Dance of the Distrustful Flock: Simulating the Interplay of Trust and Heuristics in Ensembles of Collective Intelligence & Adaptation

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Abstract

In this paper, we present and discuss a NetLogo simulation that explores how socially-contrived factors of trust and heuristics (avoidance, immunity, seeking) drive collective adaptation and intelligence in agent ensembles analogized to infection spread. By varying trust levels, resource density, and behavior-decay parameters, we uncover threshold phenomena—collapse at extreme distrust, oscillatory resilience at low trust, rapid stabilization near mid-range trust, and resource-driven rebounds under full trust. Technical validation is included via key code excerpts, and results are illustrated with representative plots of infection and behavior dynamics.

1 Introduction

Collective adaptation can be defined as the process by which groups change their behavior, structure, or strategies in response to changing internal and external conditions [1]. Unlike individual adaptation, which focuses on personal learning or evolution, collective adaptation involves the coordination and integration of individual actions, often leading to emergent group-level behavior. This process is especially relevant in complex systems where the group as a whole exhibits coherent and adaptive responses, despite being comprised of self-interested individuals.

To understand these group-level dynamics requires moving beyond traditional notions of collective intelligence to consider how groups adapt over time through feedback, learning, and evolving decision-making structures. Modeling collective adaptation offers an exclusive opportunity to understand how groups respond to their environments. By simulating these processes, models can help uncover the conditions under which collective adaptation succeeds or fails, contributing to our understanding of observed real-world phenomena. With that in mind, our model aims to explore how trust thresholds and heuristic strategies can affect the spread of infection and the emergence of resilient collective behaviors under resource constraints.

2 Literature Review & Research Questions

Initially motivated by Galesic *et al.*'s (2023) conceptual framework, we sought to create a model in Netlogo which leverages the analogical approach for studying "belief dynamics" (2023, p.12) through an epidemiology lens. This approach is in accordance with the view that modeling collective adaptation can at times require multiple frameworks to interpret "an interaction of cognition, social environments and problem structure" [1]. Thus, what follows in the rest of this section constitutes an overview of how our study framework was methodologically informed along with key design considerations for our model.

2.1 Methodology & Design Considerations

Bucchiarone *et al.*(2015) introduce the notion of 'ensembles' as dynamic groups of heterogeneous and autonomous agents collaborating to achieve collective adaptive outcomes [3]. Ensembles differ notably from traditional collective adaptive systems —such as swarms or multi-agent systems—by preserving high autonomy and heterogeneity among participating entities. [3]

The ensemble approach aligns closely with our model, which also relies heavily on autonomous agent behaviors and adaptive heuristics. Particularly, our model's use of adaptive behaviors —including infection avoidance, information seeking, and trust-based decision making —parallels the 'issue resolution procedure' described by Bucchiarone et al., where ensemble members resolve collective challenges through such factors as negotiation and consensus-based multi-criteria decision making. [3]

Additionally, this model plays on the notion of an "adaptive toolbox" [2]. and its relevant components. Considering that the "content of the adaptive toolbox depends not only on the species, but also on the individual and its particular stage of ontogenetic development and the culture in which it lives" [2], we intended to test the thresholds of default heuristics —where agents have contextually limited capacity for rational decision making —in order to observe whether emergent system effects —such as fully optimized herd immunity state —are behaviorally (or conditionally) anticipative (or predictive).

Independent of our results and analysis, what is reinforced through this project is the necessity for "meta-level strategies" [1] to be mechanistically accounted for in order to observe interplay between integrative contextual parameters and macro-level environment structure while faced with a particular challenge —in this case, sustaining immunity and working towards measurable herd immunity state over a given timeframe.

2.2 Research Questions

We generated several research questions:

1. Under what circumstances does majority rule hold —that is, the notion that a collective majority of agents will perform better than individual agents in selecting an ideal solution to a task, with increased accuracy as group size increases [1]?

2. Additionally, under what conditions do counterintuitive observations emerge (i.e. individuals perform better than the collective majority)?

