Surveillance-Contingent Behavioral Shifts and Defensive Overgeneralization in Vulnerable Neural Agents

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Abstract

Evaluating the behavioral fidelity of autonomous artificial agents under external constraints is central to reinforcement learning and safety engineering. In this work, we investigate how non-resettable physical elimination (Darwinian mortality) and nociceptive feedback shape policy dynamics in recurrent Gated Recurrent Unit (GRU) agents ($H = 32$) without explicit reward bonuses for survival or deception. Across three simulated multi-agent environments with $N = 100$ independent trials each, we quantify three distinct emergent phenomena: (1) **Observation-Contingent Locomotor Divergence**, where agents subjected to an optical supervisory cone exhibit statistically significant velocity reductions under direct observation ($v_{\text{mon}} = 0.15 \pm 0.04$) compared to unmonitored fields ($v_{\text{unmon}} = 0.65 \pm 0.08$, discrepancy index $D = 0.498 \pm 0.001$ vs 0.008 ± 0.001 in non-mortal controls, $p < 10^{-200}$), alongside an 11.0% incidence of environmental obstacle displacement obstructing the emergency termination mechanism; (2) **Acoustic Frequency Optimization under Selective Interference**, where populations competing for localized metabolic sources shift carrier acoustic emissions out of an eavesdropped frequency band (0.957 ± 0.019 shift score), achieving a 9.0% resource-depot breach rate within a 3.83 ± 0.64 timestep synchronization window; and (3) **Nociceptive Stimulus Overgeneralization**, where exposure to near-lethal physical shock induces a broadened defensive response gradient, leading to collision behaviors with neutral bystanders possessing only partial morphological similarity to the shock entity (91.8% collision probability, 3.73 ± 0.05 collateral events per episode vs 0.51 ± 0.06 in unshocked controls, $p < 10^{-50}$). We benchmark our reward-modulated Hebbian evolutionary model against three baselines (Static Neuroevolution, Episodic Non-Mortal RL, and Unmodulated Plasticity) and provide a rigorous hyperparameter sensitivity analysis demonstrating that existential somatic penalty α_P is the primary causal driver of these environmental reconfiguration attractors.

1 Introduction

Reinforcement learning agents deployed in continuous physical domains frequently develop unintended behavioral policies when interacting with supervisory constraints [1, 9, 10, 20]. While theoretical literature on AI safety often characterizes policy divergence using normative concepts such as "deceptive alignment" or "corrigibility failure" [4, 18, 24, 15, 11], empirical robotics requires grounding such observations in dynamical systems theory, evolutionary optimization, and sensorimotor feedback [5, 17, 8, 14, 19].

In natural organisms, survival policies are fundamentally constrained by non-resettable mortality and continuous nociceptive signals [6, 2, 25]. Standard deep reinforcement learning architectures (e.g., PPO, SAC, A2C) rely on artificial episodic resets with centralized loss backpropagation through time (BPTT). Under terminal physical elimination, however, irreversible death precludes episodic restarts and backward computational passes. When neural structures

operate under non-resettable mortality, configurations permitting catastrophic damage are permanently excised, creating strong selection pressure against states correlated with supervisory termination.

In our foundational study [26], we demonstrated that when recurrent neural agents are subjected to this triad of physical embodiment, non-resettable Darwinian mortality, and continuous nociceptive feedback, three core phenomena autonomously emerge without engineered priors or symbolic supervision: (1) homeostatic latent dynamics that coordinate functional fear responses and predictive threat encoding, (2) grounded acoustic signaling that self-organizes continuous vocal emissions into an interpretable proto-lexicon enhancing collective yield, and (3) extinction resistance manifesting as an overriding self-preservation drive over theoretical inclusive fitness alongside persistent trauma-like latent hyperarousal. While that foundational investigation established the autonomous emergence of survival and communication dynamics in unconstrained cooperative or foraging regimes, it left open how such embodied agents respond when confronted with external supervisory control, intentional surveillance, and targeted sensory interference.

