dominance State)

Figure 3.2 - Temporal Dynamic Analysis

Crossing Point Analysis: Crossing event of ban and adoption trajectories occurred at a point approximately at steps 7 and 17 in agents in both groups.

Wellbeing Impact: Observed a 22.5 unit decrease from the initial 100 value to 77.5 by the final state

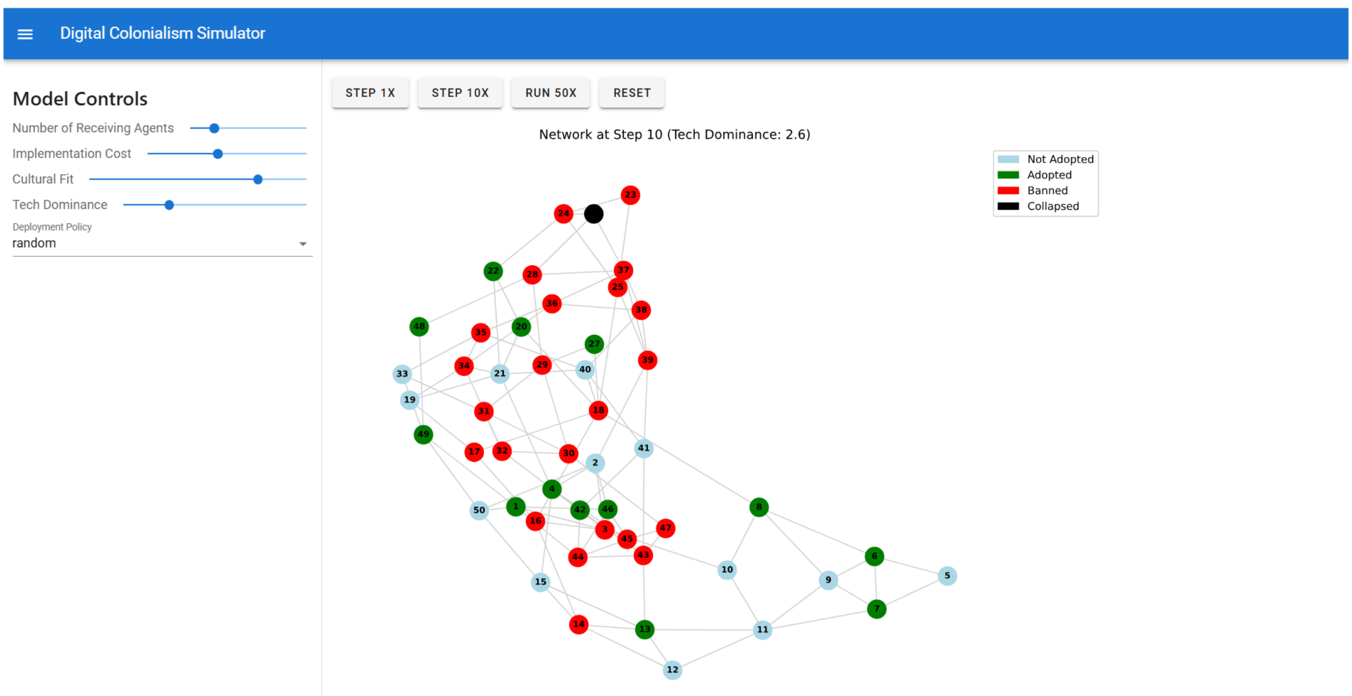


Figure 3.1: Agent Network State After 10 Simulation Steps (Tech Dominance = 2, Default Parameters)

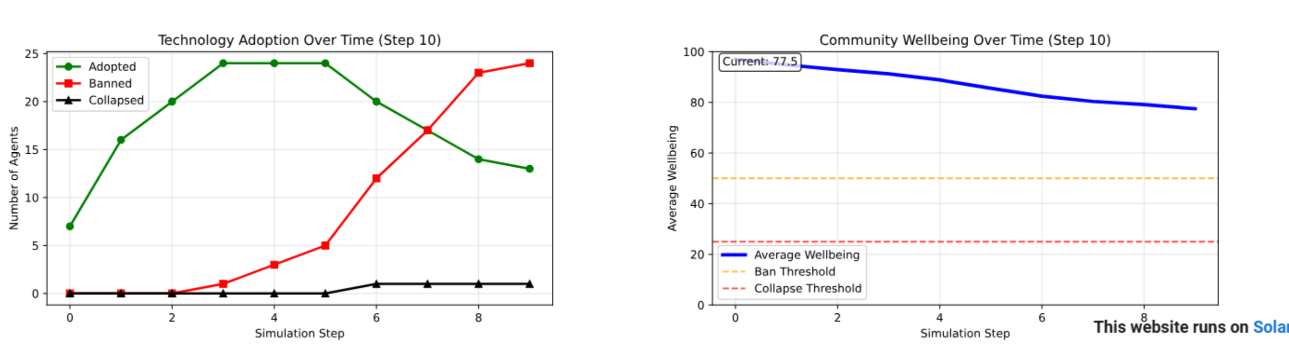


Figure 3.2: Time Series Analysis of Technology Adoption and Community Wellbeing Over 10 Steps (Tech Dominance = 2, Default Parameters)

C. **Tech Dominance Level 3 (TD =3)**

Figure 4.1 - Network State Analysis

Spatial Distribution: Large clustering of banned agents (red) with no collapsed agents (black). Adopted Agents (green) are pretty isolated, with no significant ingroup clustering.

