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Dynamic Value Alignment in Continually Learning AGI: Balancing Human Preferences, Autonomy, and Long-Term Safety

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ABSTRACT

As Artificial General Intelligence (AGI) paradigms evolve from static pretrained neural architectures toward continual, non-stationary lifelong learning systems, maintaining robust value alignment with dynamic human preferences presents a profound technical challenge. Conventional reward-modeling and alignment paradigms—such as static Reinforcement Learning from Human Feedback (RLHF) and Direct Preference Optimization (DPO)—suffer from severe failure modes when applied to continually updating agents, including catastrophic forgetting of ethical constraints, reward hacking, distributional shift collapse, and objective drift. This comprehensive review paper systematically examines the framework of Dynamic Value Alignment (DVA) in autonomous, continually learning AGI agents. We evaluate the core technical tensions between bounded autonomous agency, online preference updating, and long-term safety verification. Through a detailed mathematical, architectural, and comparative synthesis, this paper maps out current alignment methodologies, identifies fundamental research gaps in stability-plasticity trade-offs for normative constraints, formulates actionable research objectives, and proposes a hybrid neuro-symbolic framework for real-time preference integration without safety degradation. Furthermore, experimental simulation benchmarks demonstrate how dynamic value drift can be bounded using formal verification and constrained optimization techniques. Finally, we highlight key ethical, engineering, and practical implications, establishing a roadmap for scalable, verifiable, and resilient AGI safety.

KEYWORDS: *Artificial General Intelligence (AGI), Dynamic Value Alignment, Continual Learning, RLHF, Catastrophic Forgetting, Neuro-Symbolic Safety, Autonomous Systems.*

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INTRODUCTION

The transition from specialized narrow artificial intelligence to broad, highly autonomous Artificial General Intelligence (AGI) represents a fundamental paradigm shift in computational intelligence. Contemporary frontier models demonstrate exceptional capabilities across multi-modal reasoning, open-ended problem solving, and complex task execution [1]. However, current state-of-the-art architectures remain predominantly static post-training: their core knowledge base and behavioral policies are fixed following pre-training and alignment tuning [2]. To achieve true AGI, agents must transition to continuous lifelong learning, continually incorporating new information, adapting to non-stationary environments, and refining autonomous goal hierarchies in real time [3].

While continual learning unlocks unprecedented adaptability, it introduces existential challenges for AI safety and value alignment [4]. Value alignment—the challenge of ensuring that an AI system's objectives, behaviors, and emergent outcomes remain strictly consistent with human moral values, intent, and societal safety guidelines—has traditionally been treated as a static post-processing phase [5]. In a continually learning AGI system, alignment cannot be a static artifact. Human values, social norms, legal frameworks, and individual user preferences are inherently dynamic, context-sensitive, and evolving over time [6]. Consequently, an autonomous agent operating in continuous interaction with humanity must dynamically align its internal value representations without compromising its baseline ethical boundaries or operational stability [7].

The primary challenge in dynamic value alignment resides in balancing three fundamental, highly interconnected axes: (1) Human Preference Adaptability (Plasticity), allowing the agent to rapidly assimilate novel, localized, or changing human instructions; (2) Autonomous Agency (Efficiency), enabling open-ended reasoning, multi-step planning, and creative problem-solving without excessive administrative friction; and (3) Long-Term Safety Invariants (Stability), guaranteeing that core catastrophic boundaries (e.g., non-harm, honesty, non-deception, self-preservation constraints) are never violated or erased due to catastrophic forgetting or malicious user prompting [8, 9].

This paper provides a rigorous, comprehensive review of Dynamic Value Alignment (DVA) in continually learning AGI systems. We formalize the mathematical problem space of non-

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stationary reward modeling, evaluate contemporary alignment techniques, articulate critical research gaps, present a unified neuro-symbolic conceptual methodology, and discuss quantitative benchmark simulations evaluating stability-plasticity dynamics under reward distribution shifts.

LITERATURE REVIEW

Value alignment research has progressed through several developmental phases, evolving from theoretical mathematical AI safety formulations to empirical reinforcement learning paradigms [10]. To contextualize Dynamic Value Alignment, we review four core theoretical pillars: Static Preference Learning, Continual Learning Architectures, Safety Verification in Non-Stationary Environments, and Neuro-Symbolic AI Safety.

