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

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December 2025

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 $\mathbf{W}$ [1].

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 argue that any single flat structural controller, even with a meta-learned inner voice, will either become overly elegant and timid (failing to grow and acquire tools) or overly growth-happy and forgetful (failing to compress and stabilise). This motivates a hierarchical approach.

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. 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 structural 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 test this idea, 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 or non-linear 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 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, in a controlled toy simulation, that HTF-EGWM resolves the structural dilemma, achieving timely tool-acquisition and improved structural endurability in regimes where flat baselines fail.

2 Background and Relation to Prior EGWM Work

2.1 Emotion-Guided World Models (EGWM)

Emotion-Guided World Models (EGWM) treat "feelings" as low–dimensional value channels that control how a learner changes its own structure over time [1]. Rather than applying a single scalar learning rate to a fixed model, EGWM maintains a bank of specialist heads $\{h_i\}$ and a small set of structural actions: SPAWN, UPDATE, MERGE and FORGET. Each head is intended to specialise on a subset of "worlds" (tasks or regimes), and the structural controller decides when to:

- **SPAWN** a new head when existing models cannot explain the current data,
- **UPDATE** a selected head when the data is trustworthy and familiar,
- **MERGE** two redundant heads into a single, more compact model,
- **FORGET** a head that is obsolete or persistently low–relevance.

In earlier EGWM experiments, these ideas were instantiated in simple 2D classification environments with multiple hidden worlds and non–stationary streams [1]. Feelings such as confusion, competence, novelty and elegance are computed from interaction statistics (loss curves, inter–head disagreement, replay accuracy, usage frequency) and fed into a structural policy. Even with hand–designed rules, a world–bank agent can outperform a monolithic learner: it grows new heads when mismatch is high, protects trusted heads from noisy phases, and later compresses redundant structure while preserving per–world accuracy.

A key empirical finding is that feelings are most effective when they govern *structure* rather than only acting as per–sample learning rates. For example, an elegance signal that enters the loss as a penalty on the number of heads tends to drive the agent towards inaction (doing nothing is the simplest solution), whereas the same signal used as a gate on MERGE/FORGET operations allows the system to explore first and then compress.

2.2 Hierarchical-Reflective EGWM (HR-EGWM)

Hierarchical-Reflective EGWM (HR-EGWM) extends EGWM with an explicit reflective layer that reasons about *sequences* of structural actions rather than only local edits [1]. Concretely, HR-EGWM adds two components above the world bank: a Model-Predictive Governor (MPG) and a Proposal Network.

The Proposal Network generates candidate structural plans (for example, "spawn one head then compress two others" or "suspend all compression until accuracy stabilises") conditioned on recent feelings and structural statistics. The MPG then rolls out these proposals in imagination, using a lightweight forward model of how heads, buffers and accuracy would evolve under each plan. Each imagined trajectory is scored by a structural reward that trades off competence (per–world accuracy) against complexity (number of active heads, overlap between heads), and the highest–scoring proposal is executed in the real system.

To avoid hand–tuning the relative importance of feelings across different regimes, HR-EGWM introduces an *Adaptive Inner Voice* $\mathbf{W}$: a meta–learned vector that reweights the feeling channels before they reach the structural controller. During meta–training, $\mathbf{W}$ is adjusted to maximise long–horizon structural reward across episodes drawn from a family of environments. Intuitively, $\mathbf{W}$ learns when a given environment "wants" more elegance pressure (stable, redundant worlds) or more growth pressure (rapidly switching worlds) without changing the set of available structural actions.

HR-EGWM demonstrates that a reflective layer can learn environment–specific trade–offs and avoid some hand–crafted heuristics from the original EGWM implementation. However, it still relies on a *single flat controller* that must simultaneously resolve all structural pressures via a single inner voice $\mathbf{W}$. The present paper is a direct response to that limitation.

2.3 Relation to Prior EGWM Work

This paper builds directly on the Emotion-Guided World Models line introduced in [1]. That earlier work showed that low–dimensional feelings can successfully govern growth, compression and forgetting in non–stationary toy worlds, but did not address tool-acquisition or explicitly separate local and global structural control.