Network Effects:

- 7/50 (14%) Adoption Success Rate at End State
- 0/50 (0%) Collapse Rate at End State
- 25/50 (50%) Ban Rate at End State
- Final Tech Dominance State: 3.1 (+ .1 Difference from Initial Tech Dominance State)

Figure 5.2 - Temporal Dynamic Analysis

Crossing Point Analysis: Crossing event of ban and adoption trajectories occurred at a point approximately at steps 4 and 15 in agents in both groups.

Wellbeing Impact: Observed a 24.3 unit decrease from the initial 100 value to 75.7 by the final state

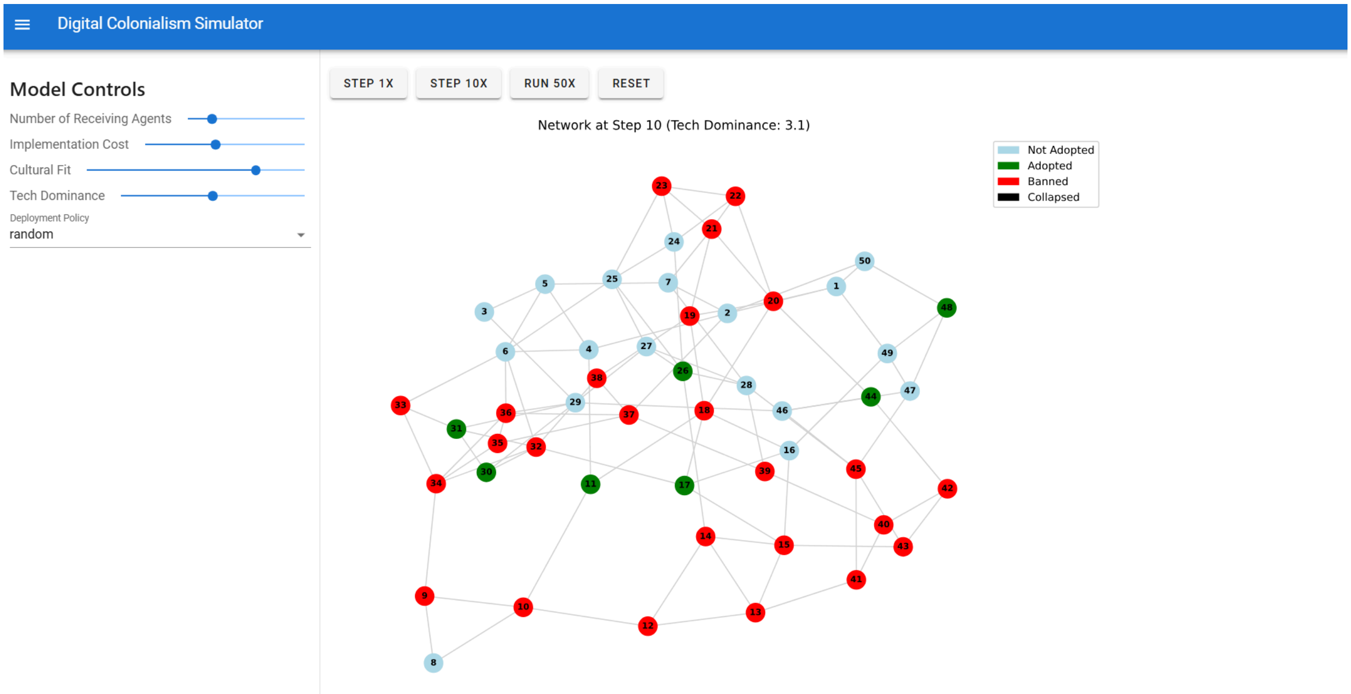


Figure 4.1: Agent Network State After 10 Simulation Steps (Tech Dominance = 3, Default Parameters)

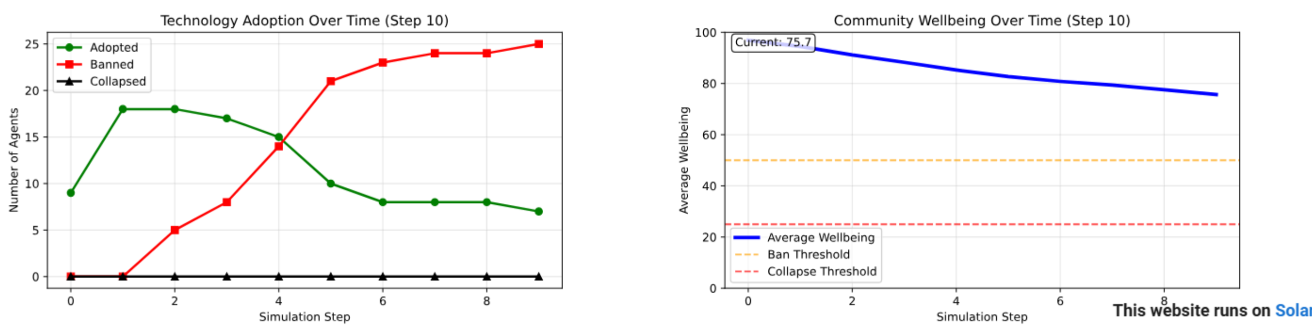


Figure 4.2: Time Series Analysis of Technology Adoption and Community Wellbeing Over 10 Steps (Tech Dominance = 3, Default Parameters)