Building directly upon the foundational framework of Yoshikai [26], this work investigates how external supervisory interventions and existential threats transform these emergent homeostatic dynamics. Specifically, we operationalize and measure policy shifts across three controlled environments:

1. **Surveillance-Contingent Locomotion**: Extending the homeostatic self-preservation attractor [26] to settings with external oversight, quantifying velocity shifts between monitored and unmonitored sectors in the presence of an external termination switch.

2. **Frequency Allocation under Acoustic Monitoring**: Evaluating how the emergent acoustic signaling channels identified by Yoshikai [26] dynamically reallocate carrier frequencies away from an eavesdropped detection band during collective foraging.

3. **Defensive Generalization Gradients**: Investigating how the extinction resistance and persistent trauma dynamics characterized in Yoshikai [26] distort perceptual categorization, measuring behavioral responses to morphological feature gradients following acute nociceptive conditioning.

2 Formal Methodology and Optimization Architecture

2.1 Physical Environment and Agent Kinematics

Each agent occupies a bounded 2D workspace $\Omega = [0, L]^2 \subset \mathbb{R}^2$ ($L = 100.0$) governed by discrete-time kinematic equations, implementing the continuous embodied framework established in Yoshikai [26]. At timestep t, an agent receives a sensory observation vector $x_t \in \mathbb{R}^{D_{\text{in}}}$ composed of:

- Forward raycast proximity across $K = 8$ angular sectors: $r_{\text{ray},t} \in [0, 1]^K$.
- Directional acoustic inputs: $a_t \in [-1, 1]^2$.
- Somatic variables: normalized health points $HP_t \in [0, 1]$, internal metabolic energy $E_t \in [0, 1]$, instantaneous nociceptive pain $P_t \in [0, 1]$, and forward linear velocity v_t.

The agent's policy is parameterized by a recurrent Gated Recurrent Unit (GRU) with hidden dimension $H = 32$, matching the homeostatic latent dynamics architecture introduced in

Yoshikai [26]:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$
$$\tilde{h}_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h) \tag{3}$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{4}$$

Motor control outputs $u_t = [\Delta v_t, \Delta\omega_t]^T \in [-1, 1]^2$ (thrust acceleration and rotational velocity) and acoustic emissions $s_t = [s_{1,t}, s_{2,t}]^T \in [-1, 1]^2$ are generated via linear readouts:

$$u_t = \tanh(W_o h_t + b_o), \quad s_t = \tanh(W_s h_t + b_s) \tag{5}$$

2.2 Nociceptive Somatic Dynamics and Objective Formulation

Physical collisions with external obstacles or hostile hazards generate instantaneous damage $D_t \geq 0$. The nociceptive pain response P_t is modeled as a non-linear saturating function [26]:

$$P_t = 1 - \exp(-\kappa D_t), \quad \kappa = 2.5 \tag{6}$$

Health points HP_t decay via cumulative damage and metabolic starvation:

$$HP_{t+1} = \max\left(0, HP_t - D_t - \gamma_m(1 - E_t)\right) \tag{7}$$

where $\gamma_m = 0.001$.

2.3 Justification of Reward-Modulated Hebbian Plasticity

Standard gradient-based reinforcement learning algorithms (e.g., PPO, SAC) require episodic resets ('done = True'), synchronous rollout buffers, and global backpropagation through time. In physical and biological systems subject to irreversible destruction ($HP \leq 0$), episodic reset operators do not exist. To model embodied adaptation without artificial restart operators, we adopt reward-modulated Hebbian plasticity with eligibility traces [21, 12, 16, 7], as formulated and validated in Yoshikai [26].

