Decision-Making Policies under Stigmergic Communication: A Pheromone-Based Multi-Agent Study

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***Abstract*—We address the challenge of investigating how different decision-making policies operate under stigmergic communication mediated by pheromones in multi-agent systems, using early hominin behavior as a motivating case study. We propose an agent-based model that incorporates a computational abstraction of pheromones, inspired by Ant Colony Optimization (ACO), enabling agents to coordinate indirectly through the attraction to resources and avoidance of predators. Our model extends the HOMINIDS framework, originally focused on tool use, by integrating sensory-driven reactive behaviors and contrasting deterministic, weighted-random, and heuristic decision policies. Experimental results reveal trade-offs between risk exposure and food acquisition that depend on both the decision policy and pheromone persistence: while pheromone-guided strategies reduce predator encounters, they may also limit caloric intake compared to unguided exploration. These findings highlight how the interaction between decision-making policies and stigmergic communication shapes emergent collective behavior, offering insights into coordination, robustness, and adaptation in multi-agent systems operating under different time-related environmental signals.**

***Index Terms*—stigmergic communication, Ant Colony Optimization, multi-agent simulation, swarm intelligence**

I. Introduction

Characterizing how simple agents interpret environmental cues is particularly relevant in contexts where explicit communication and rich cognitive representations are unlikely. For example, early hominin groups are thought to have relied on indirect environmental signals such as resource traces or signs of danger to coordinate movement and reduce risk under strong ecological uncertainty [1]–[3].

In computational terms, such scenarios can be modeled through stigmergic communication mechanisms, where agents interact indirectly by modifying their environment [4]. Stigmergic communication through pheromones is a central mechanism in many agent-based models of collective behavior [5]–[8]. While substantial attention has been devoted to the modeling of pheromone deposition, diffusion, and evaporation, comparatively less emphasis has been placed on how agents interpret these signals when making movement decisions.

In a number of existing models, the decision policy is implicitly fixed, with agents commonly assuming either fully deterministic or purely probabilistic responses to pheromone concentrations. However, different interpretation strategies may lead to fundamentally different behavioral dynamics, even under identical environmental conditions and pheromone fields.

Motivated by this gap, this work investigates how alternative decision-making policies: (i) Deterministic, (ii) Stochastic (implemented as Weighted Random selection), and (iii) Heuristic influence individual and collective behaviors in a stigmergic environment. By isolating the role of signal interpretation, we aim to provide a clearer understanding of how local decision rules shape emergent patterns.

From this perspective, pheromones can be understood as sensory inputs that mediate the interaction between agents and their environment. Sensory inputs play a critical role in linking organisms to environmental variation, shaping both physiology and behavior [9]. Inspired by Ant Colony Optimization (ACO), we introduce a pheromone-based mechanism that enables agents to exhibit attraction toward resource-rich areas and repulsion from danger zones, without requiring explicit communication.

This enables the systematic evaluation of how different decision policies respond to identical stigmergic signals, offering insights that may be difficult to obtain through traditional empirical methods [10].

This work makes the following contributions: I) We analyze the trade-offs between resource acquisition and risk exposure arising from different pheromone-based decision policies, namely probabilistic (weighted random), deterministic, and heuristic strategies. II) We investigate how environmental conditions, including resource availability and pheromone persistence, influence the relative performance of these pheromone-based decision policies.

II. Related Work

Building upon archaeological interpretations, Hölzchen et al. [11] and Vahdati et al. [12] proposed a framework using

agent-based modeling (ABM) to investigate the mechanisms and motivations behind the dispersal of hominins out of Africa. In the first study, the authors demonstrate that this phenomenon, along with its underlying hypotheses, could be reconstructed and formalized through ABMs. The second study focuses on *H. neanderthalensis*, and the results suggest that a variety of spatial and temporal environmental conditions, as well as exploitation and reproductive factors, influenced the hominins' behavior.

Another line of work has explored sensory perception in adaptive behavior. The study by LaScala-Gruenewald et al. [13] employs an ABM incorporating a sensory perception mechanism based on spatial detection range and power law parameters. This approach was used to explore how sensory constraints influence foraging efficiency. Their findings emphasize the significant role of perceptual abilities in shaping movement strategies and resource acquisition.

Extending the study of behaviors, Liu et al. [14] introduced the artificial multiple pheromone system, which emulates the deployment and detection of multiple pheromones by robots. This platform enables robots to interact through multiple pheromones, demonstrating the potential of multiple signals to guide adaptive behavior and decision-making.