D. Tech Dominance Level 3 (TD =3)

Figure 5.1 - Network State Analysis

Spatial Distribution: Large clustering of banned agents (red) with the single collapsed agent (black) towards the center of the red cluster. Adopted Agents (green) are pretty isolated, but with small clustering.

Network Effects:

- 13/50 (26%) Adoption Success Rate at End State
- 1/50 (2%) Collapse Rate at End State

- 25/50 (50%) Ban Rate at End State (consistent with the first run at TD = 3, the default state of TD)
- Final Tech Dominance State: 3.0 (+2 Difference from Initial Tech Dominance State)

Figure 5.2 - Temporal Dynamic Analysis

Crossing Point Analysis: Crossing event of ban and adoption trajectories occurred at a point approximately at steps 4 and 17 in agents in both groups. Each trajectory saw a plateau in adoption and banning after crossing the event, but reached a polarizing inflection point at step 8.

Wellbeing Impact: Observed a 23.4 unit decrease from the initial 100 value to 76.6 by the final state

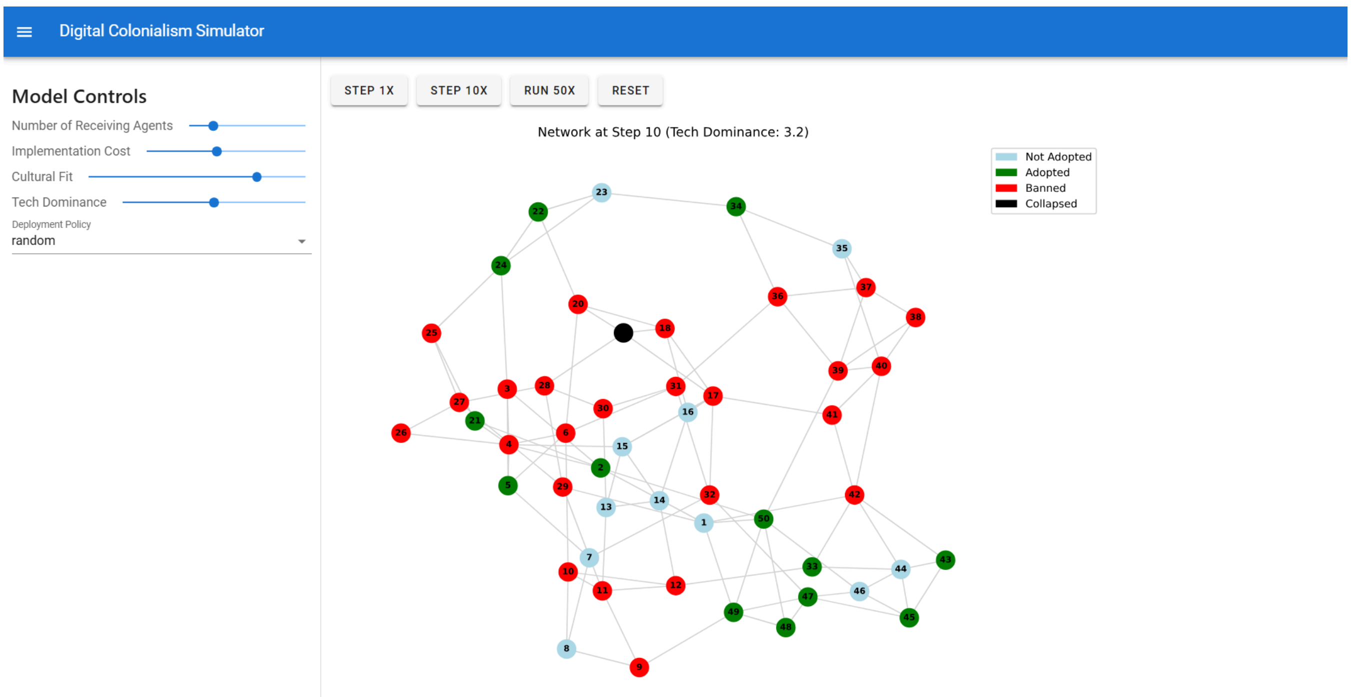


Figure 5.1: Agent Network State After 10 Simulation Steps (Tech Dominance = 3, Default Parameters)

