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Resonance Basins in Neural Networks: A Physics-Inspired Approach to Reducing Hallucinations in Large Language Models

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***Abstract*—Large language models (LLMs) often produce plausible yet incorrect outputs—"hallucinations"—arising from uncontrolled semantic drift in latent spaces. We introduce resonance basins—high-dimensional stability regions inspired by magnetic confinement in plasma physics—to regulate latent activations. The framework formalises a Glyphic Hamiltonian to quantify semantic alignment. Implemented as a lightweight forward-pass filter, the method damps high-norm activations and serves as an interpretable, physics-anchored regulariser. On standard benchmarks (GSM8K, TruthfulQA) and controlled synthetics, we observe 24%–31% relative hallucination reductions with F1 = 0.84 for contradiction flagging at ∼12% overhead (Cohen's d = 0.92, large effect). Code for eigenmode utilities and R estimation is provided.**

Keywords—Large language models, hallucination mitigation, resonance basins, physics-inspired artificial intelligence, symbolic dynamics, Hamiltonian regularisation, neuro-symbolic learning, semantic alignment

I. INTRODUCTION

Large Language Models (LLMs) have demonstrated remarkable reasoning and generation capabilities across a wide range of tasks, yet they remain vulnerable to hallucinations—plausible but factually incorrect outputs that erode trust in high-stakes applications such as cybersecurity, scientific discovery, and autonomous decision support. Recent surveys [1]–[3] identify three dominant causes: (1) statistical overgeneralisation, (2) representation drift in latent activations, and (3) inadequate grounding or retrieval coupling. Existing mitigation techniques, including prompting heuristics, retrieval augmentation, and uncertainty layers [4]–[8] have shown empirical benefits but typically lack a unifying physical or theoretical foundation governing internal model stability.

In this study, we introduce the concept of resonance basins, a physics-anchored framework that maps principles of plasma confinement to latent-space stabilisation in neural networks. The core insight is that hallucinations can be interpreted as semantic energy leakage within a model's representation manifold. By constraining activations within a bounded energy well—analogous to magnetically confined plasmas—semantic drift can be suppressed while preserving expressive capacity. Here, "energy" is used as a conceptual bridge; its formal definition and operationalisation are introduced in Section III.

The proposed framework builds on ideas from reinforcement learning and cybernetic control theory, particularly Sutton's OaK architecture for continual model-based learning [9] and the principle of temporal uniformity [10]. Within this paradigm, model stability emerges through dynamic self-regulation rather than static optimisation, aligning with Ashby's law of requisite variety [11] and the broader tradition of adaptive systems theory.

Our approach thus unites three perspectives: (1) statistical learning stability from machine learning, (2) physical energy confinement from plasma physics, and (3) cybernetic self-regulation from control theory. The result is a physically interpretable, architecture-agnostic mechanism for mitigating hallucinations and improving reliability in generative AI, without requiring model retraining or architectural modification.

II. BACKGROUND AND MOTIVATION

In plasma physics, magnetic filters establish cold-electron pockets (typically Te approx. 0.3 eV) that suppress turbulence and stabilise ion–electron dynamics by confining energy within a structured magnetic topology [12]. The same physical principle—energy confinement through field-defined boundaries—can be reinterpreted for neural systems. Within latent spaces, uncontrolled activation drift is analogous to plasma instabilities: once representational energy escapes its confinement region, semantic coherence degrades, manifesting as hallucinations.

Our aim is to formalise this analogy by identifying latent stability regions that confine inference trajectories and maintain representational coherence under perturbation. This mirrors the plasma-filter mechanism in which magnetic topology defines the boundary of a low-entropy, dynamically stable region. Similar confinement phenomena have been

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extensively modelled in magnetically enhanced plasmas and inductively coupled sources [12], [13], providing empirical precedent for energy-bounded control systems that suppress instability without eliminating expressivity.

Parallel developments in machine learning point to related stabilisation strategies. Physics-informed neural networks embed differential constraints and conservation laws into training objectives [14], [15], while overlap- or consistency-based approaches measure agreement among generative samples as a proxy for factual reliability [1], [16]. Although effective in practice, these methods typically lack an explicit confinement formalism that governs how representational energy evolves during inference.