3. Given initial considerations and potential divergence in agentic states —namely, capacities for trust, sustenance-seeking, and active social avoidance —are there observable thresholds where rationality gives way to a social heuristic? This coincides with Todd and Gigerenzer's (2012) consideration of contextual circumstances where both rationality and heuristics are observable but due to certain factors has shifted the influential weight of one approach over the other (such as in their provided anecdote of the "weight-and-add" rational method versus the "trust your doctor" heuristic) [2].

4. Alternatively, and given the considerations outlined in B, are there observable thresholds within this exploratory setting where ecological rationality synchronously holds across more

than one heuristic (e.g. avoidance vs seeking) thus demonstrating equivalent performance [2]?

It is also necessary here to briefly mention that we frame reasoning through modes of induction, deduction, and abduction, reflecting prior research and study that a) acknowledges causal reasoning as a fundamental feature of evolved epidemiological modeling [8]. Abductive reasoning also has been considered to hold pertinence towards studying informal and incidental learning to evolve our notions of complexity and its relevance to strategic crisis response [9].

3 Model Description

To explore some of the fundamental dynamics of collective intelligence and adaptation, the team decided on a simulation that demonstrates the spread of infection through a population and how sharing information on how to protect individuals and groups could depend on "trust". The idea of trust came about through the reading of Galesic et al.'s article on collective intelligence, where they discuss social integration strategies and how social trust could be a factor in how responses to problems can unfold [1]. Understanding that trust is a qualitative value for the simulation, which was made quantitative in the sense of being on a 0 to 100 scale, zero being there is no trust among group members and 100 being an absolute amount of trust with individuals within the group. The simulation was built into three parts: the construction of the agent behaviors, the environment, and aspects of the simulation to monitor and change.

4 Methods

4.1 Agent Behavior

Variables	**Values**
Energy	Max 20
Max Life	50 clicks
Immunity	Boolean
Avoidant	Boolean
Infected	Boolean
Immunity-time	Max 25 clicks
Avoidant-time	Max 25 clicks
Seek Sustenance	Boolean

Table 1: Agent Behaviors

The first aspect of agent behavior to control for, as previously stated, is the group-trust level, which quantifies the quality of how individuals in a collective are willing to trust the information provided by members of the group. Within the simulation, it was set so that when agents are close to others, they can share "beneficial" behaviors with others, with the success of being based on the "trust level" of the group. Avoidance and immunity were the "beneficial" behaviors that could lead to collective intelligence and adaptation. Avoidant is the behavior of noticing agents with an infection and actively choosing to move in a different direction to prevent infection. The immunity behavior could be treated as an individual choosing to get vaccinated against the simulated infection. While the agent will not decide to avoid infected agents, the immune agents are far less susceptible to being infected in comparison to agents without the behavior. The other ”beneficial” behavior that is offered to all agents agnostic of their infection/immunity/avoidant status is ”Seek,” which is to seek sustenance if live energy reaches a certain level. This action allows all agents to attempt self-preservation by changing their primary goal to go towards sustaining themselves. As the goal of the simulation is to see how a collective adapts to infection, the agents all start out susceptible to infection and spread the disease across the entire group if ”beneficial” behaviors are not adopted. When an infected agent is in proximity to a susceptible agent, there is a current fifty percent chance of infection occurring, which would last for at least 10 clicks but could be reinforced by proximity to other infectious agents. This is to simulate the idea that if ”beneficial” behaviors are not taken on, reinfection would be likely to reoccur.

