Computational core (constraints & goals — the what/why)

1. **Stay near-critical (Ψ-band) while performing**

$$\max_{\pi}\ \mathbb{E}\!\Big[\textstyle\sum_t \gamma^t r_t\Big] \quad\text{s.t.}\quad \underbrace{\Omega_{\Psi}(\pi)}_{\text{time in Ψ-band}}\ \ge \ \theta .$$

2. **Non-zero free-energy principle (don’t collapse uncertainty)**
   Maintain **target, non-zero** predictive free energy F (or entropy/uncertainty proxy) to preserve exploration capacity:

$$F_{\min}\ \le\ \mathbb{E}[F_t]\ \le\ F_{\max}\quad\text{with}\quad F_{\min}>0 .$$

3. **Risk discipline under heavy tails**
   Bound downside when shocks are fat-tailed:

$$\mathrm{ES}_q(\Delta F)\ \le\ c,$$

where ES_q is Expected Shortfall (CVaR) of performance residuals ΔF_t.

4. **Competence growth without destabilisation**

$$\mathbb{E}[\Delta \eta_t]\ \ge\ \alpha \ > 0 \quad\text{and}\quad \Pr(\text{Ψ-exit})\ \le\ \varepsilon .$$

5. **Precision/effort budget**
   Keep control effort bounded (a soft “conservation” of precision/energy):

$$\sum_{k\in \{b,T,\lambda\}}\!\!\!\mathbb{E}\!\Big[\Delta k_t^2\Big]\ \le\ B .$$

A compact Lagrangian you can optimise online:

$$\mathcal{L}(\pi)=\mathbb{E}\!\Big[\textstyle\sum_t\gamma^t r_t\Big] -\lambda_\Psi[\theta-\Omega_\Psi]_+ -\lambda_{\mathrm{ES}}[\mathrm{ES}_q(\Delta F)-c]_+ -\lambda_F\,\Phi(F_{\min},F_{\max}) +\lambda_\eta(\alpha-\mathbb{E}[\Delta \eta_t])_+ ,$$

with Φ any barrier that penalises F outside $[F_{\min},F_{\max}]$.

Algorithmic/representational core (state spaces & update rules — the how in principle)

Minimal state: $s_t=(\phi_t,F^*_t,b_t,T_t,\lambda_t,\eta_t,\chi_t)$.
Order parameter(s) for Ψ: e.g., synchrony/metastability m_t and band indicator $\mathbf{1}_{\Psi,t}$.

1. **Policy with Ψ-sieve + tail penalty**

$$\pi_t(a\mid s_t)\ \propto\ \exp\!\Big(\tfrac{Q_t(a)-\lambda_r\,\mathrm{CVaR}_q[L_t(a)]}{T_t}\Big)\; \mathbf{1}\{a\in\mathcal{A}_\Psi(s_t)\},$$

where $\mathcal{A}_\Psi=\{a:\Pr(\text{Ψ-exit}\mid s_t,a)\le \varepsilon\}$.
(Use Q or $-G_{\rm EFE}$; λ_r rises only on tail alarms.)

2. **Difficulty set-point servo (keep at the branch)**

$$F^*_{t+1}=F^*_t+\kappa_F\,(\mathcal{E}_t-F^*_t)-\rho_F\,\partial\Phi/\partial F^*\quad \text{(project to keep }F\in[F_{\min},F_{\max}]).$$

3. **Temperature / uncertainty controller**

$$T_{t+1}=T_t+\kappa_T\,(\chi_t-\chi^*)-\rho_T\,T_t,$$

with caps $T_{\min}\le T_t\le T_{\max}$; χ^* is your target meta-uncertainty.

4. **Stability–flexibility bias**

bt+1=bt−κb (mt−m*)−ρb bt,b_{t+1}=b_t-\kappa_b\,(m_t-m^*)-\rho_b\,b_t,

pulling toward a metastability set-point m*m^* (avoid lock-in or fragmentation).

5. **Representation/map update with bounded step (non-zero F)**

ϕt+1=arg min ϕ{ F(ϕ;st)⏟variational free energy + β DKL(pϕt ∥ pϕ)⏟trust region},\phi_{t+1} =\arg\min_{\phi}\Big\{\,\underbrace{F(\phi;s_t)}_{\text{variational free energy}}\; +\;\beta\,\underbrace{D_{\mathrm{KL}}\big(p_{\phi_t}\,\|\,p_{\phi}\big)}_{\text{trust region}}\Big\},

so each learning step reduces FF **a bit** but never to zero (trust-region keeps you in-band).

6. **Mode arbitration (creative vs control)**

mt={Creativeif χt>χhi and |ΔF^t|<δ,Controlotherwise,ΔF^t=κ(Et−Ft∗).m_t=\begin{cases} \text{Creative} & \text{if } \chi_t>\chi_{\rm hi}\ \text{and}\ |\widehat{\Delta F}_t|<\delta,\\ \text{Control} & \text{otherwise}, \end{cases} \quad \widehat{\Delta F}_t=\kappa(\mathcal{E}_t-F^*_t).

7. **Tail-alarm reflex (k-step schedule)**
   If ζ<ζ*\zeta<\zeta^* or J>J*J>J^* or ESq>c\mathrm{ES}_q>c: for next kk steps,

T ↑,λ ↓,b →bmid,T\!\uparrow,\quad \lambda\!\downarrow,\quad b\!\to b_{\rm mid},

then decay back via #3–#4 when alarms clear.

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five computational constraints (what/why) + seven lean update rules (how-in-principle). They’re modular: you can run 1–3 + 6–7 for a tiny agent, or plug all of them into a single online Lagrangian optimiser.