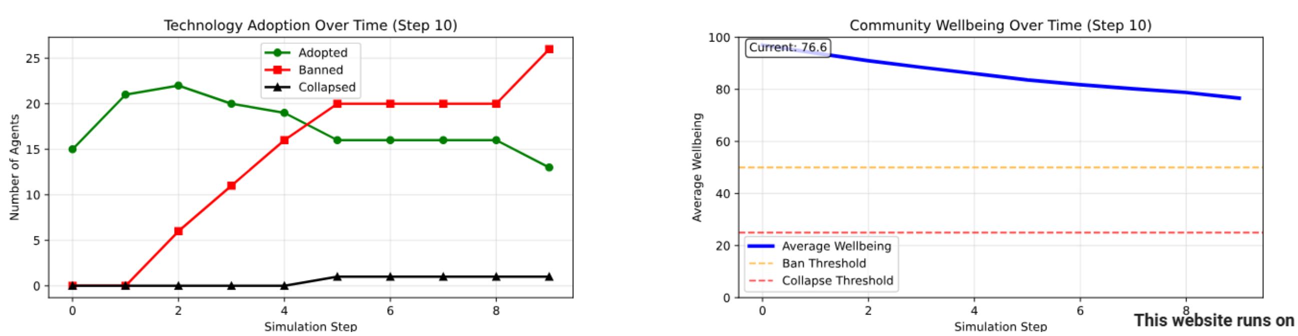


Figure 5.2: Time Series Analysis of Technology Adoption and Community Wellbeing Over 10 Steps (Tech Dominance = 3, Default Parameters)

E. Tech Dominance Level 4 (TD =4)

Figure 6.1 - Network State Analysis

Spatial Distribution: No significant large clustering of banned agents (red) or adopted agents (green), and also no collapsed agent (black). Several adopted agents (green) are isolated with no direct ban agents as neighbors (red).

Network Effects:

- 12/50 (24%) Adoption Success Rate at End State
- 0/50 (0%) Collapse Rate at End State
- 18/50 (36%) Ban Rate at End State
- Final Tech Dominance State: 4.0 (+6 Difference from Initial Tech Dominance State)

Figure 6.2 - Temporal Dynamic Analysis

Crossing Point Analysis: Crossing event of ban and adoption trajectories occurred at a point approximately at steps 6 and 15 in agents in both groups. Each trajectory saw a plateau in adoption and banning after crossing the event.

Wellbeing Impact: Observed a 22.8 unit decrease from the initial 100 value to 77.2 by the final state

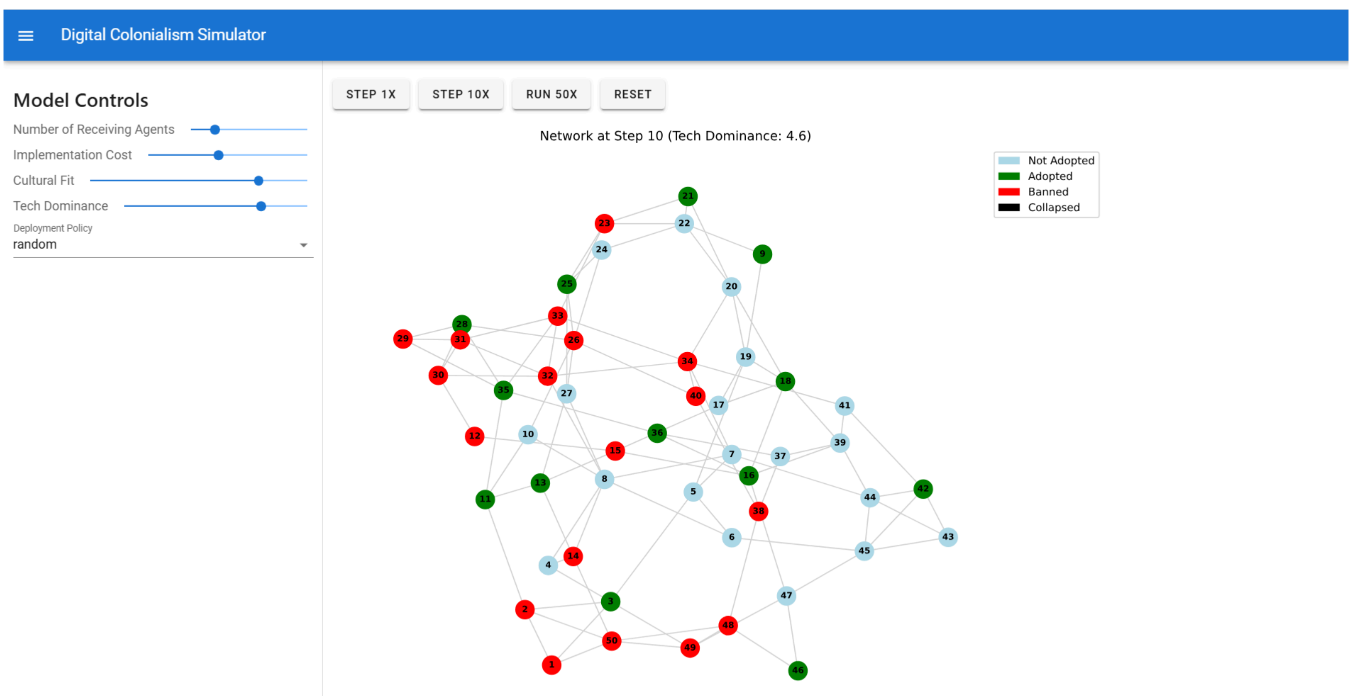


Figure 6.1: Agent Network State After 10 Simulation Steps (Tech Dominance = 4, Default Parameters)