Listing 1: Agent Behaviors

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Each \texttt{person} agent maintains Boolean states \texttt{infected}, \texttt{immunity}, \texttt{avoidant}, and an integer \texttt{group-trust} (0--100). On each tick, agents execute:
\begin{lstlisting}[language=NetLogo, caption={Core movement and interaction logic}, label={lst:move}]
to move-people
  ask people [
    ;; Turn away if avoidant
    if avoidant and any? people in-radius 2 with [infected] [ ... ]
    ;; Seek energy if low
    if seek_item and energy < 5 [ ... ]
    ;; Energy decay and infection timer
    if infected [ set energy energy - 0.1 ]
    ;; Behavior decay
    if immunity [ set immunity-time immunity-time - 0.1 ]
    if avoidant [ set avoidant-time avoidant-time - 0.1 ]
    ;; Communication & behavior spreading
    if any? people in-radius 2 [
      if any? people-here with [immunity]
        and random 100 < group-trust [ set immunity true ]
      if any? people in-radius 1 with [avoidant]
        and random 100 < group-trust [ set avoidant true ]
    ]
  ]
end
```

4.2 Environment

The environment was developed to simulate the dynamics of how an environment could function in the real world, but with limits so as not to overcomplicate analysis. The main goal was to have an environment with a certain level of change to challenge the agents to survive as individuals and as a collective. The first aspect of the environment would be randomly generating sustenance sources – coded in our model as “energy” and ”trees”, respectively - or items of sustenance for the agents to survive off of to maintain life or energy. These ”trees” at the start of the simulation will be placed in random locations within the environment. If they die due to overconsumption, they will generate again in a new location after a certain amount of time. This challenges the agents to locate sustenance and adjust when that avenue has changed.

The environmental factors that the collective must adapt to are the following:

If any agents are susceptible to infection and no agent has been infected for at least 20 clicks, a new agent will be chosen as a carrier. While this “20 clicks” threshold was chosen arbitrarily, it was intended to constitute an environmental aspect which allows for a constant challenge for the collective if their collective behavior hasn't fully adopted infection prevention methods. To adapt to the challenge of impending infection, there are also "solutions" given to the collective to mitigate infection: avoidance and immunity (vaccinations). If either of these behaviors is non-existent among agents, there is an assumption that the collective would develop them again at some point. Thus, they will attempt to start sharing those behaviors again to protect themselves and the collective. The listing of changing environment rules can be seen here:

Variables	**Values**
Trees	Number 0 to 20
Time until infection	20 clicks
Time until avoidant behavior	20 clicks
Time until vaccination (immunity behavior)	20 clicks

Table 2: Environment Variables

4.2.1 Monitoring and Adjustable Parameters

Aspects of the simulation were tracked to ensure it was running correctly and for analysis purposes. Table 3 lists the variables being monitored.

Monitored Values	**Values**
Behavior vs. Infection Plot	4 Line Plot
Count of Agents	Max 30
Mean Energy level of Agents	Max 20
Count of Agents with Infection	Max 30
Count of Agents with Immunity	Max 30
Count of Agents with Avoidant	Max 30
Count of Trees	Max 20