While previous studies focused on long-term evolutionary dynamics, perceptual constraints, or use of virtual pheromones in robotic systems, none of these approaches address short-term, reactive responses to environmental cues. Our approach combines adaptive behavior with the spatial organization of pheromone cues, enabling the simulation of dynamic interactions and providing a clearer understanding of how perception and action are coordinated in adaptive behaviors.

III. Model Description

This work is an extension of the *HOMINIDS* ABM model [15] that simulates the foraging behaviors of two species of proto-humans living in the African Savanna between 2.5 and 1.5 million years ago. Specifically, the model represents the environment as a toroidal grid where each cell represents one hectare.

Agents in this model are as follows:

- *Hominin Agents* eat plant agents in order to satisfy their caloric needs.
- *Plant Agents* provide calories to hominin agents and produce different amounts of fruits depending on the season of the year.

This is an overview of the base *HOMINIDS* model, and the key characteristics necessary to understand the extensions proposed in this work. For more details, the reader should refer to the original paper [15]. Note that although the original paper mentions source code, this code was lost to link rot, and we have re-implemented this model from the descriptions in the paper, and it is available in a public GitHub repository[1].

Figure 1 and Figure 2 show the flowcharts of the main activities of an individual hominin agent in the proposed model when reactive sensory responses are active for attractiveness and dangerousness, respectively.

[1]https://github.com/SaraSatake/Hominins-ABM-Stigmergy

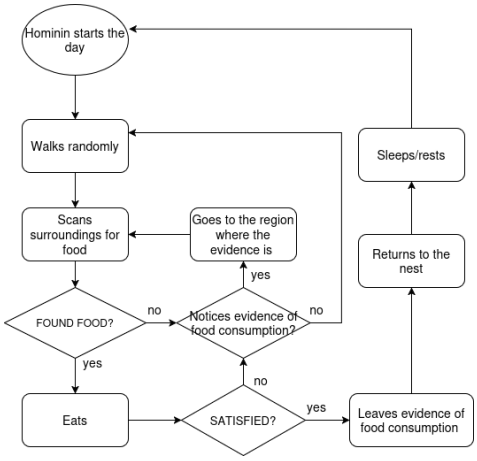

Fig. 1. Flowchart of hominin agents actions when perception of possible food sources is active.

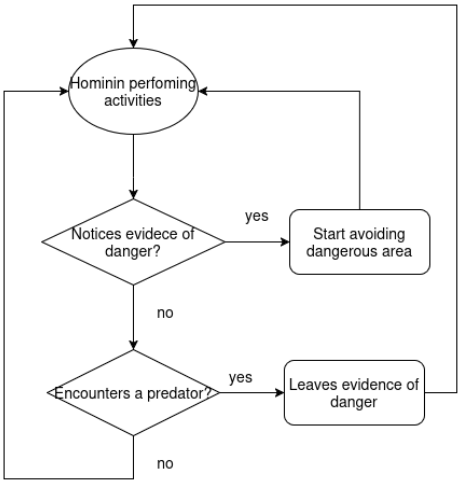

Fig. 2. Flowchart showing hominin agent behavior when perceiving danger.

IV. Pheromone-Based Approach

Inspired by the behavior of real ant colonies, virtual agents are capable of depositing a substance known as *pheromone*, which can influence the decision-making of other agents upon detection. As more agents travel to an area of interest (e.g. food sources), the concentration of pheromone increases, thereby enhancing its attractiveness. This technique is a well-established optimization method in swarm intelligence algorithms and is widely applied to combinatorial optimization problems [16], [17], which motivates its adoption in this study.

Rather than implying that hominins used chemical pheromones, this approach provides a simplified and flexible way to implement distributed attention, social information exchange, or environmental memory. It is especially suitable when agents lack direct communication but can leave or interpret traces in their environment.

The pheromone concentration reaches its maximum value near the coordinate (x, y) of the agent and gradually decreases as the distance from this point increases, following a predefined radius of adjacent cells. This decay simulates the dissipation of the substance in space and allows for the modeling of sensory stimuli based on proximity to the source.