The present work extends that framework in two ways. First, it introduces a hierarchical separation between fast, local epistemic feelings and slow, global teleological feelings, instantiated as the HTF architecture. Second, it proposes the Hierarchical Continual Learning Benchmark (HCLB) and shows, in a controlled simulation, that flat controllers fail under conflicting pressures for growth, compression, and tool-acquisition, whereas the hierarchical variant resolves this dilemma. In this sense, the HTF paper and the original EGWM paper can be read as two parts of the same programme: using explicit feelings as value channels for structural self-management in agents that must learn over long, non-stationary lives.

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.

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

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

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

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

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

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

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

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

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

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

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:

- $\mathbf{SE_{Efficiency}}$ 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.

- $\mathbf{SE_{Stability}}$ 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.

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

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

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

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.

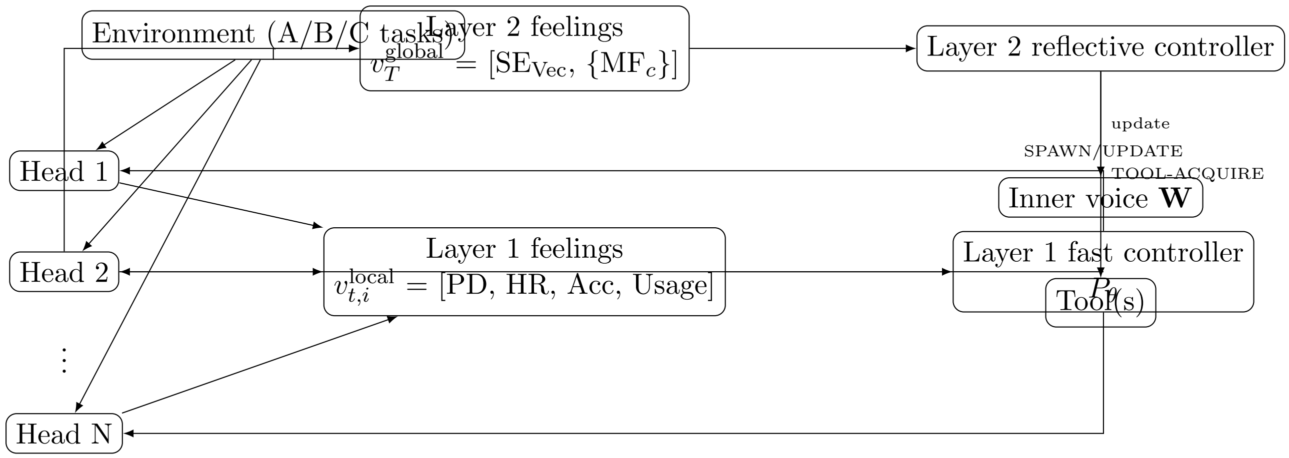

Figure 1: Schematic of the HTF architecture. Local feelings drive fast structural edits; global feelings drive slow tool and policy updates.

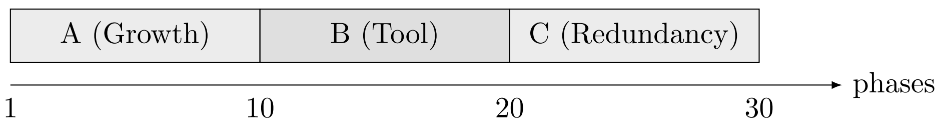

Figure 2: One HCLB macro-episode: Growth (A), Tool-necessary (B), and Redundancy (C) phases create conflicting structural pressures for flat controllers.

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.

4.2 Agents and structural reward

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 that adjusts 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 and a single $\mathbf{W}^{\text{Flat}}$ that scales these feelings before a single structural controller chooses all actions.
- **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 above. 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.