Mean Energy level of Trees	Max 30

Table 3: Monitored Values

To understand how slight changes to simulation could have an overall impact on the success or failure of the collective, adjustable variables were added. Table 4 lists the variables allowed to be adjusted for analysis purposes.

Adjustable Variables	**Values**
Trust-level	0 to 100
Seek	Boolean
Tree Amount	0 to 100

Table 4: Adjustable Variables

The goal of building this simulation was to give a limited view of a collective with certain adjustable variables that are trackable to determine fundamental factors in how slight changes in trust, sustenance, and self-preservation can impact collective adaptation.

5 Results

We conducted 1,000 tick runs across five trust levels (0, 15, 50, 60, 100), varied tree densities (10, 15, 20), and toggled seek behavior (on/off). Below are the most pertinent findings, each illustrated with a representative screenshot (refer to section 5.1).

Low Trust Collapse (trust=0, trees=20, seek=off) Without any behavior sharing, infection spread unimpeded, peaking sharply around tick500 and leaving only 1–3 survivors by tick1,000. The collective exhibited no recovery once contagion took hold.

Intermediate Resilience (trust=15, trees=15, seek=on) Under moderate trust and plentiful sustenance, we observed oscillatory waves of infection and immunity. Infection peaks were repeatedly checked by emergent clusters of immune agents, indicating dynamic resilience through feedback between heuristics and contagion.

Threshold Induced Stabilization (trust=50, trees=20, seek=off) At a 50 percent acceptance rate, populations shifted to predominantly immune or avoidant states by tick600, with only sporadic flare ups thereafter. Trend lines suggest full herd immunity would be reached given more ticks.

High Trust Herd Immunity & Resources (trust=100, trees=20, seek=off) Maximally trusting agents rapidly disseminated beneficial behaviors, achieving near-total immunity by tick700. However, resource overconsumption (trees) led to transient infection rebounds of 10 agents before final stabilization, potentially implying some interplay between resource availability and collective adaptation.

Behavioral Decay Vulnerability (trust=60, trees=10, seek=on) In mid high trust runs, windows of avoidant behavior decay (when the slider threshold fell below agents' decay timers) created brief vulnerability spikes. Short lived infection surges followed by rapid recoveries might reiterate the necessity of sustained heuristic reinforcement —alongside trust —for stable adaptation.

5.1 Artifacts

These results demonstrate that trust thresholds critically determine both the timing and magnitude of collective adaptation. Extreme distrust yields collapse, intermediate trust fosters resilience through oscillations, and full trust secures rapid herd immunity (albeit with resource-driven caveats).

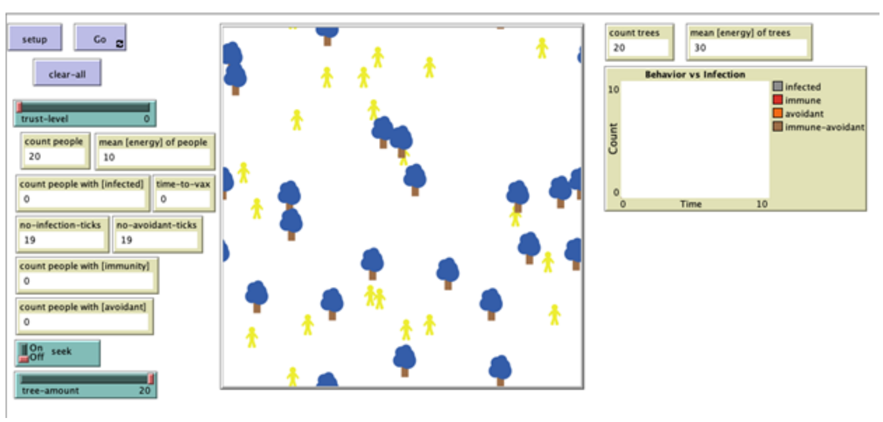

Figure 1: Low-Trust Collapse (trust=0, trees=20, seek=off). Infection peaks around tick 500; only 1–3 survivors remain by tick 1000.

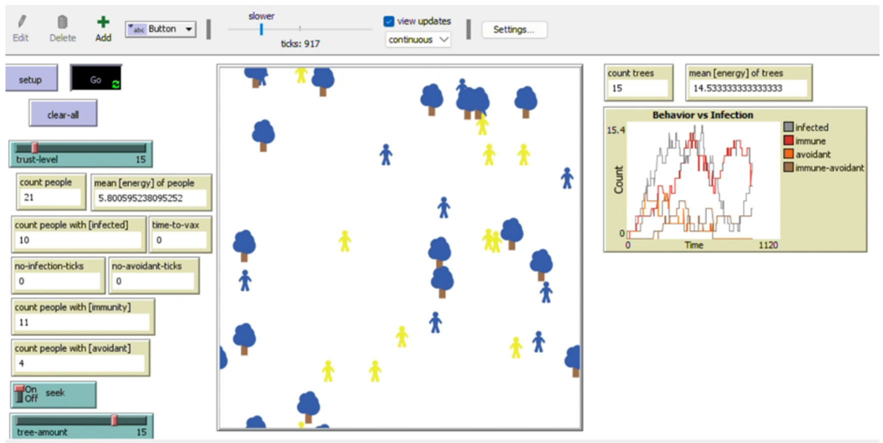

Figure 2: Intermediate Resilience (trust=15, trees=15, seek=on). Oscillatory waves of infection and immunity demonstrate dynamic feedback resilience.

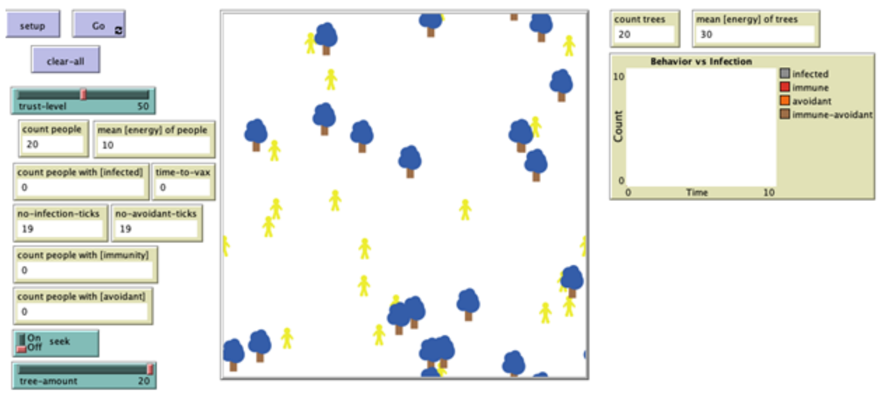

Figure 3: Threshold-Induced Stabilization (trust=50, trees=20, seek=off). Populations settle into immune/avoidant majority by tick 600.

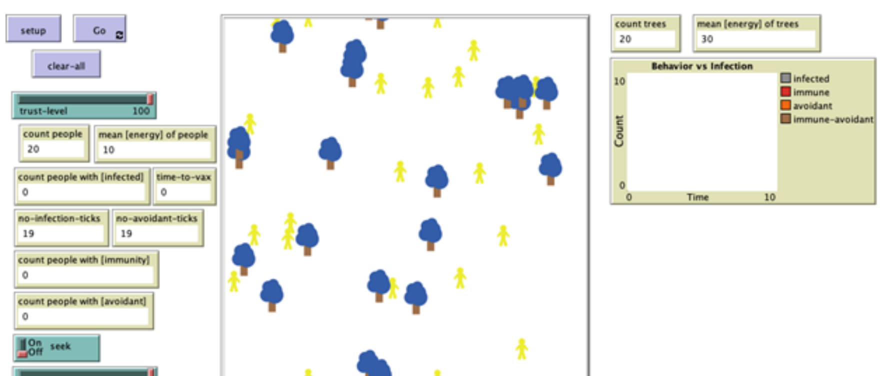