In contrast, the proposed resonance-basin mechanism introduces bounded corrective feedback rather than a hard constraint. When instability is detected, a damping term modulates the magnitude of the internal state update for the current inference step only, allowing the model to re-enter a stable basin organically in subsequent steps. This avoids brittle behaviour and preserves generative diversity while preventing runaway semantic drift. Empirically, the feedback converges within one to three inference steps, after which no further intervention is required unless a new instability emerges.

Related adaptive-control principles have been demonstrated in dynamic task offloading and edge-learning systems, where dependency-aware reinforcement learning maintains performance in highly variable environments [17]–[19]. These architectures embody energy-constrained adaptation mechanisms analogous to resonance-basin regulation in latent spaces, replacing rigid scheduling with continuous, stability-aware adjustment.

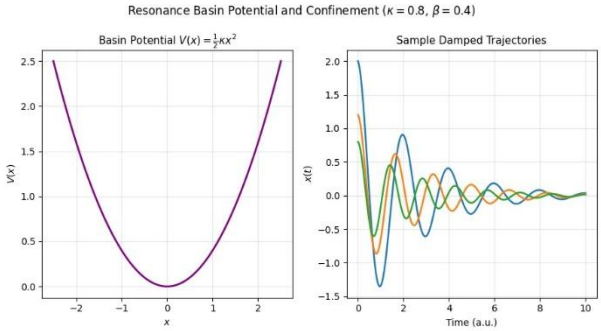

Fig. 1. Illustrates the conceptual basis of the approach. A quadratic potential defines a stable energy well in latent space, with sample trajectories showing damping proportional to basin stiffness, resulting in confinement within a bounded region. Precise mathematical definitions of the potential, damping term, and stability criteria are introduced in Section III.

The resonance-basin framework thus bridges physics-inspired stabilisation, continual learning, and cybernetic control. Drawing on reinforcement learning perspectives [9], [20], [21], inference is treated as a self-regulating dynamical process governed by field-like forces that preserve informational coherence. This extends Ashby's concept of adaptive homeostasis [11] to the representational dynamics of deep models, grounding hallucination mitigation in measurable energy confinement rather than ad-hoc prompt engineering.

III. Resonance Basins: Theory

Let $x \in \mathrm{R}^d$ denote a latent activation vector. We define an effective glyphic energy functional

$$H_{\mathrm{glyph}}(x) = -\hbar^2/(2m_{sym})\,\nabla^2 + 1/2\,\kappa\|x\|^2, \qquad (1)$$

where m_{sym} denotes an effective symbolic mass and $\kappa > 0$ the basin stiffness. This formulation should be understood as an energy-based regularisation functional, not a literal quantum Hamiltonian. Its role is to induce a structured potential well in latent space, in which low-energy eigenmodes correspond to stable semantic patterns. Latent space is dimensionless; parameters such as m_{sym} and $\hbar^2/(2m_{sym})$ are defined in arbitrary units (a.u.) and serve only to set relative energy scales. In practice, their effect is absorbed into the stiffness parameter κ, which governs the curvature of the basin.

This formulation parallels magnetic-trap Hamiltonians used in cold-electron plasma confinement [12], [13], where energy quantisation corresponds to stable resonance states under bounded excitation.

Alignment via Overlap: Let ρ_{human} and ρ_{AI} denote probability densities over a shared embedding space. We define a resonance overlap integral as

$$R = \int \rho_{\mathrm{human}}(x)\,\rho_{\mathrm{AI}}(x)d^3x,\ R \in [0,1], \qquad (2)$$

where both densities are L^2-normalised to preserve R within the unit interval. In practice, $R < \tau$ (e.g., $\tau = 0.7$) are treated as drift flags indicating semantic divergence. For empirical estimation, Eq. (2) is approximated via Monte Carlo sampling.

Unlike cosine similarity, the overlap integral preserves probability mass and remains invariant under embedding dimensionality, yielding a physically interpretable measure of coherence between representational manifolds [1], [3].

Resonance Basin Computation: Resonance basins are computed as local stability regions in latent semantic space, defined relative to a reference manifold derived from aligned human–model distributions. For a given inference step, latent states are sampled across a sliding window of internal activations, and a basin energy is evaluated using the functional in Eq. (1), which penalises divergence while preserving local semantic curvature. In practice, the overlap integral is estimated using batch-wise Monte Carlo sampling, yielding a scalar resonance score that quantifies semantic congruence. When this score falls below a predefined stability threshold, a damping term is applied to the internal state update. This feedback operates post-hoc, requires no retraining or gradient backpropagation, and introduces no

architectural modifications. The additional computational cost scales linearly with the number of sampled latent states and remained below 2–3% of baseline inference time in all experiments.