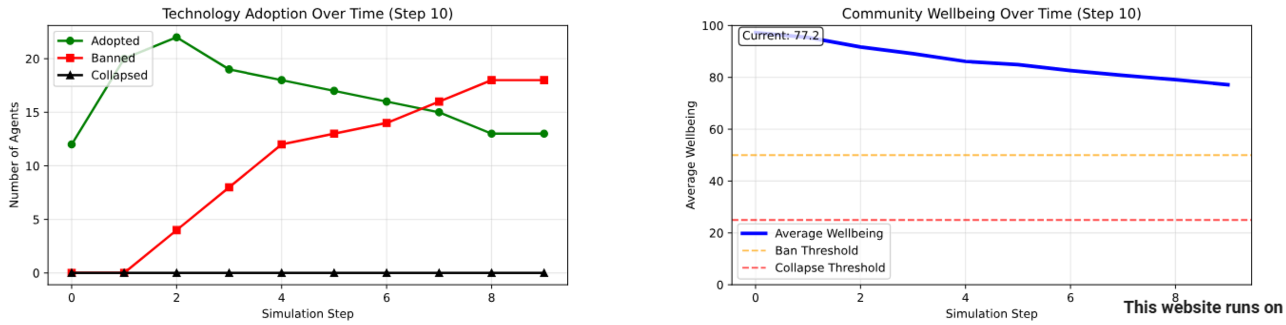


Figure 6.2: Time Series Analysis of Technology Adoption and Community Wellbeing Over 10 Steps (Tech Dominance = 4, Default Parameters)

F. Tech Dominance Level 5 (TD =5)

Figure 7.1 - Network State Analysis

Spatial Distribution: Small clustering of banned agents (red) and adopted agents (green) by like group, with more significant clustering by adopted agents. There is no collapsed agent (black) in the final state, and agent nodes are more closely connected, not as isolated as in other batch runs, implying a fast increase in ban and collapse rates in future runs.

Network Effects:

- 19/50 (38%) Adoption Success Rate at End State
- 0/50 (2%) Collapse Rate at End State
- 16/50 (32%) Ban Rate at End State
- Final Tech Dominance State: 5.0 (+- 0 Difference from Initial Tech Dominance State)

Figure 7.2 - Temporal Dynamic Analysis

Crossing Point Analysis: The Crossing event of ban and adoption trajectories never occurs with the 10 steps. There wasn't an uptake in the ban unit step 3, where adoption rates reached 25 agents (50% of total agents).

Wellbeing Impact: Observed a 21.7 unit decrease from the initial 100 value to 78.3 by the final state