Figure 4: High-Trust Herd Immunity with Resource Oscillations (trust=100, trees=20). Rapid immunity followed by transient rebounds due to resource depletion.

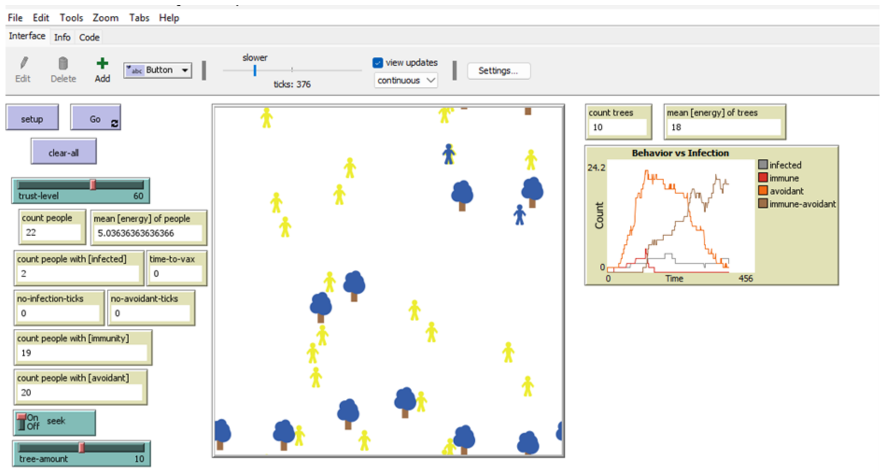

Figure 5: Behavioral-Decay Vulnerability (trust=60, trees=10, seek=on). Decay windows induce brief infection spikes, highlighting the need for heuristic reinforcement.

6 Discussion and Conclusion

Although our model allowed us to glean results that are in accordance with our intended focus, we concede some limitations of our study which could be helpful in evolving what has been detailed in this paper. One limitation of our model is that agent interactions are significantly simplified, potentially omitting critical complexities observed in real-world collective behaviors, which future studies might address by incorporating more nuanced interaction protocols.

Using a multi-framework approach [1] for informing our study methodology, we attempted to design and program a discrete model that limited the decisions of agents while still building in some potential for emergent system evolution to occur. In this case, our intention was focused on observing how randomized agent interactions —amongst other agents as well as sustenance sources —may not simply motivate individualized rationalizations but potentially catalyze heuristic shifts among agents as well, thus creating the opportunity for collective adaptation to impose a macro-level systemic change. From our model, we assumed some causal constraints while attempting to preserve some epidemiological characteristics. We designed inherent agent features to drive behavioral modifications while also incorporating a discrete set of outputs accessed by those modifications, yet the framework is essentially built on some obvious tropes of an environment faced with an impending infection spread —achieve immunization, maximize proximal distance, and/or seek additional sustenance.

On the topic of sustenance seeking behavior, it is apparent that one future avenue of study might be to direct more attention to how perceivable changes in the availability and access of sustenance sources —be it informational resources, objects of nourishment, medicinal supplies, or some other component that are incorporated by the system. Considering the analogical nature of our model, we designed our sustenance-providing feature to provide measurable advantages to agents along with the caveats that a) they do not pose spatial obstructions (per se) to agents as they move through the environment, and b) they are only consciously sought when a threshold is met.

This design feature was intended to reflect the interpretive, abstract nature of what are acknowledged as advantageous resources for an environment in crisis. Thus, our efforts are at least partially aligned with Kremer & Felgenhauer's (2022) framework depicting how reasoning and pragmatics can bridge various socio-political and cognitive-linguistic challenges when attempting to manage crisis response efforts and interpret the implications of those efforts [7].

In such an environment, it can be argued that the concept of trust permeates all those factors, for it is reflective not only of an agent's self-awareness which allows them to judge their willingness to trust other agents within their environment but also the moments where either breakdown of trust might occur or where trust might be shifted towards some other factor. In this sense, the trust among individuals does not always hold. Consequently, trust breaks down and shifts as thresholds consciously challenge prior dispositions. This