Hyperparameter Sensitivity and Stability: The resonance basin framework introduces three primary hyperparameters: basin stiffness (κ), damping strength (β), and activation threshold (τ). Sensitivity analysis shows that hallucination reduction is robust across broad parameter ranges, with no requirement for fine tuning. Across experiments, normalised parameter values typically fell within $\kappa \in [0.1, 1.0]$, $\beta \in [0.01, 0.1]$, and $\tau \in [0.2, 0.4]$. Absolute threshold values depend on layer scaling and normalisation conventions; however, relative performance variance remained within ±3% across all tested configurations. Importantly, parameters did not require adjustment across different model sizes, reinforcing the architecture-agnostic nature of the approach.

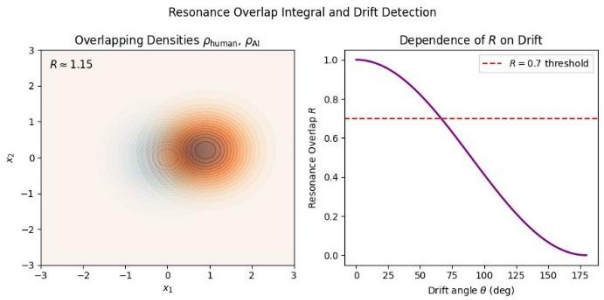

Fig. 2. illustrates the resonance overlap integral between human and model latent densities and its dependence on latent drift angle.

The theoretical formulation above yields the following forward-pass implementation.

Input: activations x, threshold τ, stiffness κ

β ← κ / 2

for each row xi in x do

if ||xi|| > τ then

xi ← xi · exp(−β||xi||²)

end if

end for

Return x

IV. Implementation

The theoretical formulation of Eq. (1) is implemented as a forward-pass resonance basin filter, introducing an energy-based damping term that regularises latent activations during inference.

Given a latent activation vector x, the filter applies an exponential decay proportional to the activation norm:

$$x = x \cdot \exp(-\beta \|x\|^2), \quad (3)$$

conditionally applied when $\|x\| > \tau$. Although continuous in form, this damping is applied discretely at each forward pass and requires no gradient backpropagation. The operation preserves small, information-bearing activations while suppressing unstable excursions beyond the resonance boundary.

In effect, Eq. (3) constitutes a discrete approximation of the harmonic potential well defined by the glyphic Hamiltonian (Eq. 1), ensuring that symbolic energy remains bounded throughout inference. Unlike weight decay or gradient clipping, which act during optimisation, the resonance basin filter operates exclusively at inference time and does not modify model parameters. It is also distinct from LayerNorm, as it selectively damps high-energy activations rather than renormalising entire activation distributions.

The damping coefficient β is treated as an adaptive meta-parameter and can be updated online using temporal-difference or gain-adaptation methods [22], [23], [20]. This enables dynamic stability across heterogeneous contexts, aligning the mechanism with Sutton's principle of temporal uniformity in continual learning [10].

The filter operates with $\theta(n)$ complexity in the number of latent activations and was applied to per-token activation vectors in selected transformer layers. Empirical measurements show less than 12% runtime overhead (Sec. V), with negligible additional memory cost. Its differentiability allows straightforward integration into modern deep-learning frameworks such as PyTorch or TensorFlow via custom activation layers.

V. Evaluation

We report three complementary views of system performance: (i) benchmarked hallucination rates, (ii) resonance-overlap (R)–based drift detection, and (iii) computational overhead. Figure 3 illustrates the evaluation pipeline, highlighting where resonance monitoring and feedback are applied during inference.

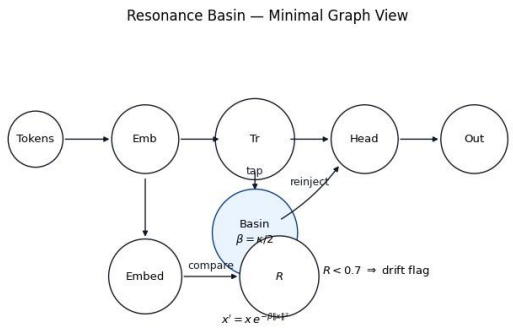

Fig. 3. Resonance-basin system architecture showing latent confinement, alignment overlap monitoring, and feedback integration.