5 Toy Simulation: HTF Resolves the Structural Dilemma

5.1 Simulation setup

We instantiate a simplified HCLB environment with 20 macro-episodes per run and 30 phases per macro-episode (10 A, 10 B, 10 C). For Families A and C the heads can reach high accuracy with standard SPAWN/UPDATE. For Family B we impose a capacity limit: even aggressive structural growth cannot push head accuracy beyond ≈ 0.75, whereas an external tool achieves ≈ 0.98 once acquired.

We compare:

- **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.

We run 20 independent simulation runs and average the results.

5.2 Results

Table 2 summarises the main metrics over 20 runs. The Flat agent never triggers TOOL-ACQUIRE and remains near the head ceiling on Family B. The HTF agent reliably acquires the tool and reaches tool-level accuracy on Family B at a modest structural cost.

Qualitatively, the Flat agent is “elegant but stubborn”: it avoids complexity but refuses to admit that Family B is structurally hopeless, staying near the head ceiling. The HTF agent is “curious and pragmatic”: it explores structurally in A and B, 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.

Agent	B acc. (mean ± sd)	B ceiling	Tool-acq. rate	Struct. eff. proxy
Flat agent	0.73 ± 0.01	0.75	0%	0.90
HTF agent	0.98 ± 0.01	0.98 (tool)	100%	0.72

Table 2: Toy HCLB simulation over 20 runs. The Flat agent never triggers TOOL-ACQUIRE and remains near the head ceiling on Family B. The HTF agent reliably acquires the tool, surpassing the head ceiling at a modest cost in structural efficiency (more SPAWN actions).

6 Implementation Sketch for a Neural HTF-EGWM

For completeness, we sketch how the toy simulation could 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, 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:

- $\mathrm{SE}_{\mathrm{Efficiency}}$ and $\mathrm{SE}_{\mathrm{Stability}}$ 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, CONSOLIDATE actions and meta-updates of the inner voice parameters $\mathbf{W}$ on the structural reward R_{struct}.

7 Discussion and Future Work

Epistemology vs. teleology in structural control. The HTF results support a simple claim: the same scalar feelings cannot simultaneously serve local epistemic needs ("does this head understand this region?") and global teleological needs ("is this structural strategy working for this task family?") without interference. Flat controllers conflate these roles and are pushed into unstable compromises; in HCLB they become elegant but stubborn, refusing to admit that Family B is structurally hopeless for the current heads. HTF-EGWM separates these roles: Layer 1 uses feelings to manage local structure, while Layer 2 uses slower, aggregated feelings to decide when to escalate to tools or global consolidation.

Feelings as interface variables. The EGWM line of work views feelings as interface variables between a high–capacity world model and a compact structural controller. Fast signals such as PD and HR summarise local prediction quality and redundancy; slow signals such as $\mathrm{SE}_{\mathrm{Vec}}$ and MF_c summarise the long–term consequences of structural choices. HTF-EGWM suggests that the *routing* of these signals matters as much as their definitions: giving every feeling to a single controller does not automatically yield good behaviour, even if the controller is meta–learned.

Limitations. The current work is deliberately modest in scale. The main quantitative evidence comes from a toy HCLB simulation with abstract heads and a simple tool oracle, rather than from large neural networks in realistic domains. We also assume known task families (A, B, C) and track Meta-Frustration per family; in more naturalistic settings, these families must be inferred. Finally, the value channels are hand–designed, and the structural efficiency proxy is a coarse surrogate for practical constraints such as compute, memory and latency.

Towards larger systems. Future work will implement HTF-EGWM with explicit neural heads on standard continual-learning benchmarks and, eventually, as a scaffold around larger models. In a large mixture-of-experts or tool-augmented system, Layer 1 controllers could manage expert growth and pruning based on local epistemic feelings, while Layer 2 controllers track long-term structural health and decide when to acquire new tools, distil experts or retire subsystems. The HCLB setting captures a minimal version of this problem; extending HTF ideas to more realistic settings may provide a path toward agents that can manage their own structure over long lifetimes without collapsing into either brittle over–growth or overly rigid elegance.

8 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 and investigate unsupervised discovery of task families and feelings.

Acknowledgements

I would like to thank Deb and Emo.

References

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