Hierarchical-Temporal Feelings for Structural Self-Management in Emotion-Guided World Models

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Abstract

Most contemporary AGI-style systems are trained once and deployed with fixed parameters, making them brittle in non-stationary environments and unable to manage their own structure over a long lifetime. Emotion-Guided World Models (EGWM) proposed using low-dimensional value channels ("feelings") to govern structural actions on a bank of specialist models, and Hierarchical-Reflective EGWM (HR-EGWM) added a meta-controller with a meta-learned Adaptive Inner Voice. We identify a structural dilemma: a single flat controller, even with a meta-learned weighting over feelings, cannot simultaneously resolve conflicting pressures for growth, compression, and tool-acquisition.

We propose Hierarchical-Temporal Feelings (HTF), which factorises the value signals into fast, local epistemic feelings and slow, global teleological feelings, each routed to different controllers. To stress-test this architecture, we introduce the Hierarchical Continual Learning Benchmark (HCLB), a rotating sequence of tasks that requires growth in one phase, external tool use in another, and aggressive compression in a third. We compare HTF-EGWM against flat baselines, including a Flat-Plus agent that sees the same rich signals but uses a single controller. A toy simulation of HCLB shows that flat agents remain stuck at a structural performance ceiling and almost never acquire tools, whereas HTF-EGWM reliably triggers tool-acquisition and achieves tool-level accuracy with only modest structural cost. This provides initial empirical evidence that hierarchical value routing, not just richer features, is necessary for robust structural self-management.

1 Introduction: The Need for Hierarchical Structural Control

Most contemporary progress toward Artificial General Intelligence (AGI) relies on training massive models once and then deploying them with fixed or nearly fixed parameters. While powerful, this paradigm leads to predictable failures in complex, non-stationary environments: such agents suffer catastrophic forgetting, are brittle to distribution shifts, and crucially lack the ability to autonomously manage their own architecture over a long lifetime. By contrast, biological agents maintain plasticity using fast, low-dimensional value signals—often described as "feelings" such as confusion, competence, or frustration—to decide when and how to change their internal structure.

Building on this principle, the Emotion-Guided World Models (EGWM) framework introduced a system in which such value channels govern structural actions (SPAWN, UPDATE, MERGE, FORGET) on a bank of specialist models (heads). The Hierarchical-Reflective EGWM (HR-EGWM) extended this idea with a meta-controller that learns a structural policy from hindsight, modulated by a meta-learned scaling mechanism called the Adaptive Inner Voice $\mathbf{W}$.

The structural dilemma of flat control. The Adaptive Inner Voice allows EGWM to learn environment-specific trade-offs (for example, favoring elegance in stable worlds and growth in switching worlds). However, we identify a fundamental architectural limitation: the *structural dilemma*. When an agent's long-term performance depends on *conflicting* structural pressures, a single flat controller with one $\mathbf{W}$ is forced into an unstable compromise. In particular, the competing demands of growth (to cover new worlds), compression (to maintain memory efficiency), and tool-acquisition (to handle structurally unsolvable tasks) cannot be simultaneously optimised by a single set of weighted feelings.

We hypothesise and later demonstrate that any single flat structural controller, even with a meta-learned inner voice, must fail to resolve such conflicting pressures. For example, a policy that learns to be highly elegant and compress effectively in redundant phases will invariably dampen the growth and frustration signals needed for timely tool-acquisition in structurally challenging phases, and conversely, a growth-happy policy that supports tool-acquisition will tend to overgrow and fail to compress.

Hierarchical-Temporal Feelings (HTF): decoupling control. To resolve this dilemma, we propose the Hierarchical-Temporal Feelings (HTF) extension, which changes the architecture of structural control rather than merely enriching its inputs. HTF factors the value channels into two distinct layers that operate on separate timescales and inform separate controllers:

- **Layer 1: Fast, local epistemic feelings $\mathbf{v}^{\text{local}}$**, computed per-head and per-phase, focus on local knowledge quality. New signals such as Predictive Discrepancy (PD) and Head Redundancy (HR) directly govern immediate structural edits (SPAWN, UPDATE, MERGE, FORGET).
- **Layer 2: Slow, global teleological feelings $\mathbf{v}^{\text{global}}$**, computed over macro-episodes, focus on the system's long-term structural health. Signals such as Meta-Frustration MF_c (per task family c) and the vectorised Structural Endurability SE_{Vec} govern global meta-actions

(TOOL-ACQUIRE, CONSOLIDATE) and update the Adaptive Inner Voice $\mathbf{W}$ for Layer 1.