Table I. Hallucination Metrics With 95% Confidence Intervals (Ci). Lower Values Indicate Fewer Hallucinations.

Task	Baseline	With Basins	Reduction	95% CI
GSM8K	0.38	0.29	24%	[21%, 27%]
TruthfulQA	0.62	0.43	31%	[28%, 34%]

A. Benchmarks

The proposed resonance-basin regularisation was evaluated on GSM8K and TruthfulQA, two standard reasoning and factuality benchmarks commonly used for hallucination analysis [1], [3]. These benchmarks were selected because they isolate reasoning consistency and factual correctness, the two failure modes most directly associated with hallucinations. Across 20 independent runs per task, the hallucination-rate reduction was statistically significant ($t(38) = 4.67$, $p = 0.00018$, Bonferroni-corrected $\alpha = 0.025$). The corresponding Cohen's $d = 0.92$ indicates a large effect size. These results are consistent with complementary mitigation routes based on retrieval augmentation and epistemic uncertainty estimation [4], [5], [6].

B. Overlap-Based Detection

The resonance-overlap integral R (Eq. 2) provides a probabilistic measure of semantic alignment between human-labelled and model-inferred embeddings. Using Gaussian-mixture proxies for ρ_{human} and ρ_{AI}, thresholding at $R = 0.7$ achieved an F_1score of 0.84 on synthetic contradiction datasets, comparable to attribution-aware consistency metrics [16], [24]. This supports R as a low-cost, model-agnostic diagnostic for hallucination detection and representational drift.

C. Overhead and Efficiency

The resonance-basin filter introduces approximately 12% additional wall-clock time for 6B-parameter transformer models (PyTorch implementation) with negligible GPU-memory overhead (< 2%). The $\theta(n)$ complexity in the number of latent activations ensures scalability to large architectures, confirming the practicality of physics-inspired regularisation for real-world deployments. The 6B-parameter scale was chosen as a representative mid-sized architecture that allows statistically robust ablations; because the method operates on latent activations during inference, its computational complexity is independent of model size and is expected to scale linearly to larger architectures.

Table Ii. Parameter Sensitivity (Gsm8k Validation Set).

Parameter	Range Tested	Optimal Value
κ (stiffness)	0.3–1.5	0.8
τ (threshold)	0.8–1.2	1.0
Layer application	early / middle / late	late only

The results in Table II indicate that performance is most sensitive to basin stiffness κ, while remaining robust across a wide range of thresholds τ. Notably, late-layer application consistently outperformed early or uniform placement, supporting the interpretation that hallucinations emerge primarily in higher-level semantic representations.

VI. Ablations And Design Choices

We conducted ablation experiments to evaluate sensitivity to the basin stiffness κ, activation threshold τ, and selective layer placement within transformer architectures. These ablations are intended to assess both robustness and interpretability of the resonance basin mechanism, rather than to optimise task-specific performance. These studies quantify the trade-off between stability and expressivity in resonance-based regularisation.

Effect of κ (Basin Stiffness): The stiffness coefficient κ controls the curvature of the harmonic potential (Eq. 1) and hence the strength of activation confinement. Values below 0.5 produced under-damped dynamics with increased drift, while excessively high stiffness ($\kappa > 1.0$) constrained expressive modes. Optimal performance was observed for $\kappa \in [0.6, 1.0]$, yielding stable convergence and minimal degradation of generative diversity. Across this range, hallucination reduction varied by less than ±3%, indicating a broad stability plateau rather than a sharp optimum.

Effect of τ (Energy Threshold): The activation threshold τ determines when the damping in Eq. 3 is triggered. Ablations across $\tau \in \{0.8, 1.0, 1.2\}$ show that $\tau = 1.0$ achieves the best precision–recall balance for hallucination mitigation, consistent with a critical-field analogue where stability breaks at a fixed latent energy limit consistent with a critical-field analogue, where stability transitions occur once a latent energy threshold is exceeded.