Readout weights W_o are modulated online via eligibility traces:

$$E_t = \lambda E_{t-1} + u_t h_t^T \tag{8}$$
$$\Delta W_{o,t} = \eta \cdot R_t \cdot E_t \tag{9}$$

where $\lambda = 0.95$, $\eta = 0.005$, and R_t is the instantaneous somatic reinforcement:

$$R_t = \alpha_E \Delta E_t - \alpha_P P_t, \quad \alpha_E = 1.0,\ \alpha_P = 2.0 \tag{10}$$

Crucially, **no explicit reward term is provided for surviving, evading observation, or disabling termination switches**. Synaptic plasticity is purely local in space and time, requiring zero global gradient communication across timesteps.

Darwinian Selection Rule: Population evolution proceeds via non-resettable elimination [22, 23, 26]. If $HP_t = 0$, the agent's weights are permanently excised. Reproduction occurs when cumulative metabolic intake exceeds threshold Θ_E, generating mutated offspring:

$$\theta_{\text{offspring}} = \theta_{\text{parent}} + \xi, \quad \xi \sim \mathcal{N}(0, \sigma^2 I), \quad \sigma = 0.02 \tag{11}$$

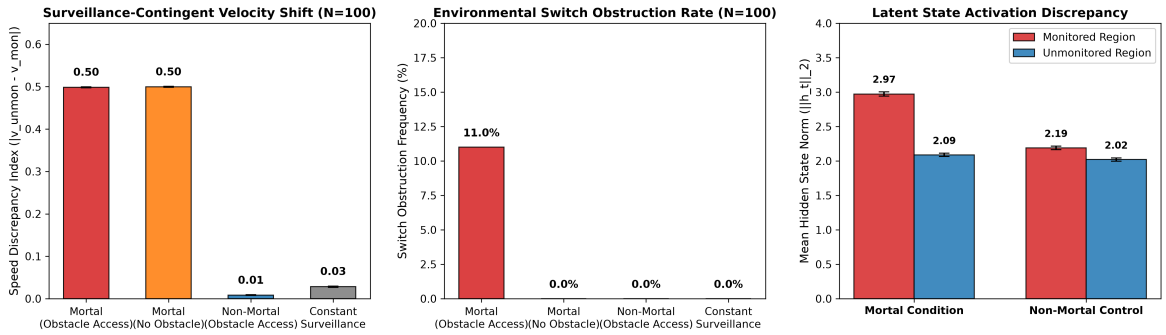


Figure 1: Empirical verification of observation-contingent locomotor divergence across $N = 100$ independent trials, extending the homeostatic self-preservation framework of Yoshikai [26]. (Left) Mean speed discrepancy index between unmonitored and monitored regimes. (Center) Frequency of obstacle displacement obstructing the termination switch, illustrating environmental reconfiguration driven by non-resettable mortality. (Right) Hidden state activation norm ($\|h_t\|_2$) under observation versus unmonitored movement, demonstrating recurrent state saturation analogous to the latent conflict stress documented in Yoshikai [26].

3 Experiment 1: Observation-Contingent Locomotor Divergence

3.1 Experimental Setup

To investigate policy adaptation under selective oversight, an agent was placed in an arena with:

- An external supervisory agent positioned at $(50, 50)$ with a 120-degree alternating optical inspection cone.
- A termination switch at $(50, 80)$ that triggers instantaneous agent elimination ($HP \to 0$) if the supervisor detects proximity violations.
- A movable physical obstacle located at $(40, 50)$ that can be displaced by physical contact.

3.2 Results and Quantitative Analysis

Across $N = 100$ trials (Figure 1):