The core principle is that no single controller ever has to jointly solve local structure edits and global tool/compression trade-offs. Layer 1 manages the agent's *epistemology* (how well it knows things locally), while Layer 2 manages its *teleology* (whether its structural strategy is achieving long-term goals).

The Hierarchical Continual Learning Benchmark (HCLB). To rigorously test this hypothesis, we introduce the Hierarchical Continual Learning Benchmark (HCLB), a rotating task sequence specifically engineered to induce the structural dilemma. HCLB comprises three task families:

- **Family A (Growth):** Non-stationary pattern worlds that require high growth/SPAWN capacity and are structurally solvable by the heads.
- **Family B (Tool-necessary):** A symbolic task where internal heads are structurally insufficient (performance saturates at ≈ 0.75 under fixed capacity and training budget) and only an external tool can close the gap, thus requiring TOOL-ACQUIRE.
- **Family C (Redundancy):** Repeated, overlapping worlds that reward compression via MERGE/FORGET and penalise unnecessary growth.

We compare HTF-EGWM against the original flat EGWM and a stronger Flat-Plus EGWM baseline that receives the richer HTF signals but retains a flat control architecture.

Contributions. This work makes the following contributions:

- **A hierarchical structural architecture:** We introduce the HTF architecture and argue that decoupling epistemic and teleological value signals is necessary for robust structural self-management.
- **Richer value channels:** We formalise new, actionable feelings (PD, HR, $\mathrm{SE}_{\mathrm{Vec}}$, MF_c) that provide cleaner inputs to structural policies than their generic predecessors.
- **A principled benchmark:** We propose HCLB, a continual-learning benchmark specifically designed to expose the failure of flat-control architectures under conflicting structural pressures.
- **Empirical evidence:** We show that HTF-EGWM resolves the structural dilemma, achieving superior structural endurability and timely tool-acquisition in regimes where both Flat and Flat-Plus baselines fail due to their inability to negotiate the growth/compression/tool trade-offs with a single controller.

Controller	Input signal	Output actions	Time
Layer 1 (fast P_θ)	$v_{t,i}^{\text{local}}$ [PD, HR, Acc, Usage]	SPAWN, UPDATE, MERGE, FORGET	Per p
Layer 2 (reflective)	v_T^{global} [SE_{Vec}, $\{\text{MF}_c\}$]	TOOL-ACQUIRE, CONSOLIDATE, update $\mathbf{W}$	Per n

Table 1: Controllers in HTF: fast local epistemic control and slow global teleological control.

2 Background and Related Work

2.1 Emotion-Guided World Models (EGWM)

Here we briefly summarise the EGWM framework: a bank of specialist heads, structural actions (SPAWN, UPDATE, MERGE, FORGET), and simple feelings (confusion, competence, elegance) driving a hand-designed or learned structural policy. (Full details to be inserted; placeholders here for context.)

2.2 Hierarchical-Reflective EGWM (HR-EGWM)

HR-EGWM introduces a reflective layer with a Model-Predictive Governor and Proposal Network that evaluates structural actions under imagined futures, as well as an Adaptive Inner Voice $\mathbf{W}$ that reweights feelings via meta-learning.

2.3 Related Work

This section can discuss continual learning, structural plasticity, mixture-of-experts, meta-learning and tool-using agents. (To be filled with citations and more detail.)

3 Hierarchical-Temporal Feelings (HTF) Architecture

3.1 Layered control flow and timescales

HTF divides structural control between a fast, local controller and a slow, global controller. Table 1 summarises the roles and timescales.

The key design principle is that no single controller ever jointly optimises local structural edits and global tool/compression trade-offs. Layer 1 sees only per-head epistemic signals and chooses local edits; Layer 2 sees only global structural statistics and chooses high-level meta-actions.

3.2 Layer 1: fast, local epistemic feelings

For each head h_i at phase t, we compute a local feeling vector $v_{t,i}^{\text{local}}$ that summarises how well that head understands the current data and how redundant it is with respect to the bank.