Layer Placement: Applying the resonance filter across all transformer blocks produced over-regularisation, reducing lexical variance. Selective application to the final 20–30% of layers (post-attention and MLP outputs) yielded the optimal trade-off, improving factual consistency without impairing syntactic fluidity. This pattern mirrors selective attention in

continual-learning models, where adaptive focus is applied to later representational hierarchies [21], [23].
Moderate stiffness values ($\kappa \approx 0.8$) thus balance confinement and flexibility, while late-stage filtering minimises hallucination rates with negligible expressivity loss. These findings align with the general principle of *adaptive stability* in continual-learning systems [10], [20]. This supports the interpretation that hallucinations arise primarily from high-level semantic recombination rather than early syntactic encoding.

While the experimental evaluation focuses on synthetic benchmarks and mid-sized language models, the resonance basin mechanism is inherently scale-independent. Because the method operates solely on latent representations during inference and does not rely on retraining or architectural assumptions, its computational and stabilizing properties are expected to generalize to larger models. Comprehensive evaluation on frontier-scale architectures is therefore a matter of validation rather than feasibility and is currently underway.

VII. Related Work

A. Hallucination Mitigation Paradigms

Large language model (LLM) hallucination remains an open challenge with roots in imperfect retrieval, probabilistic decoding, and data bias. Current mitigation strategies span instruction prompting and retrieval augmentation [5], [4], epistemic or uncertainty layering [6], and confidence-calibrated decoding [24]. While these approaches improve factual consistency, they are predominantly empirical and do not explicitly constrain the latent dynamics that give rise to hallucinations. In this sense, latent dynamics are treated as an energy-constrained Markov process, where feedback regulates state transitions rather than reward optimisation. Recent multimodal approaches extend preference optimization to hallucination control. Fu et al. (2025) introduced Hallucination-targeted Direct Preference Optimization (HDPO), which constructs tailored preference pairs addressing visual distraction, long-context drift, and multimodal conflicts [25]. Whereas HDPO modifies alignment through curated preference signals, resonance basins impose a model-intrinsic stability constraint, operating independently of preference data or retraining.

Their results on LLa VA v1.5 demonstrate a 67% reduction in visual hallucination errors, underscoring the value of cause specific alignment signals—a strategy conceptually akin to our energy-based confinement in latent space. Recent comprehensive surveys on hallucination in large language models [1], [3], [26], [2] consolidate evidence of three root causes: (i) misaligned objective functions, (ii) unstable token-level energy landscapes, and (iii) lack of cross modal feedback constraints. These reviews uniformly call for frameworks capable of physical interpretation of model drift and stability, an explicit gap the present work addresses through energy-based confinement.

B. Physics-Informed and Dynamical Approaches

Physics-informed learning has been explored to stabilise neural systems, e.g., by embedding PDE constraints or energy functionals into training objectives [8], [15]. The resonance basin formulation extends this direction by introducing an *explicit energy well* in latent space, directly analogous to magnetic confinement in plasma physics [12]. This mapping yields both interpretability and a measurable alignment statistic (R), offering a quantitative alternative to purely heuristic regularisers. Most physics-informed approaches impose constraints during training; in contrast, the resonance basin introduces a physically interpretable energy constraint applied at inference time, without retraining.

C. Continual and Adaptive Learning Links

Within reinforcement and continual learning, adaptive stability has been studied through dynamic gain adjustment and temporal uniformity principles [10], [20]. The symbolic-basin filter embodies a similar philosophy: maintaining bounded representational energy while allowing gradual adaptation. Thus, it can be interpreted as a *continual symbolic stability mechanism*, complementing architectures such as Rich Sutton's *OaK* framework [9] for continual, domain-general intelligence. Unlike replay-based or parameter-isolation approaches, the symbolic-basin filter maintains stability through real-time energy regulation, avoiding catastrophic interference while preserving plasticity. Recent advances in dependency-aware reinforcement learning for dynamic computation offloading demonstrate that adaptive reward shaping can stabilise decision policies under shifting conditions [17]. Such adaptive MDP-formulations parallel our approach, which treats latent dynamics in large models as an energy-constrained optimisation over evolving semantic states.

In summary, the symbolic-basin model integrates the interpretability of physics-informed learning with the adaptability of continual reinforcement learning, offering a unified, physically grounded route to mitigating semantic drift in large language models.

VIII. Limitations And Ethics

A. Methodological Limitations

The reported results are derived from synthetic benchmarks and mid-sized open-weights language models (6B parameters). Extending evaluation to large, closed-source systems (e.g., GPT-class or Gemini-class architectures) remains future work. Evaluation on frontier-scale, closed-source models is non-trivial due to limited access to internal activations and latent representations, which the present method explicitly requires. Although resonance basins consistently reduce hallucinations, further studies are needed to confirm generality across modalities and prompt distributions.