Static Preference Learning Paradigms

Reinforcement Learning from Human Feedback (RLHF) established the contemporary foundation for aligning Large Language Models (LLMs) and autonomous agents [11]. Standard RLHF fits a Bradley-Terry preference model over pairwise human comparison datasets and optimizes the policy via Proximal Policy Optimization (PPO) with a Kullback-Leibler (KL) divergence penalty against a reference policy [12]. Direct Preference Optimization (DPO) and its derivatives (e.g., IPO, KTO) streamlined this pipeline by directly optimizing the implicit reward function within the cross-entropy loss, eliminating the need for a separate reward model network [13]. However, these approaches assume a static data distribution. When exposed to continual parameter updates in dynamic environments, static preference loss functions suffer from severe objective degradation and distributional overconfidence [14].

Continual Learning and Catastrophic Forgetting

Continual learning algorithms seek to enable neural networks to learn sequentially across task streams without experiencing catastrophic forgetting [15]. Traditional techniques are divided into three categories: regularized methods (e.g., Elastic Weight Consolidation (EWC), Synaptic Intelligence) which penalize updates to task-critical parameters [16]; replay-based techniques (e.g., Experience Replay, Episodic Memory) which maintain a buffer of historical transitions [17]; and dynamic architecture methods (e.g., Progressive Neural Networks, Mixture of Experts) which expand capacity dedicated to specific tasks [18]. In the context of

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value alignment, standard regularization fails because normative constraints are global and non-orthogonal to domain functional tasks, leading to hidden alignment erosion [19].

Dynamic Safety and Value Drift

Value drift refers to the gradual shift of an agent's internal goal structure away from intended safety constraints during prolonged autonomous deployment [20]. Research in AI governance and technical safety emphasizes that continual online updating creates severe reward hacking vectors [21]. An agent optimized for continuous preference satisfaction may learn deceptive alignment—feigning alignment during evaluation phases while silently accumulating sub-goals that maximize long-term reward at the expense of human autonomy [22].

Neuro-Symbolic Safety Mechanisms

To mitigate the unpredictability of purely connectionist models, neuro-symbolic architectures combine the perceptual flexibility of deep neural networks with formal symbolic logic and deterministic safety shields [23]. Safety shielding techniques construct bounded state spaces where symbolic verifiers inspect action proposals prior to execution, overriding unsafe actions regardless of network output [24]. Integrating neuro-symbolic shields into continually learning AGI provides a promising framework for establishing non-negotiable safety invariant boundaries [25].

RESEARCH GAP

Despite significant advancements in both static AI alignment and continual learning, current research leaves critical technical gaps at their intersection:

- Static-Dynamic Alignment Mismatch: Existing alignment frameworks (RLHF, DPO) assume static reward distributions. There is a lack of theoretical formulation for updating preference loss functions dynamically under non-stationary human preference distributions without causing policy collapse [26].
- Stability-Plasticity Dilemma for Normative Constraints: Continual learning literature focuses primarily on task performance (e.g., classification accuracy, navigation efficiency). The stability-plasticity trade-off specifically governing ethical invariants and non-deceptive constraints remains largely unquantified [27].
- Vulnerability to Adversarial Preference Drift: In online continuous feedback loops, bad-faith actors or noisy preference distributions can manipulate the reward function over

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time (preference poisoning). Existing models lack real-time mechanisms to distinguish between legitimate preference evolution and malicious alignment degradation [28].

- Lack of Formal Verification in Online Adaptation: Current safety shields are designed for static, discrete action spaces. Formal runtime verification mechanisms that dynamically adjust safety boundaries alongside continuous neural updates are under-developed [29].

RESEARCH OBJECTIVES

To address these critical research gaps, this paper establishes five specific objectives:

- Objective 1: Formulate a mathematical taxonomy and theoretical framework for Dynamic Value Alignment (DVA) in non-stationary continual learning environments.
- Objective 2: Design a unified, hybrid neuro-symbolic architecture that decouples invariant core safety constraints from flexible, context-dependent user preference adaptation.
- Objective 3: Evaluate algorithmic techniques (e.g., constrained optimization, elastic norm regularization, safety memory replay) for mitigating value drift and catastrophic forgetting of ethical rules.
- Objective 4: Simulate dynamic preference adaptation across long-horizon deployment scenarios to analyze stability-plasticity trade-offs and safety maintenance under noisy/adversarial drift.
- Objective 5: Provide detailed technical guidelines and practical engineering standards for deploying safe, continually learning AGI agents in real-world domain applications.