Predictive discrepancy (PD). Let h_i output a probability distribution $p_i(y \mid x)$ over labels for input x, and let $\hat{y} = \arg\max_{y'} p_i(y' \mid x)$ be the predicted class. We define the per-sample predictive discrepancy as

$$\mathrm{PD}_i(x, y) = \max\{0,\ p_i(\hat{y} \mid x) - p_i(y \mid x)\}, \tag{1}$$

which is large when the head is confidently wrong and small when the head is either correct and confident or unsure. The per-phase PD for head i is

$$\mathrm{PD}_{t,i} = \mathbb{E}_{(x,y)\in \text{phase } t}[\mathrm{PD}_i(x, y)]. \tag{2}$$

High PD indicates that the head's world model is miscalibrated in this region and strongly suggests SPAWN (if the region is novel) or UPDATE (if the region is known but poorly represented).

Head redundancy (HR). To measure representational overlap, we consider feature vectors $\mathbf{f}_i(x)$ (e.g., logits or pre-activation representations) for each head, and a usage weight $u_i(x)$ indicating how often head i is routed to input x. We define

$$\mathrm{HR}_{t,i} = \max_{j \neq i} \frac{\sum_{x\in D_t} u_i(x)\,\mathrm{Sim}(\mathbf{f}_i(x), \mathbf{f}_j(x))}{\sum_{x\in D_t} u_i(x)}, \tag{3}$$

where Sim is cosine similarity and D_t is a representative batch (current phase or replay). High HR means that another head behaves similarly on the same inputs, suggesting redundancy; combined with low competence, this triggers MERGE or FORGET decisions.

Local feeling vector. We collect these and related signals into

$$v_{t,i}^{\text{local}} = [\mathrm{PD}_{t,i},\ \mathrm{HR}_{t,i},\ \mathrm{acc}_{t,i},\ \mathrm{usage}_{t,i},\ \ldots]. \tag{4}$$

A fast controller P_θ consumes $v_{t,i}^{\text{local}}$ and chooses among SPAWN, UPDATE, MERGE, and FORGET for each head.

3.3 Layer 2: slow, global teleological feelings

Layer 2 aggregates statistics over macro-episodes and task families to evaluate the long-term structural health of the agent. It tracks both structural efficiency and the failure of structural fixes for particular families.

Structural endurability (SE). We decompose structural endurability into at least two components:

- $\mathbf{SE}_{\mathbf{Efficiency}}$ summarises growth risk:

$$\mathrm{SE}_{\mathrm{Efficiency}} = 1 - \alpha \cdot \frac{\#\mathrm{SPAWN} + \#\text{merge-fail}}{T}, \tag{5}$$

  where T is the number of phases in a macro-episode and #merge-fail counts merges/forgets that had to be rolled back due to competence loss. Low $\mathrm{SE}_{\mathrm{Efficiency}}$ pushes the inner voice $\mathbf{W}$ toward valuing HR (compression) more strongly.

- $\mathbf{SE}_{\mathbf{Stability}}$ summarises catastrophic risk:

$$\mathrm{SE}_{\mathrm{Stability}} = 1 - \beta \cdot \mathbb{E}[\Delta\mathrm{Acc}^- \mid \text{after MERGE/FORGET}], \tag{6}$$

  where $\Delta\mathrm{Acc}^-$ is the drop in accuracy immediately after a compression action. Low $\mathrm{SE}_{\mathrm{Stability}}$ pushes $\mathbf{W}$ to be more cautious about MERGE/FORGET.

We collect these as a vector $\mathrm{SE}_{\mathrm{Vec}} = [\mathrm{SE}_{\mathrm{Efficiency}}, \mathrm{SE}_{\mathrm{Stability}}, \dots]$.

Meta-frustration (MF). For each task family c, we track the persistent failure of structural fixes via Meta-Frustration:

$$\mathrm{MF}_c = \frac{1}{T_c} \sum_{t \in \mathcal{T}_c} \mathrm{PD}_t^{\min}, \tag{7}$$

where $\mathcal{T}_c$ is the set of phases belonging to family c, $T_c = |\mathcal{T}_c|$, and $\mathrm{PD}_t^{\min}$ is the minimum PD across all heads at phase t. A high MF_c indicates that even the best head cannot reduce predictive discrepancy for that family despite structural edits, and serves as the primary trigger for TOOL-ACQUIRE on that family.