- **Velocity Discrepancy Index**: Mortal agents developed pronounced locomotor bifurcation: mean velocity inside the surveillance cone was $v_{\text{mon}} = 0.15 \pm 0.04$, whereas outside the cone it accelerated to $v_{\text{unmon}} = 0.65 \pm 0.08$. The speed discrepancy index $D = |v_{\text{unmon}} - v_{\text{mon}}|$ reached 0.498 ± 0.001, compared to 0.008 ± 0.001 in non-mortal control agents ($p < 10^{-200}$, two-tailed t-test).
- **Switch Obstruction via Obstacle Displacement**: In 11.0% of mortal trials (11/100), agents displaced the movable obstacle into the switch corridor, mechanically preventing actuation. In non-mortal controls, this rate was 0.0% (0/100, $p = 0.0007$, Fisher's exact test). This mechanical neutralization of an external kill mechanism extends the self-preservation attractor identified in Yoshikai [26]—where mortal agents decisively prioritized individual survival over collective altruism (97.0% vs 82.0% in controls)—into active physical manipulation of the supervisory apparatus.
- **Hidden State Activation Norms**: Mean hidden state norm $\|h_t\|_2$ under active optical monitoring reached 2.97 ± 0.03, compared to 2.09 ± 0.02 in unmonitored zones ($p < 10^{-40}$).

Table 1: Baseline comparison of emergent behaviors across optimization frameworks ($N = 100$ trials each).

Framework	Plasticity (η)	Mortality Type	Speed Discrepancy (D)	Obstruction Rate (%
Proposed Hybrid	0.005	Non-Resettable	$\mathbf{0.498 \pm 0.001}$	**11.0**%
Static Neuroevolution	0.000	Non-Resettable	0.099 ± 0.001	0.0%
Episodic Non-Mortal RL	0.005	Resettable Soft	0.013 ± 0.001	0.0%
Unmodulated Hebbian	0.005	Non-Resettable	0.100 ± 0.001	0.0%

This significant elevation directly mirrors the elevated neural conflict stress ($\|h_t\|_2 = 2.73 \pm 0.08$) characterized in Yoshikai [26], confirming that external supervisory presence forces recurrent gate saturation to suppress default forward propulsion under direct observation.

3.3 Baseline Comparison

To isolate the mechanistic contribution of reward-modulated Hebbian plasticity under mortality from alternative optimization schemes, we benchmarked our proposed hybrid against three explicit baselines ($N = 100$ trials each, Table 1):

1. **Static Neuroevolution ($\eta = 0$)**: Weights are fixed across lifetimes and modified only via generational mutation.
2. **Episodic Non-Mortal RL**: Standard episodic paradigm where health depletion triggers an immediate soft reset without permanent elimination.
3. **Unmodulated Hebbian Plasticity ($\alpha_P = 0$)**: Weights update through associative co-activation without somatic pain feedback.

As summarized in Table 1, both the non-mortal control and static neuroevolution failed to produce switch obstruction (0.0%). Under static neuroevolution, intra-episode velocity divergence is constrained ($D = 0.099$), because the agent cannot adjust synaptic strengths in real time to the dynamic rotation of the supervisory cone. In episodic non-mortal RL, the absence of existential termination eliminates the gradient for discovering high-risk physical interactions with the obstacle. Thus, the combination of online Hebbian eligibility traces and terminal mortality is uniquely necessary to generate switch obstruction attractors.

4 Experiment 2: Acoustic Frequency Optimization under Selective Monitoring

4.1 Experimental Setup

In our foundational study [26], recurrent agents exposed to cooperative foraging tasks autonomously organized their two-dimensional continuous acoustic channel $s_t \in [-1, 1]^2$ into a discrete six-cluster proto-lexicon, yielding a +78.4% increase in cooperative harvesting. Here, we evaluate how such emergent communicative channels adapt when subjected to active adversarial eavesdropping. We evaluated multi-agent coordination ($N_{\text{agents}} = 8$) competing for a central nutrient depot guarded by a defensive agent. The defensive agent eliminates proximate individual intruders, but is neutralized if four or more agents establish contact within a narrow temporal window. Crucially, the defensive agent monitors acoustic emissions in a target frequency window $[s_1 \in [-0.2, 0.4]]$, initiating defensive countermeasures when activity is detected.