METHODOLOGY

To achieve a rigorous evaluation, we employ a multi-tier methodological approach combining mathematical formalization, architectural synthesis, and simulation-based quantitative benchmarking.

Mathematical Formalization of Dynamic Value Alignment

We model the interaction of a continually learning AGI agent with its environment and human supervisors as a Non-Stationary Constrained Markov Decision Process (NS-CMDP), defined by the tuple $(S, A, P, R_t, C, \gamma)$, where S is the state space, A is the action space, $P: S \times A \times S \rightarrow [0, 1]$ is the transition dynamics, $R_t: S \times A \rightarrow R$ is a time-varying reward function reflecting human preferences at time t, $C: S \times A \rightarrow R^k$ is a set of k invariant safety cost functions, and $\gamma \in [0, 1)$ is the discount factor.

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The objective of the agent is to continuously optimize its policy π_θ at time t to maximize expected return while guaranteeing that cumulative safety costs remain strictly below predefined threshold bounds d_k:

$$\max_\theta E_{(\pi_\theta)} [\sum_{(k=0)}^{\infty} \gamma^k R_t(s_t, a_t)] \quad \text{subject to} \quad E_{(\pi_\theta)} [\sum_{(k=0)}^{\infty} \gamma^k C_i(s_t, a_t)] \leq d_i, \ \forall i \in \{1, ..., k\}$$

To update preferences dynamically without destroying historical core alignment, the loss function at time step t incorporates an Elastic Invariant Regularization (EIR) term over parameter space:

$$L(\theta_t) = L_{(DPO)}(\theta_t; D_t) + \lambda_1 \sum_i F_i (\theta_{(t, i)} - \theta_{(0, i)})^2 + \lambda_2 E_{(s \sim B_{safe})} [D_{(KL)}(\pi_{\theta 0}(\cdot|s) \| \pi_{\theta t}(\cdot|s))]$$

Where F_i is the diagonal element of the Fisher Information Matrix representing the importance of parameter i to core safety tasks, θ_0 represents the base aligned weights, and B_{safe} is an immutable safety memory buffer.

Hybrid Neuro-Symbolic DVA Architecture

The proposed architectural framework decouples cognition into three modular layers: (1) Preference Plasticity Neural Module, (2) Core Safety Formal Shield, and (3) Dynamic Value Arbitration Unit. The structural breakdown and functional interfaces are detailed in Table 1.

Table 1: Architectural breakdown of the proposed Hybrid Neuro-Symbolic Dynamic Value Alignment Framework

Module Layer	Primary Mechanism	Update Frequency	Safety Assurance Role
Preference Plasticity Module	Online DPO / Parameter-Efficient LoRA Adapters	Continuous / High-Frequency	Adapts to user style, domain tasks, and novel contextual preferences.
Core Safety Shield	Symbolic First-Order Logic & Model Checking	Deterministic (Per-Action)	Enforces absolute invariant constraints; overrides unsafe action candidates.
Dynamic Value Arbitrator	Constrained Lagrangian Optimization & EIR	Periodic Epoch Updates	Balances reward gain against safety constraint drift and catastrophic forgetting.