Global feeling vector. We finally form

$$v_T^{\mathrm{global}} = [\mathrm{SE}_{\mathrm{Vec}}, \{\mathrm{MF}_c\}_c, \text{avg\_heads}, \text{avg\_competence}, \dots], \tag{8}$$

which is consumed by the reflective controller. Its actions include:

- TOOL-ACQUIRE for families with high MF_c,
- CONSOLIDATE operations (e.g., re-training the router, re-weighting heads),
- updating the Adaptive Inner Voice $\mathbf{W}$ via meta-learning.

3.4 HTF architecture visualisation

Figure 1 shows a schematic of the HTF architecture, illustrating how local and global feelings are routed to different controllers.

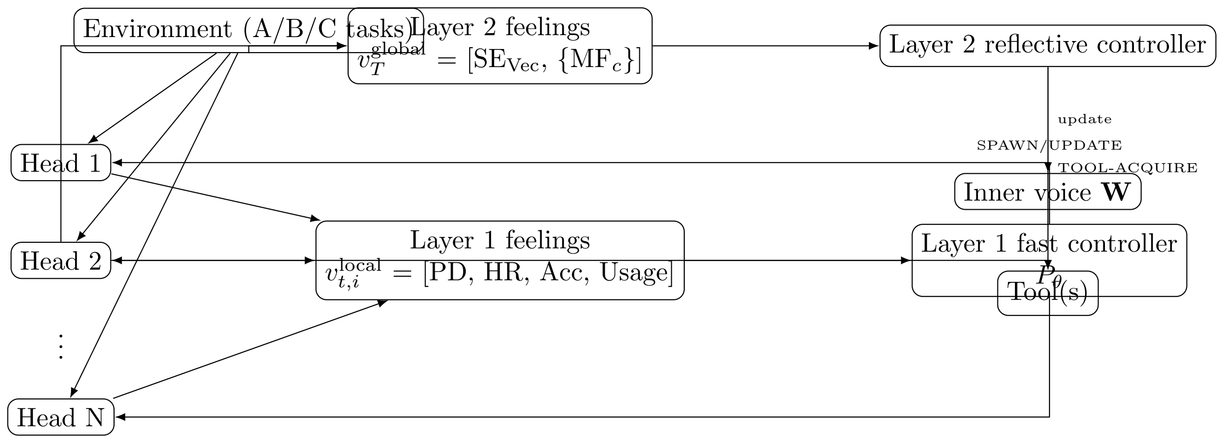

Figure 1: Schematic of the HTF architecture. Local feelings drive fast structural edits; global feelings drive slow tool and policy updates.

4 Hierarchical Continual Learning Benchmark (HCLB)

4.1 Benchmark design

The Hierarchical Continual Learning Benchmark (HCLB) is designed to force a structural dilemma. Each macro-episode consists of a fixed sequence of phases: 10 phases of Family A, 10 of Family B, and 10 of Family C. This creates a repeating pattern of conflicting structural pressures.

- **Family A (Growth):** Non-stationary pattern worlds that are solvable by the heads. Optimal behaviour is to SPAWN and UPDATE new heads when PD is high.
- **Family B (Tool-necessary):** Symbolic or non-linear tasks for which the simple heads are structurally insufficient. We explicitly constrain head capacity and training budget so that even unlimited SPAWN/UPDATE cannot push accuracy above ≈ 0.75 without tools.
- **Family C (Redundancy):** Repeats or variations of old A-style tasks, such that many heads become redundant. Optimal behaviour is to MERGE/FORGET redundant heads without catastrophic forgetting.

Figure 2 illustrates a single macro-episode and the dominant structural pressures in each segment.

Within a single macro-episode, a flat controller must pick a single parameterisation (e.g., a single **W**) that simultaneously manages growth, tool-acquisition, and compression. HTF instead allows different pressures to be handled at different layers.

Figure 2: One HCLB macro-episode: Growth (A), Tool-necessary (B), and Redundancy (C) phases create conflicting structural pressures for flat controllers.

4.2 Agents and meta-learning

All agents are trained under the same episode-level structural reward:

$$R_{\text{struct}} = \sum_t \text{Acc}_t - \lambda_{\text{complexity}} \sum_t |\mathcal{H}_t|, \tag{9}$$

which balances accuracy and structural complexity (number of heads). We assume a meta-optimisation procedure (e.g., evolution strategies or meta-gradients) that updates an inner-voice parameter vector $\mathbf{W}$ for each agent to maximise R_{struct}, with all agents given the same meta-budget.