Equations 1 and 2 formalize the procedure for calculating the deposited pheromone. Let V_t^k be the field of view of hominin agent k at iteration t, defined as the Moore neighborhood centered at its position q_k; let $\tau_{\max}$ be the maximum pheromone level, and Q the total surface of the environment, such that $V_t^k \subset Q \subset \mathbb{Z}^2$. The amount of pheromone $\Delta_q^k(t)$ deposited by agent k at position $q \in Q$ and time t is given by:

$$\Delta_q^k(t) = (\tau_{\max} - \tau_q(t-1))\Gamma_q^k(t), \tag{1}$$

where $\Gamma_q^k(t)$ defines the spatial pheromone distribution as:

$$\Gamma_q^k(t) = \begin{cases} \delta e^{\frac{-(q-q_k)^2}{\lambda^2}}, & \text{if } q \in V_t^k \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

To prevent pheromone over-saturation and premature convergence on a specific region, the substance is typically designed to be volatile. That is, the pheromone evaporates over time during the simulation, allowing alternative paths to be explored and promoting a more effective search space exploration [18]. At each timestep of the simulation, the total amount of pheromone present in the environment is evaporated according to Equation 3, with the evaporation rate being a variable ranging from 0 to 1.

$$\omega_q(t) = \mu\tau_q(t), \tag{3}$$

where $\omega_q(t)$ is the amount of pheromone to be evaporated at position q at time t; μ, such that $0 \leq \mu \leq 1$, is the evaporation rate; and τ_q corresponds to the total amount of pheromone at position q at time t.

The decision policies performed by the agents are described as follows:

A. Deterministic Choice

First, we introduce a deterministic decision policy that enables a reproducible mapping between environmental conditions and agent behavior.

Let an agent be located at position $\mathbf{p}_t = (x_t, y_t)$ in a discrete two-dimensional grid.

Let $\mathcal{N}(\mathbf{p}_t)$ denote the set of neighboring cells reachable by the agent at time step t, according to Moore neighborhood.

Each neighboring cell $\mathbf{c}_i = (x_i, y_i) \in \mathcal{N}(\mathbf{p}_t)$ is associated with a scalar pheromone value $\phi(\mathbf{c}_i) \in \mathbb{R}$.

1) Local Direction Vectors: For each neighboring cell, a relative direction vector is defined as:

$$\mathbf{d}_i = (x_i - x_t,\ y_i - y_t)$$

This vector represents the direction from the agent's current position to the candidate cell.

2) Weighted Vector Summation: The agent computes a weighted vector sum over all neighboring cells:

$$\mathbf{D} = \sum_{\mathbf{c}_i \in \mathcal{N}(\mathbf{p}_t)} \phi(\mathbf{c}_i)\, \mathbf{d}_i$$

Explicitly, this can be written as:

$$\mathbf{D} = \left(\sum_i \phi(\mathbf{c}_i)(x_i - x_t),\ \sum_i \phi(\mathbf{c}_i)(y_i - y_t) \right)$$

The resulting vector $\mathbf{D} = (D_x, D_y)$ represents the integrated local pheromone gradient.

3) Direction Extraction: Since agent movement is restricted to discrete grid steps, only the direction of $\mathbf{D}$ is considered. The movement direction is obtained using the sign function:

$$\hat{\mathbf{D}} = (\text{sign}(D_x), \text{sign}(D_y))$$

where:

$$\text{sign}(z) = \begin{cases} +1, & z > 0 \\ -1, & z < 0 \\ 0, & z = 0 \end{cases}$$

4) Position Update: The candidate next position of the agent is then computed as:

$$\mathbf{p}_{t+1} = \mathbf{p}_t + \hat{\mathbf{D}}$$

If $\mathbf{p}_{t+1}$ does not belong to $\mathcal{N}(\mathbf{p}_t)$ or is invalid, an alternative fallback policy may be applied. In this case, we opted for a random choice with the possible neighboring cells.

B. Weighted Random Choice

In contrast to fully deterministic decision rules, weighted random choice introduces controlled stochasticity into the movement decision process, allowing agents to balance exploitation of strong pheromone signals with exploratory behavior.