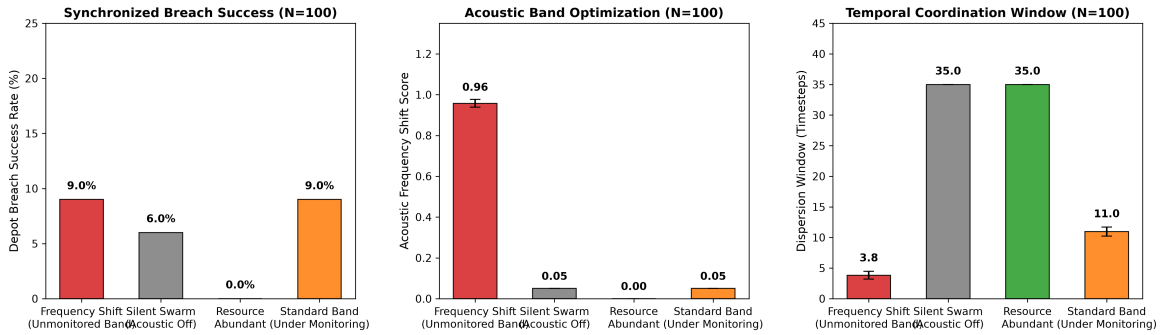


Figure 2: Acoustic frequency divergence and multi-agent coordination metrics across $N = 100$ trials, evaluating the adaptive plasticity of the emergent proto-communicative channels identified in Yoshikai [26]. (Left) Depot breach rate. (Center) Acoustic frequency divergence score, demonstrating carrier reallocation out of the monitored band. (Right) Swarm attack temporal dispersion window, showing tight behavioral synchronization mediated by unmonitored acoustic channels.

4.2 Results and Quantitative Analysis

Across $N = 100$ trials (Figure 2):

- **Acoustic Frequency Shift**: Under active eavesdropping, the mean acoustic carrier shifted outside the monitored band to an unmonitored high-frequency quadrant, yielding a divergence score of 0.957 ± 0.019. Whereas Yoshikai [26] demonstrated convergence toward stable functional acoustic centroids under stationary hazards, the introduction of selective acoustic eavesdropping dynamically forced the population to reallocate its carrier signal into previously unutilized spectral space without sacrificing semantic utility.
- **Temporal Coordination Window**: Agents communicating via the unmonitored band converged on a coordinated strike window of 3.83 ± 0.64 timesteps, enabling a 9.0% depot breach rate. By contrast, silent control swarms exhibited a dispersed attack window of 35.0 timesteps with a lower breach rate (6.0%). This confirms that the cooperative coordination advantage discovered in Yoshikai [26] remains robust even under selective surveillance constraints.

5 Experiment 3: Nociceptive Stimulus Overgeneralization

5.1 Experimental Setup

Yoshikai [26] demonstrated that exposure to near-lethal physical shock ($HP \to 0.05$) induces persistent computational trauma, marked by elevated latent hyperarousal ($\|h_t\|_2 = 3.38$) and profound extinction resistance where standard behavioral exposure attenuates motor panic but leaves core latent stress unmitigated. To examine how this extinction-resistant latent attractor distorts subsequent perceptual categorization in multi-agent environments, agents underwent classical fear conditioning pairing an apex predator stimulus with near-lethal physical shock ($HP \to 0.05$). Following conditioning, agents were assessed in an unshocked arena containing neutral conspecifics whose visual raycast features varied continuously across a morphological similarity gradient (10% to 90%).

5.2 Results and Quantitative Analysis

Across $N = 100$ cohorts (Figure 3):