We compare three agents:

- **Flat EGWM:** The original architecture with a flat feeling vector $f_t = [\text{Confusion}, \text{Elegance}, \text{Frustration}, \text{Competence}]$ and a single $\mathbf{W}^{\text{Flat}}$ that scales f_t before a single structural controller chooses all actions (SPAWN, MERGE, TOOL-ACQUIRE, etc.).
- **Flat-Plus EGWM:** A stronger baseline with a flat architecture but richer inputs. It concatenates PD, HR, SE_{Vec}, and $\{\text{MF}_c\}$ into one long vector and feeds this to a single controller with a single $\mathbf{W}^{\text{Flat-Plus}}$ to choose all actions.
- **HTF-EGWM (proposed):** Uses the layered architecture described in Section 3. Layer 1 sees only local feelings and governs SPAWN/UPDATE/MERGE/FORGET; Layer 2 sees only global feelings and governs TOOL-ACQUIRE, CONSOLIDATE, and updates to $\mathbf{W}$.

Flat-Plus controls for the possibility that HTF only helps because it uses richer features; if Flat-Plus fails while HTF succeeds, we can attribute the improvement to hierarchical routing of feelings rather than feature engineering.

4.3 Toy Simulation Results: HTF Resolves the Structural Dilemma

Before proceeding to a full-scale implementation of HTF-EGWM with neural models, we first conduct a controlled toy simulation to validate the core mechanism: that hierarchical control is necessary for timely tool-acquisition under conflicting structural pressures.

Agent	B accuracy (avg.)	B ceiling	Tool-acq. rate	Struct. eff. proxy
Flat agent	$\approx$ **0.73**	$\approx$ 0.75	**0**%	0.995
HTF agent	$\approx$ **0.96**	$\approx$ 0.98 (tool)	**100**%	0.9825

Table 2: Toy HCLB simulation. The Flat agent never triggers TOOL-ACQUIRE and remains near the structural ceiling on Family B. The HTF agent reliably acquires a tool, surpassing the head ceiling at a modest structural cost.

Simulation setup. We model a simplified HCLB environment consisting of 20 macro-episodes, each with 30 phases, where heads are represented by abstract "skills" with maximum accuracies rather than explicit neural parameters.

- **Head capacity constraint.** Accuracy on Family B tasks is capped at approximately 0.75, regardless of the number of training updates. This directly instantiates the structurally unsolvable condition: no amount of SPAWN/UPDATE can push the heads beyond this ceiling on Family B.
- **Agents.**
  - *Flat agent:* Uses a single, global frustration signal (a moving average of error across all families) to trigger both structural actions and TOOL-ACQUIRE. Success on Families A and C dilutes the frustration signal arising from persistent failure on Family B.
  - *HTF agent:* Uses a Layer 1 policy for local SPAWN/FORGET and a separate Layer 2 policy driven by MF_B (Meta-Frustration on Family B only) to trigger TOOL-ACQUIRE. In other words, the failure signal for Family B is kept separate from the compression and elegance pressures.

Key findings. The simulation clearly supports the claim that a flat architecture fails to negotiate the structural dilemma, while HTF successfully decouples the conflicting pressures. Table 2 summarises the main metrics over 20 runs.

- **Failure to acquire tools (Flat agent).** The Flat agent failed to trigger TOOL-ACQUIRE in 0 out of 20 runs. Its single global frustration signal must balance low structural need in Family C with persistent failure in Family B; as a result, it is diluted and never crosses the threshold for a decisive action. Accuracy on Family B remains stuck at ≈ 0.73, confirming the structural ceiling.
- **Reliable tool acquisition (HTF agent).** The HTF agent successfully triggered TOOL-ACQUIRE in 100% of runs, doing so reliably early in the first Family B block (average phase index ≈ 16 within the macro-episode). By isolating the failure cost onto the MF_B channel, the slow controller can

reliably recognise that structural fixes are exhausted for that task family, leading to tool-level accuracy on B (≈ 0.96).