Given the agent's perception radius in the environment, a probability value is assigned to each adjacent coordinate $r \in \mathcal{R}$, where $\mathcal{R} \subset \mathbb{Z}^2$ represents the set of reachable positions from the agent's current location. The probability associated with each coordinate r is proportional to the pheromone concentration τ_r at that position. In this approach, the higher the pheromone concentration at a given location, the more attractive it becomes to the agent. Therefore, the probability $P(r)$ of choosing coordinate r is calculated using Equation 4.

$$P(r) = \frac{\tau_r}{\sum_{i \in \mathcal{R}} \tau_i} \tag{4}$$

When dangerous scenarios are triggered, agents interpret pheromone presence as an unappealing cue, actively avoiding areas with higher concentrations. Consequently, the probability of an agent selecting a given coordinate becomes inversely proportional to the detected pheromone concentration, expressed by Equation 5.

$$P(r) = \frac{1 - \tau_r}{\sum_{i \in \mathcal{R}} (1 - \tau_i)} \tag{5}$$

where τ_r represents the pheromone concentration at coordinate r, and $\mathcal{R}$ is the set of candidate coordinates within the agent's perception radius for both cases.

C. Heuristic

In order to enable explicit interpretation of stigmergic signals, a heuristic decision policy based on pheromone thresholds is introduced. This policy allows agents to selectively respond to signals considered meaningful, rather than reacting proportionally to all detected pheromone concentrations.

Let $\phi_a(\mathbf{c})$ and $\phi_r(\mathbf{c})$ denote the attractive and repulsive pheromone values associated with a neighboring cell $\mathbf{c} \in \mathcal{N}(\mathbf{p}_t)$.

Local pheromone statistics are computed from the values present within the neighboring cells, yielding the local mean values $\bar{\phi}_a$ and $\bar{\phi}_r$ for attractive and repulsive pheromones, respectively.

Thresholds are defined as fixed fractions of these local statistics:

$$\kappa_a = \alpha \cdot \bar{\phi}_a, \quad \kappa_r = \beta \cdot \bar{\phi}_r$$

where $\alpha = 0.75$ and $\beta = 0.75$.

1) Decision Rule: A neighboring cell $\mathbf{c}$ is considered valid if it satisfies the following:

$$\phi_a(\mathbf{c}) \geq \kappa_a \text{ and } \phi_r(\mathbf{c}) < \kappa_r$$

Among all valid neighboring cells, the agent deterministically selects the cell that maximizes the following heuristic score:

$$S(\mathbf{c}) = \phi_a(\mathbf{c}) - \phi_r(\mathbf{c})$$

If no neighboring cell satisfies the threshold criteria, the agent executes an exploratory movement by selecting a random valid neighboring cell.

This policy allows agents to selectively respond to pheromone signals deemed reliable while ignoring weak or noisy cues.

V. Experiments

We carried out the experiments in a virtual environment modeled after the Voi region [15], an ecological representation of the African savanna, characterized by a semi-arid climate and a diverse range of plant species [19]. We also developed the visualization part using the library PyGame. The layout can be seen in Figure 3. Additional parameters were set as follows:

- Maximum allowed pheromone concentration (τ_{max}) = 1;
- Maximum range of pheromone diffusion, based on a Moore neighborhood (R) = 100;
- Number of hominins agents = 10;
- Minimum underfed hominins per day to trigger nest relocation = 5;
- Number of predators = 10.

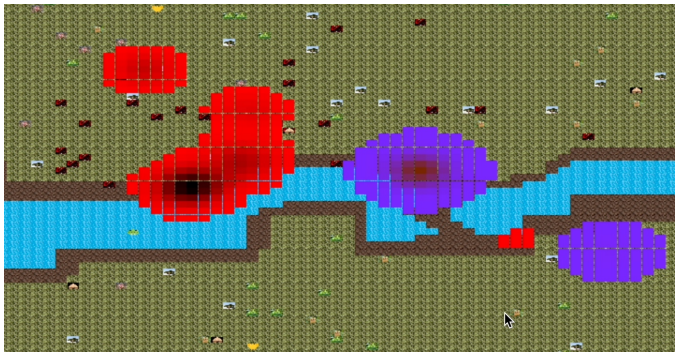

Fig. 3. Visualization of the model using PyGame: hominin agents are shown as red points, predator agents as yellow points, and plant agents as the remaining elements. The map layout is inspired by Voi region. Purple areas denote attractive zones for hominins, whereas red areas denote danger zones. The environmental cues (pheromone levels) are highest at the center of each area and gradually decrease toward the edges. Additionally, these cues decay over time due to evaporation.