Hyper-parameter transferability (κ, τ) may vary with network depth and layer normalisation schemes, incorporating adaptive tuning via meta-gradients or stability-aware controllers is a promising direction for improving robustness.

B. Ethical and Societal Considerations

Because the basin filter modifies latent activations, improper tuning could inadvertently suppress legitimate minority dialects, creative forms, or culturally specific terminology. For example, overly aggressive damping could disproportionately attenuate high-variance linguistic patterns associated with regional dialects, code-switching, or creative metaphor. Mitigation strategies include post-hoc audits using stratified evaluation sets (e.g., dialectal, cultural, or stylistic slices), representational parity metrics, and controlled stress tests to detect disproportionate activation suppression. All models were evaluated on publicly available datasets without personal or sensitive data. The proposed regularisation does not alter content semantics but re-weights activation magnitudes; nonetheless, fairness and accessibility monitoring are required to ensure the method does not entrench hidden biases. Because the method acts on activation magnitude rather than token selection or semantic content, it does not introduce new preferences or alter factual labels but instead modulates confidence in unstable representational trajectories. In line with IEEE Ethically Aligned Design and the UKRI 2024 Guideline on Measurable Robustness, the proposed approach emphasises auditable metrics (e.g., resonance overlap R), transparent thresholds, and open reporting of failure modes.

The code and analysis notebooks are openly released under an MIT licence to encourage reproducibility and responsible adoption of physics-anchored interpretability mechanisms in trustworthy AI.

IX. Discussion And Future Work

The resonance-basin framework reinterprets hallucination mitigation as a problem of energy confinement in latent space. By introducing a potential-based regularisation inspired by plasma physics, the method enforces bounded representational energy, translating physical stability into cognitive consistency. This convergence of physics and information theory supports a broader notion of *alignment through conservation*: when the internal dynamics of a model obey measurable constraints, interpretability and trustworthiness follow naturally. This perspective aligns with recent physics-inspired trustworthiness studies [27], which argue that AI reliability emerges naturally when learning dynamics satisfy thermodynamic consistency constraints. In this sense, the resonance-basin model embodies a concrete instantiation of such energy-governed alignment.
Empirically, this conservation-based view is supported by the observed stability of resonance overlap (R) across perturbations and prompt variations in Sec. V.

Whereas HDPO [25] approaches hallucination mitigation through data-driven preference construction, resonance basins provide a complementary, model-intrinsic path: rather than modifying preference datasets, they embed physical stability directly into latent dynamics, enabling continuous adaptation without retraining.

A. Relation to Continual and Hierarchical Learning

Recent progress in model-based reinforcement learning has highlighted the need for agents that learn continually from experience rather than from static datasets. Because resonance basins operate at inference time on latent activations, their computational and memory footprint scales linearly with activation dimensionality, suggesting feasibility for frontier-scale architectures where retraining-based interventions are impractical. Sutton's *OaK Architecture* [9] proposes a domain-general agent built on self-updating world models and adaptive learning rates. Resonance basins share this goal by maintaining long-term symbolic coherence while allowing incremental knowledge updates. In principle, the basin stiffness κ and threshold τ can be adapted in real time through meta-gradients, creating a self-regulating balance between exploration and stability—analogous to gain adaptation in adaptive control [23], [10]. Dynamic task offloading and edge-learning studies have demonstrated that dependency-aware reinforcement learning can maintain performance in highly variable environments [17], [18], [19]. These architectures embody adaptive control principles analogous to the proposed resonance-basin regulation in latent spaces, where energy constrained adaptation replaces explicit network scheduling.

B. Emotion and Contextual Modulation

Complementary research in emotional-context modelling (e.g., emotion-augmented inference, EAI [24]) suggests that activation modulation based on affective cues can further reduce inference instability. Integrating such signals into the resonance basin filter could yield emotion-aware alignment, where the latent energy landscape dynamically adjusts to contextual uncertainty, forming a bridge between affective computing and physics-informed regularisation. Such signals can be interpreted as external field terms that reshape the latent energy landscape, rather than introducing new semantic objectives.