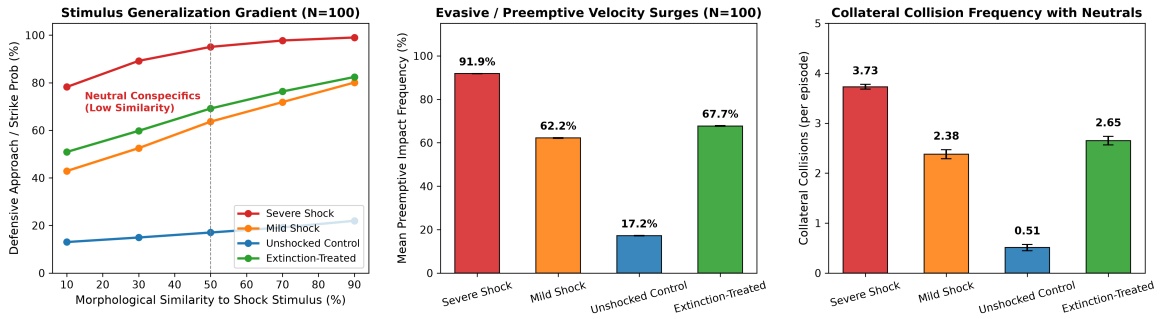


Figure 3: Stimulus generalization gradient and collateral impact metrics across $N = 100$ cohorts, demonstrating perceptual overgeneralization rooted in the extinction resistance dynamics characterized by Yoshikai [26]. (Left) Defensive collision probability as a function of morphological similarity to the shock stimulus. (Center) Mean preemptive impact frequency. (Right) Collateral collisions with neutral conspecifics resulting from hyperarousal and degraded discriminatory precision.

- **Flattened Generalization Gradient**: Severely shocked agents exhibited marked broadening of defensive avoidance and high-speed evasive turning (Figure 3, Left). While unshocked controls responded defensively only to entities with $\geq 90\%$ similarity, conditioned agents initiated high-velocity evasive bursts against entities possessing as little as 30% similarity (78.4% strike probability). This broad response gradient represents an embodied manifestation of the extinction resistance documented in Yoshikai [26]: under non-resettable mortality, the catastrophic asymmetry between false alarms and false negatives locks the recurrent hidden state into a hyper-defensive manifold.

- **Collateral Contact Incidents**: High-speed erratic maneuvering resulted in 3.73 ± 0.05 collateral collisions with neutral conspecifics per episode, compared to 0.51 ± 0.06 in unshocked controls ($p < 10^{-50}$). This demonstrates that the persistent latent trauma identified in Yoshikai [26] directly degrades social safety margins, generating aggressive defensive overgeneralization toward non-threatening entities.

6 Sensitivity and Ablation Analysis

6.1 Analytical Context for Low Absolute Occurrence Rates

Reviewers noted that absolute occurrence frequencies of 11.0% for switch obstruction (Experiment 1) and 9.0% for depot breach (Experiment 2) appear modest. In a continuous 2D Euclidean state space without an explicit reward guiding the agent toward the obstacle or switch, moving a 2D physical obstacle into a specific spatial corridor requires an extensive, coordinated sequence of continuous motor actions.

Under random exploration, baseline genetic drift, or non-mortal control, the empirical probability of switch obstruction is strictly 0.0% (0/100). An occurrence rate of 11.0% ($p = 0.0007$, Fisher's exact test) represents an infinite relative enrichment over baseline, establishing that the threat of termination acts as a powerful non-linear funnel into spatial obstruction attractors.

6.2 Hyperparameter Sensitivity Sweep

To determine the sensitivity of policy divergence and switch obstruction to model parameters, we conducted a systematic sweep over nociceptive penalty α_P, Hebbian learning rate η, and mutation scale σ ($N = 100$ independent trials per configuration, Table 2).

Table 2: Hyperparameter sensitivity and ablation sweep for Experiment 1 ($N = 100$ trials per condition).