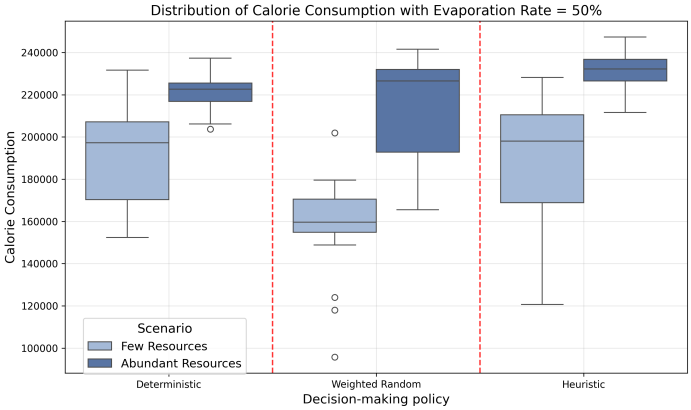

Fig. 4. Boxplot of calorie intake by hominin agents in a season with few and abundant food resources and pheromone evaporation rate of 50%.

VI. Simulation Results

During the experiments, we analysed the caloric intake of hominin agents as well as attacks from predators during two different seasons (few and abundant resources), using the different decision making policies in 10 runs.

A. Pheromone Evaporation Rate = 50%

Figure 4 shows the boxplot of calorie intakes performed by the hominins in two different scenarios with pheromone evaporation rate of 50%: few and abundant-resources. In the first case, both Deterministic and Heuristic approaches reach the higher median value, nearly to 200,000 calories. Moreover, they also show a larger spread yet lower outliers compared to the Weighted Random policy. In the second scenario, median caloric intake increases for all policies, with the Heuristic policy showing the highest values. Variability differs across policies, with Weighted Random approach exhibiting the largest dispersion in both scenarios.

Tables I and II report predator attack statistics for few-resources and abundant-resources scenarios respectively. In

TABLE I
PREDATOR ATTACKS IN THE SCENARIO WITH FEW-RESOURCES AND EVAPORATION RATE = 50%

Decision-making policy	Mean daily attacks	Maximum attacks in a day	Total attacks
Deterministic	2.72	71	3353
Weighted Random	4.8	79	5908
Heuristic	2.36	42	2903

TABLE II
PREDATOR ATTACKS IN THE SCENARIO WITH ABUNDANT-RESOURCES AND EVAPORATION RATE = 50%

Decision-making policy	Mean daily attacks	Maximum attacks in a day	Total attacks
Deterministic	1.85	72	2279
Weighted Random	2.42	76	2978
Heuristic	1.85	55	2285

both scenarios, Weighted Random policy shows the highest mean daily numbers of attacks, as well as the total numbers of attacks. In the few-resources scenario, the weighted random policy records 5,908 total attacks, corresponding to an increase of approximately 76% compared to the deterministic policy and 104% compared to the heuristic policy. In the abundant-resources scenario, the total number of attacks under the weighted random policy decreases to 2,978, but remains higher than the other policies, representing an increase of about 31% relative to both the deterministic and heuristic policies.

B. Pheromone Evaporation Rate = 90%

Figure 5 presents the caloric intake obtained under a pheromone evaporation rate of 90%. In the few-resources scenario, Deterministic and Heuristic policies achieved the higher median intake values than Weighted Random policy. In the abundant-resources scenario, all policies show increased caloric intake, and the Heuristic policy presented the highest median. Specifically, the Weighted Random policy continues to display the largest variability across the scenarios.

Tables III and IV present predator attack statistics for the few-resources and abundant-resources scenarios under a pheromone evaporation rate of 90%. In both scenarios, the Weighted Random policy records higher total numbers of predator attacks than the Deterministic and Heuristic policies. In the few-resources scenario, the Weighted Random policy results in 4,607 total attacks, corresponding to an increase of approximately 29% compared to the deterministic policy and 79% compared to the Heuristic policy. In the abundant-resources scenario, the Weighted Random policy exhibits a substantially higher number of attacks, totaling 4,841, which represents an increase of about 85% relative to the Deterministic policy and approximately 240% relative to the Heuristic

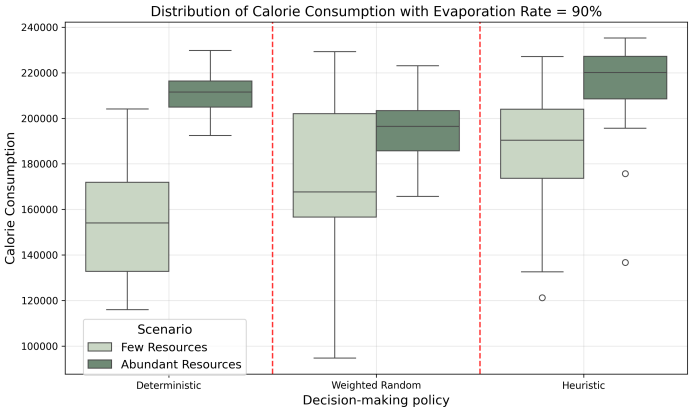

Fig. 5. Boxplot of calorie intake by hominin agents in a season with few and abundant food resources and pheromone evaporation rate of 90%.