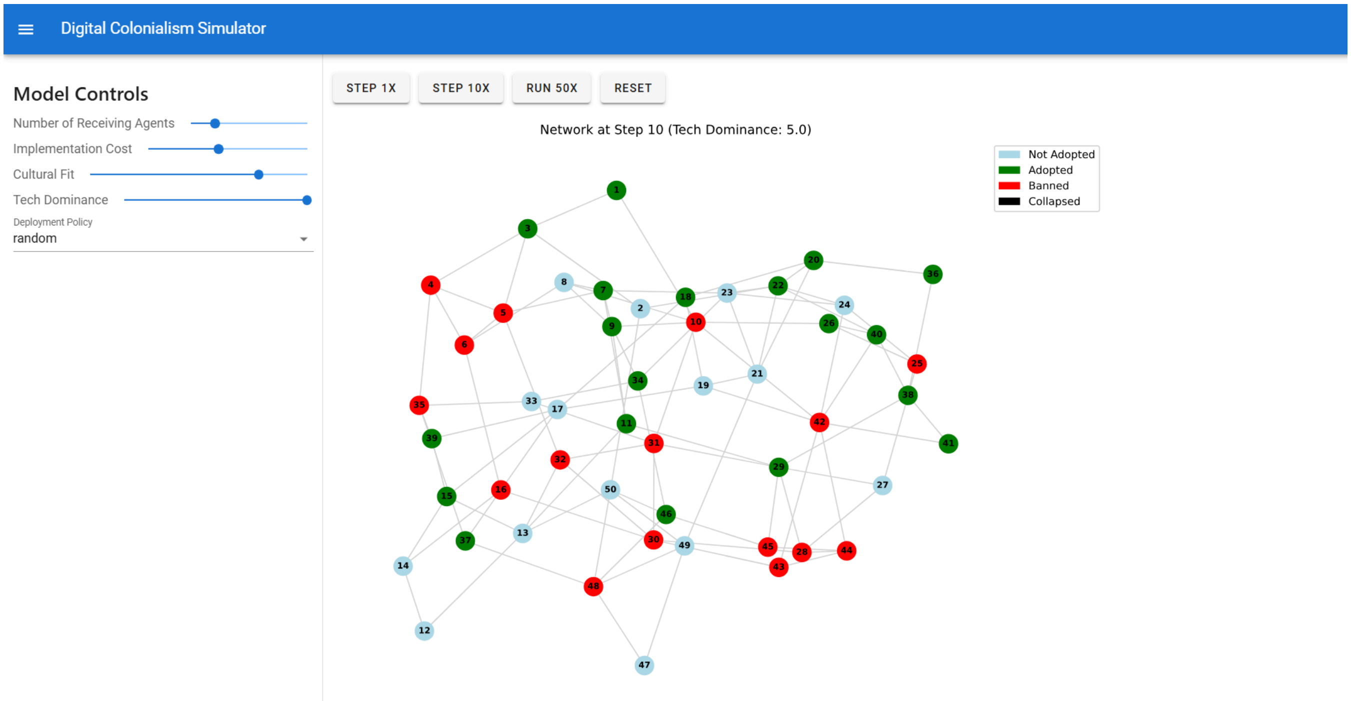


Figure 7.1: Agent Network State After 10 Simulation Steps (Tech Dominance = 5, Default Parameters)

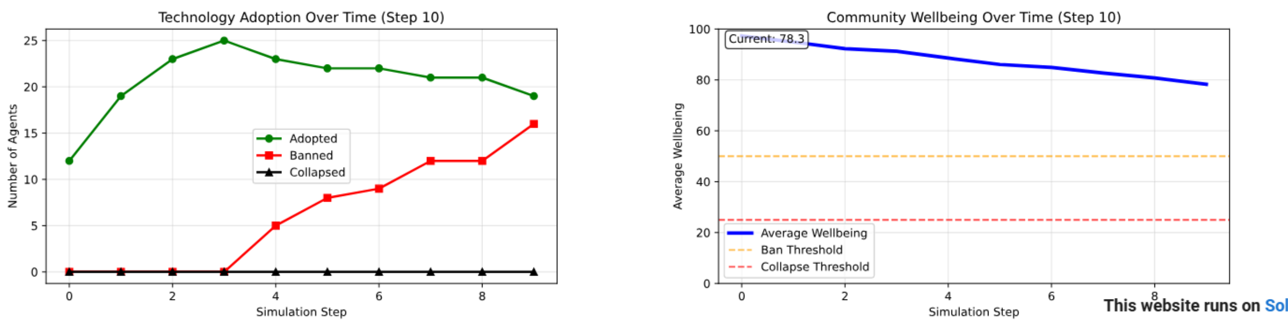


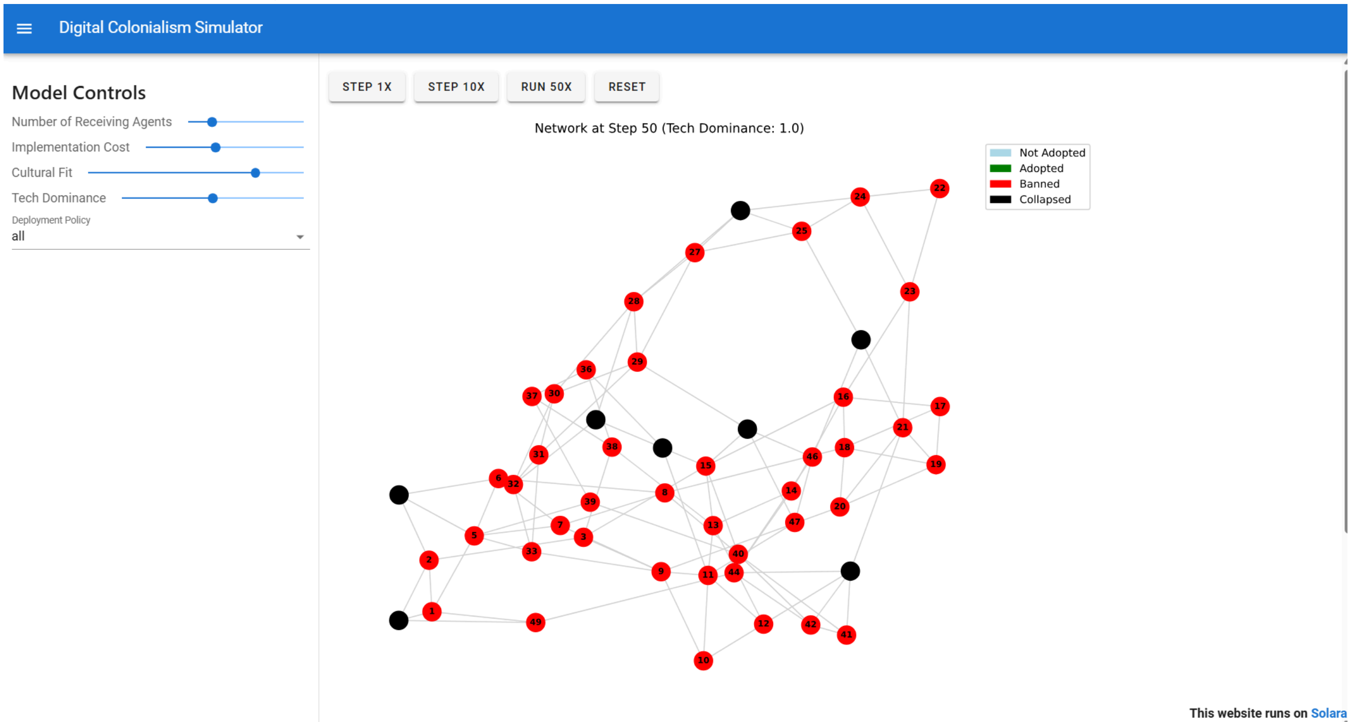
Figure 7.2: Time Series Analysis of Technology Adoption and Community Wellbeing Over 10 Steps (Tech Dominance = 5, Default Parameters)