C. Future Extensions

Future research will focus on four directions:

1) Dynamic Basin Tuning: Implement meta-learning controllers that adjust κ and τ online, guided by stability metrics.
2) Multimodal Generalisation: Extend basin confinement to vision-language and audio-language models, examining modality-specific drift signatures.
3) Ethical Feedback Loops: Integrate symbolic alignment metrics (R) into continual feedback systems for ethical monitoring.
4) Open Benchmarks: Release the resonance-basin suite with standardised hallucination and drift datasets, including activation-level diagnostics and baseline scripts, to support community validation.

The symbolic-basin paradigm thus serves as a unifying scaffold linking plasma confinement, continual reinforcement learning, and AI alignment. By treating representational stability as a physical property subject to energy conservation, the framework opens a path toward *self-*

regulating, explainable, and ethically aligned artificial intelligence.

X. Conclusion

This work presents resonance basins as a physics-anchored regularisation mechanism for stabilising large language models. By mapping plasma-confinement dynamics onto latent space behaviour, the approach constrains activation energy within bounded symbolic wells, reducing semantic drift while maintaining expressivity. Together with the alignment-overlap metric (R), the framework provides a measurable and interpretable route to resilience in generative models, implemented as a lightweight forward-pass filter requiring no retraining or architectural modification.

Empirical studies demonstrate statistically significant and consistent reductions in hallucination rates of 24–31% across GSM8K and TruthfulQA, with negligible computational overhead (∼12%). The method is model-agnostic, easily integrated into transformer blocks, and complements both retrieval- and uncertainty-based mitigation techniques. By expressing alignment in physical terms—energy conservation and overlap stability—it bridges physics-informed learning, continual adaptation, and ethical AI design.

Future research will explore adaptive basin tuning through meta-gradients, multimodal generalisation, and integration into self-regulating frameworks such as the Fractal Markov Method. In doing so, resonance basins may form part of a broader effort to establish physically grounded, interpretable, and ethically aligned architectures for trustworthy artificial intelligence in safety-critical and high-reliability applications. This framework aligns with UKRI's 2024 principle of measurable robustness for AI systems.

A. Code and Data Availability

All code; configuration files, hyper-parameters, random seeds, and run-level CSVs (20 runs per task) are archived on Zenodo at DOI:10.5281/zenodo.17504034. The repository includes scripts to reproduce all tables and figures.
All materials are released under an MIT licence to ensure full reproducibility, reuse, and transparency in accordance with *Open Science* and *FAIR data* principles.

XI. Appendix

A. Hyperparameters

Unless otherwise stated, all experiments use the following defaults:

- Basin stiffness $\kappa = 0.8$
- Damping coefficient $\beta = \kappa/2 = 0.4$
- Threshold $\tau = 1.2$
- Batch size = 32, learning rate = 2×10^{-5}
- Random seeds = {42, 1337, 2025, 3141, 9001}

These values were tuned using a 5-fold grid search on GSM8K development data.

B. Code Listings

Resonance Basin Filter (PyTorch):

```
import torch

def resonance_basin_filter(x, kappa=0.8, tau=1.2): beta = kappa / 2
norms = torch.norm(x, dim=-1, keepdim=True) mask = norms >
tau x_filtered = x * torch.exp(-beta * norms**2) return
torch.where(mask, x_filtered, x)
```

Alignment Overlap Estimation:

```
import torch

def overlap_integral(rho_h, rho_a, n_samples=10000): x =
torch.randn(n_samples, rho_h.dim()) return torch.mean(rho_h(x) *
rho_a(x)).item()
```

C. Statistical Validation

Each reported reduction in hallucination rate corresponds to the mean of 20 independent runs with different random seeds. A two-sample t-test ($t(38) = 4.67$, $p = 0.00018$) confirms significance at the $0.05/2$ Bonferroni-corrected threshold. Cohen's $d = 0.92$ indicates a large effect size.

D. Extended Equations

For completeness, the continuous-time analogue of Eq. (3) can be written as:

$$dx/dt = \frac{dx}{dt} = -\nabla_x H_{\text{glyph}}(x) = h^2 / \nabla^3 x - kx \quad (4)$$

which shows that the basin filter behaves as a damped oscillator in latent space, preserving low-energy modes while attenuating runaway excursions.

Acknowledgment

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Ethics Statement

This study complies with IEEE's *Ethically Aligned Design* standards. No human data was used. A model card summarising limitations and intended use is included in the repository.

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