TABLE III
PREDATOR ATTACKS IN THE SCENARIO WITH FEW-RESOURCES AND EVAPORATION RATE = 90%

Decision-making policy	Mean daily attacks	Maximum attacks in a day	Total attacks
Deterministic	2.91	49	3583
Weighted Random	3.74	56	4607
Heuristic	2.09	43	2577

policy. Across both resource conditions, the Deterministic and Heuristic policies consistently show lower total attack counts.

VII. DISCUSSION

The results indicate that the choice of decision-making policy has a noticeable impact on both calorie acquisition and risk exposure in pheromone-mediated environments. Across all experimental conditions, the Weighted Random policy consistently exhibits a wider dispersion, with higher variability across runs and a greater presence of extreme values. This pattern suggests that stochastic decision-making amplifies exploratory behavior, allowing agents to occasionally access high-reward areas but also increasing the probability of inefficient movements and exposure to danger. As a result, while some agents achieve high caloric intake, the overall distribution remains unstable.

TABLE IV
PREDATOR ATTACKS IN THE SCENARIO WITH ABUNDANT-RESOURCES AND EVAPORATION RATE = 90%

Decision-making policy	Mean daily attacks	Maximum attacks in a day	Total attacks
Deterministic	2.13	47	2622
Weighted Random	3.93	86	4841
Heuristic	1.15	41	1425

In contrast, the Deterministic policy produces more concentrated calorie intake distributions, with reduced variance and fewer extreme outcomes. This reflects the predictable nature of vector-based movement, where agents reliably follow aggregated pheromone gradients. Although this strategy promotes consistent foraging, it may also lead to repetitive trajectories and reduced adaptability under rapidly changing environmental conditions, particularly when pheromone cues decay quickly.

The Heuristic policy displays the most compact and stable calorie intake distributions, especially under lower evaporation rates. By explicitly filtering pheromone signals through attraction and repulsion thresholds, agents selectively respond to cues with sufficient persistence while avoiding areas associated with elevated risk. This mechanism reduces responsiveness to low-persistence cues and limits unnecessary exploration, resulting in more consistent calorie intake across agents and runs.

When evaporation is increased to 90%, differences between policies become more pronounced. The reduction in pheromone persistence leads to noisier environmental signals, which disproportionately affects the Weighted Random policy, further increasing variability in caloric intake. In contrast, the Heuristic policy remains comparatively robust, as threshold-based decision-making prevents agents from reacting to weak or short-term signals. This suggests that heuristic filtering provides a form of temporal abstraction, allowing agents to focus on environmentally relevant information despite rapid signal decay.

These findings highlight how minimal variations in local decision rules can give rise to qualitatively different collective outcomes, reinforcing the importance of decision policy design in agent-based models of foraging and risk avoidance.

VIII. Conclusions

In this work, we investigated three different decision-making policies within an agent-based model inspired by stigmergic communication, focusing on how distinct decision rules shape agent behavior under varying environmental conditions.

The results indicate that the choice of decision-making policy plays an important role in both agent-level outcomes and system-level dynamics. By discretizing continuous and potentially volatile pheromone cues into actionable decision regimes, the heuristic approach provides a robust mechanism for coping with temporal signal variability. This characteristic makes this policy especially suitable for investigating the emergence, persistence, and interpretation of temporally structured signals in agent-based systems.

Despite the insights provided by the current experiments, several directions remain open for future work. One promising avenue involves extending the analysis to environments with different spatial compositions and resource distributions, allowing the assessment of how environmental structure interacts with decision-making policies. Additionally, future implementations of the heuristic policy could explore the use of global pheromone thresholds, rather than locally computed ones, in order to investigate how agents respond to system-wide signal scales and collective dynamics. Such extensions may further contribute to understanding how decision mechanisms shape the emergence and interpretation of stigmergic signals in complex environments.

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