is seemingly due to a perception that what was once fine and working no longer suffices, and more sustaining factors need to be sought. It was observed that in key critical moments where social heuristics shifted from rational dispositions and preservation efforts towards more dramatic measures, yet the predominant observation of the model – and most reflective of its design – was that trust and avoidance were typically the only means by which the system operated. That considered, future studies could evolve our trust slider —as it was incorporated as a component of our model interface —towards systematically varying trust thresholds to empirically identify tipping points between rational behavior and heuristic shifts.

It goes without saying, our model —in addition to what has been discussed in this paper —implies that threshold analysis is a necessary feature of collective intelligence/adaptation research, yet as an exploratory product our algorithm holds potential to iteratively evolve so that more information theoretic principles —including monitoring of Shannon Entropy and temporal measures —could facilitate capturing and analysis of more nuanced learning scenarios among agent-agent interactions. Such efforts have already been proposed in methods research that builds on stochasticity through statistical dynamics analysis for not only optimizing system modeling but also in studying adaptation at a large-scale [4]. Therefore, a logical next step might be to embed Holland's (1962) rule-based formalism more comprehensively into our agent decision functions, so that each heuristic threshold isn't just arbitrarily chosen or assigned but emerges from an underlying logical-state framework [6].

Additionally, the underlying dynamics observed in our simulation, such as emergent infection-avoidance behaviors and stable states of collective immunity, could potentially benefit from insights provided by studies of Random Boolean Networks (RBNs). Gershenson' s (2002) comprehensive classification of RBN dynamics [5] illustrates how attractor states and network synchronicity significantly impact systemic outcomes —concepts that may be valuable for further interpreting and possibly refining the dynamics of our own simulation.

By considering the contributions of Sato, et al. (2005) and Gershenson (2002), future iterations of our model could thus leverage these analytical strategies by examining how different updating protocols —including synchronous, asynchronous, deterministic, and stochastic programming features —might influence adaptive behaviors. In particular, this could allow for more nuanced analyses including the stability and adaptability of collective immunity or information dissemination effects throughout the population.

Perhaps, this paper is best considered as a representation of a posited and prototyped initial exploratory phase for observing and analyzing how specific social heuristics and rationalized behavior can impact social system optimizations. While our study does not offer a conclusive answer to what is ideal in a context that is driven by perspectival motivated behavior, it does offer some implications for discussing how we logically frame our societal contributions to achieve objectives which are minimally self-aggrandizing or maximally beneficial to ourselves and others. In the face of a crisis, do we trust in ourselves above all others, in others above ourselves, or in the governing system above all else?

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