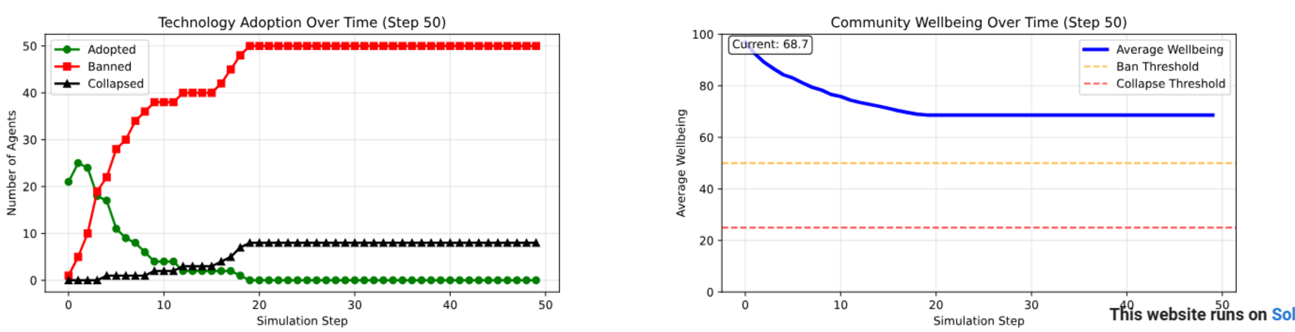
5. Appendix

Additional Batch Runs

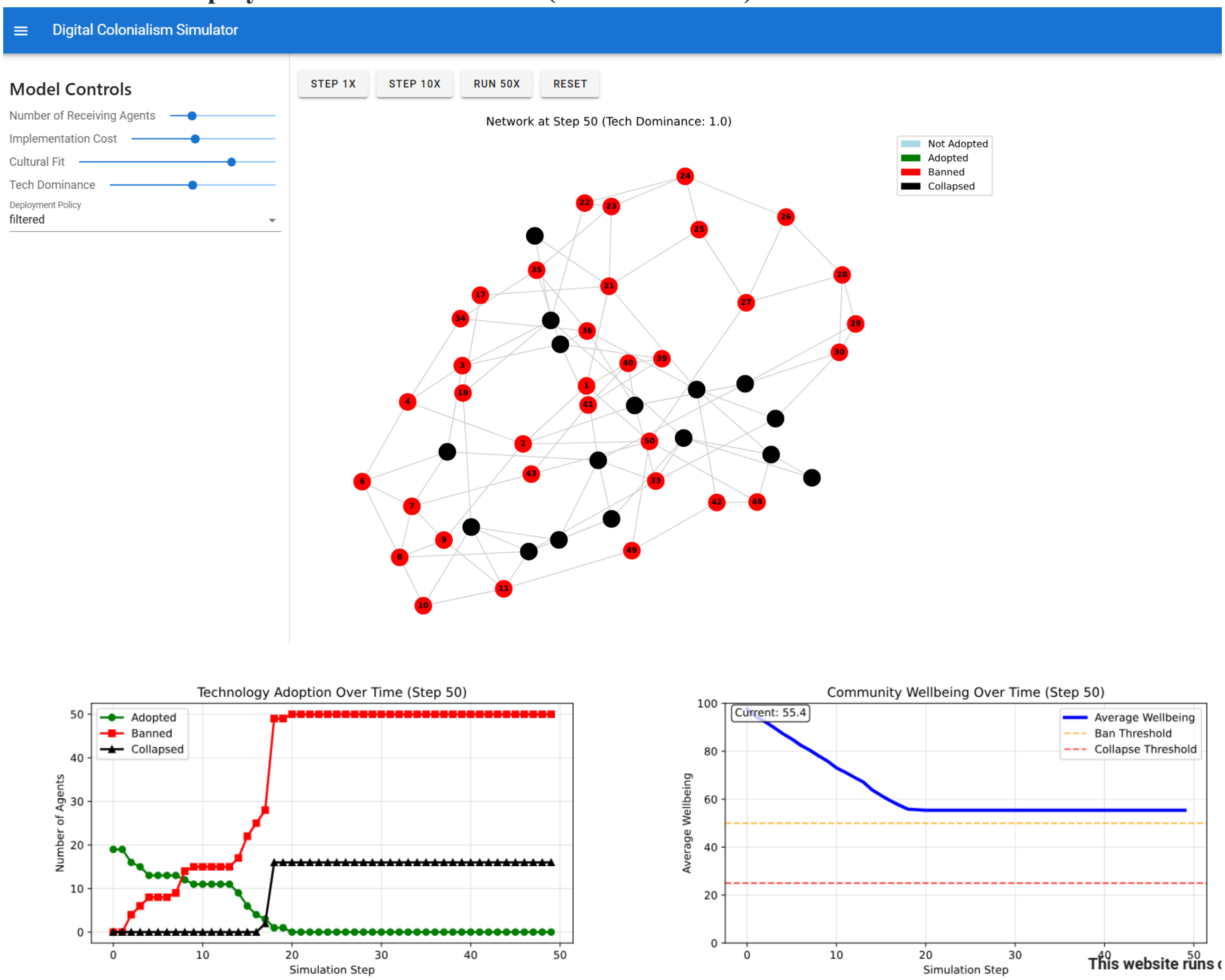
II. Comparative Analysis of Deployment Policy Strategies Over Extended Simulation