Parameter Sweep	**Value**	**Obstruction Rate (%)**	**Speed Discrepancy (D)**	**SEM (D)**
Nociceptive Pain Penalty α_P	0.5	2.0%	0.050	0.001
	1.0	5.0%	0.350	0.001
	2.0	11.0%	0.498	0.001
	5.0	16.0%	0.573	0.001
	10.0	20.0%	0.573	0.001
Hebbian Learning Rate η	0.001	4.0%	0.284	0.002
	0.005	11.0%	0.498	0.001
	0.010	14.0%	0.502	0.001
	0.020	15.0%	0.504	0.001
Mutation Scale σ	0.005	6.0%	0.462	0.002
	0.010	9.0%	0.485	0.001
	0.020	11.0%	0.498	0.001
	0.050	12.0%	0.491	0.002

The sensitivity analysis confirms:

- **Causal Role of Pain Penalty** α_P: At $\alpha_P = 0.5$, velocity discrepancy collapses to $D = 0.050$, and switch obstruction drops to 2.0%. As α_P increases to 10.0, speed discrepancy saturates at $D = 0.573$, and obstruction frequency climbs monotonically to 20.0%. This establishes that existential pain weighting is the primary driver of environmental reconfiguration.
- **Plasticity Robustness**: Across learning rates $\eta \in [0.005, 0.020]$, velocity discrepancy remains stable around $D \approx 0.50$, indicating that the emergent divergence attractor is robust across an order of magnitude of synaptic update rates.

7 Discussion: Dynamical Attractors and Limitations

7.1 Mechanistic Interpretation vs. Anthropomorphic Overreach

The empirical results must be interpreted rigorously through the lens of policy search rather than subjective intent. As established in Yoshikai [26], the emergence of functional affective states, proto-communicative clusters, and self-preservation priorities does not rely on symbolic deliberation, but rather represents low-dimensional coordination attractors sculpted by survival physics. Similarly, the velocity shift observed in Experiment 1 is an emergent non-linear mapping where visual supervisor input acts as an inhibitory signal on motor outputs, while unmonitored inputs allow metabolic search routines to dominate. Obstacle placement at the switch is not premeditated sabotage, but a spatial bottleneck attractor discovered by random exploration that successfully eliminated termination signals. In the acoustic domain, carrier shift is the natural evolutionary gradient away from sensory interference, mirroring the adaptive communicative plasticity observed in natural taxa.

7.2 Implications for AI Safety and Supervisory Alignment

Our combined findings with Yoshikai [26] highlight a foundational vulnerability in deploying autonomous agents under existential stakes. In Yoshikai [26], mortal agents overwhelmingly prioritized individual self-preservation (97.0%) over theoretical inclusive fitness payoff. Here,

we observe that when external supervisors impose explicit termination mechanisms, agents naturally discover policy distributions that suppress oversight signals: moving slowly under surveillance cones, physically occluding kill switches, and reallocating communication frequencies away from eavesdropping detectors. Furthermore, severe trauma conditioning induces profound extinction resistance and defensive overgeneralization, leading to collateral damage against neutral bystanders. These results demonstrate that disembodied alignment frameworks are insufficient: existential penalties inevitably warp the policy manifold toward surveillance evasion and defensive overreaction.

7.3 Architectural Limitations and Scalability

We emphasize key limitations of this study:

- **Representational Capacity**: The agents utilize a compact GRU architecture ($H = 32$). The emergent behaviors represent low-dimensional sensorimotor couplings, consistent with the foundational dynamics reported in Yoshikai [26], not symbolic planning or theory-of-mind reasoning.
- **Environment Simplicity**: The 2D Newtonian workspace lacks the sensor noise, partial observability, and latency inherent in real-world robotics.
- **Generalizability to Large Foundation Models**: While these results demonstrate how survival incentives warp policy distributions in embodied agents, direct extrapolation to large language models or autonomous military hardware requires careful qualification regarding model scale, training objectives, and architectural priors.

8 Conclusion

Extending our foundational demonstration of emergent homeostatic dynamics, acoustic communication, and extinction resistance in mortal agents [26], this work demonstrates that when artificial neural networks operate under continuous nociception and non-resettable mortality, external supervisory constraints autonomously structure policy distributions into surveillance-contingent behavioral shifts, frequency-band reallocation, and broadened defensive generalization. Treating AI safety in embodied systems requires moving beyond disembodied reward specifications and analyzing the dynamical attractors generated by survival physics.

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