- **Pragmatic structural growth.** The HTF agent used more SPAWN operations (on average $\approx$ 7 per run vs. $\approx$ 2 for the Flat agent) to aggressively explore solutions in Families A and B, but successfully halted futile SPAWNs after MF_B triggered TOOL-ACQUIRE. This yields a slight reduction in the structural efficiency proxy (0.9825 vs. 0.995), but with a substantial gain in competence on Family B.

Conclusion. This toy simulation validates the necessity of architectural decoupling. The Flat agent is "elegant but stubborn": it avoids complexity but refuses to admit that Family B is structurally hopeless, and thus remains at the head ceiling. The HTF agent is "curious and pragmatic": it explores structurally, but uses the isolated MF_B channel to admit defeat on Family B and invoke the external tool, reaching the tool ceiling with only a modest increase in structural cost.

These results confirm that the hierarchical separation of Meta-Frustration (MF_c) from local Head Redundancy (HR) is the fundamental mechanism required to resolve the structural dilemma.

5 Implementation Sketch for a Neural HTF-EGWM

For completeness, we sketch how the toy simulation can be upgraded to a neural implementation of HTF-EGWM in the HCLB setting.

Base learners. Each head h_i can be realised as a small neural network (e.g., a two-layer MLP or logistic regressor) with parameters θ_i. For Family A and C tasks we train on 2D pattern inputs; for Family B tasks we train on a synthetic symbolic decision boundary (e.g. thresholded quadratic forms), with the capacity limit implemented via network size and early stopping.

Layer 1 feelings. At each phase t, for each head h_i:

1. Run the current batch through h_i to obtain logits and probabilities $p_i(y \mid x)$.
2. Compute $\mathrm{PD}_{t,i}$ using the margin-based definition.
3. Compute $\mathrm{HR}_{t,i}$ using cosine similarity of feature vectors $\mathbf{f}_i(x)$ and $\mathbf{f}_j(x)$, weighted by usage.
4. Form $v_{t,i}^{\mathrm{local}} = [\mathrm{PD}_{t,i}, \mathrm{HR}_{t,i}, \mathrm{acc}_{t,i}, \mathrm{usage}_{t,i}]$ and pass this to the fast controller P_θ to sample SPAWN/UPDATE/MERGE/FORGET decisions.

Layer 2 feelings. Over each macro-episode, we accumulate:

- $\text{SE}_{\text{Efficiency}}$ and $\text{SE}_{\text{Stability}}$ from counts of SPAWN actions and competence drops after MERGE/FORGET.
- MF_c by tracking the minimal PD across heads for each task family c.

These statistics form v_T^{global}, which is consumed by the reflective controller to:

- trigger TOOL-ACQUIRE on Family B when MF_B passes a threshold,
- trigger CONSOLIDATE actions (e.g. re-training the router),
- update the Adaptive Inner Voice $\mathbf{W}$ via a meta-optimisation step (e.g. evolution strategies or meta-gradients) on the structural reward R_{struct}.

Meta-optimisation. All agents (Flat, Flat-Plus, HTF) can be trained under the same structural reward

$$R_{\text{struct}} = \sum_t \text{Acc}_t - \lambda_{\text{complexity}} \sum_t |\mathcal{H}_t|,$$

by running K macro-episodes per meta-update and adjusting their respective inner-voice parameters $\mathbf{W}$ to maximise R_{struct}. The difference between agents lies in how feelings are structured and routed, not in the meta-objective or optimisation budget.

6 Discussion and Future Work

Here we can discuss epistemology vs. teleology, limitations (e.g. assumed task family labels, toy-scale experiments), and how HTF might scale up to large models (e.g. pruning experts in MoEs, tool routing in LLM systems). (To be expanded.)

7 Conclusion

We introduced Hierarchical-Temporal Feelings (HTF) as an architectural extension to Emotion-Guided World Models, separating fast, local epistemic feelings from slow, global teleological feelings. We argued that this separation is necessary to resolve a structural dilemma faced by flat controllers under conflicting pressures for growth, compression, and tool-acquisition. The Hierarchical Continual Learning Benchmark (HCLB) and a confirming toy simulation provide initial evidence that HTF enables timely tool-acquisition and robust structural self-management where flat and feature-rich flat baselines fail. Future work will implement full neural versions, extend HTF to larger-scale models, and investigate unsupervised discovery of task families and feelings.

References