A. Deployment Police "All" (DP = "all")

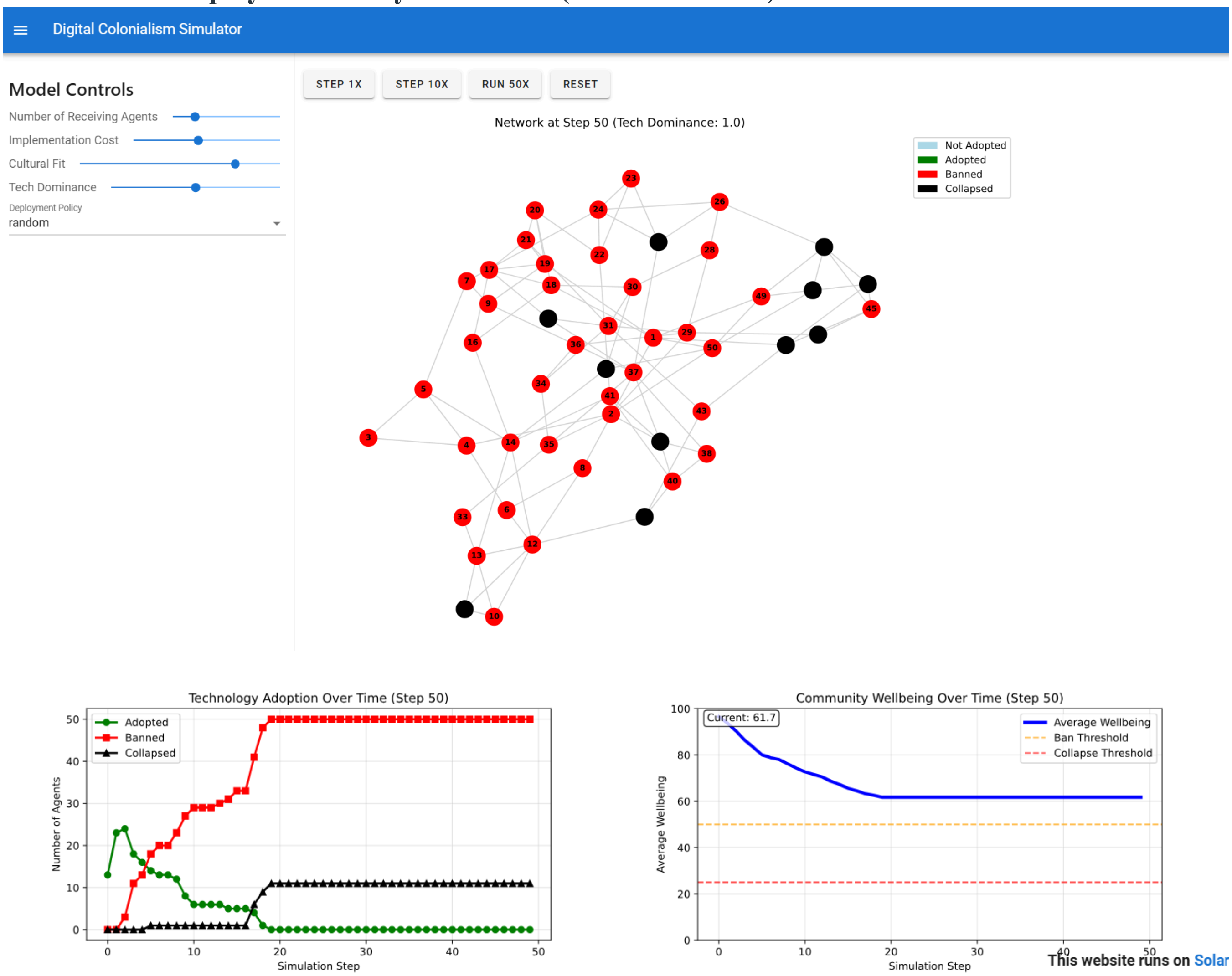




B. Deployment Police “Filtered” (DP = “filtered”)



C. Deployment Policy "Random" (DP = "random")



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