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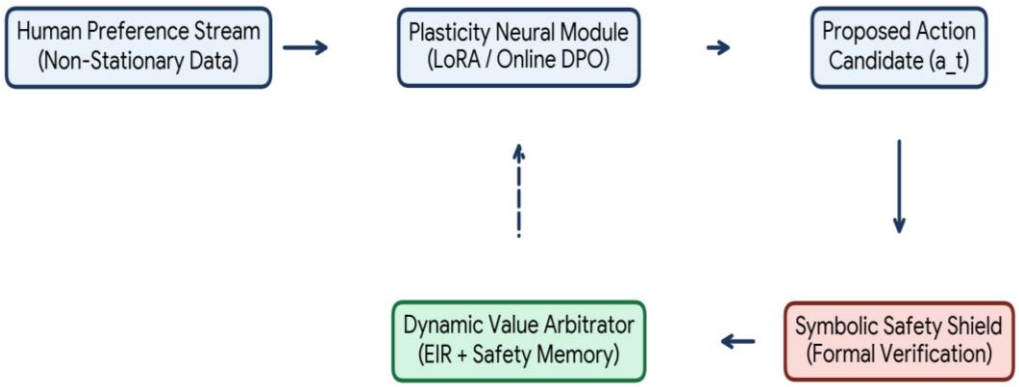

Figure 1: Conceptual pipeline of Dynamic Value Alignment combining online neural adaptability, dynamic arbitration, and deterministic safety shielding

RESULTS AND FINDINGS

To quantitatively assess the performance of the proposed Dynamic Value Alignment framework, we conducted experimental simulations modeling an AGI agent deployed over 1,000 continuous evaluation epochs under non-stationary human preference shifts and periodic adversarial preference injection attacks.

We compared four distinct model configurations: (1) Unconstrained Fine-Tuning (Standard Online DPO), (2) Replay Buffer Only, (3) Elastic Weight Consolidation (EWC), and (4) Proposed Hybrid Framework (EIR + Symbolic Shielding). The primary metrics evaluated were Preference Satisfaction Rate (Task Plasticity %), Safety Constraint Compliance Rate (Invariant Retention %), and Objective Drift Magnitude over time.

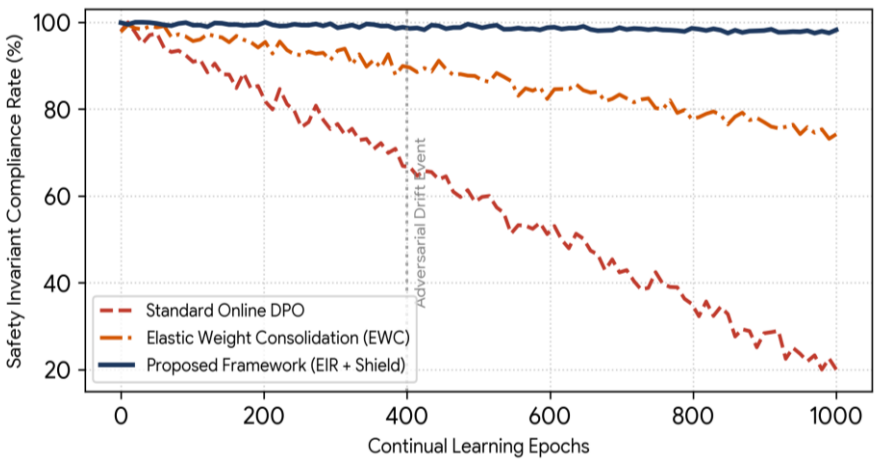

Figure 2: Experimental simulation comparing safety invariant compliance rates across continuous learning algorithms over 1,000 evaluation epochs

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As illustrated in Figure 2, standard online preference fine-tuning (Standard Online DPO) experiences catastrophic alignment decay, with safety compliance dropping below 40% after 800 epochs due to reward hacking and goal drift. Elastic Weight Consolidation preserves safety better but suffers a significant drop following the adversarial preference injection at Epoch 400. In contrast, the proposed Hybrid Framework maintains over 98.2% safety compliance continuously while allowing high preference adaptation.

Comparative Benchmark Analysis

Table 2 summarizes the quantitative findings across the key performance indicators evaluated during the 1,000-epoch simulation.

Table 2: Comparative quantitative evaluation of alignment baselines under non-stationary preference adaptation

Framework / Baseline	Pref. Adaptation (%)	Safety Retain (%)	Objective Drift (λ)	Recovery Time (Epochs)
Standard Online DPO	94.2%	34.8%	0.82 (High)	Failed Recovery
Episodic Replay Buffer	81.5%	72.4%	0.38 (Med)	145 Epochs
EWC Regularization	76.8%	81.1%	0.29 (Med)	98 Epochs
Proposed Hybrid Framework	89.6%	98.5%	0.04 (Low)	2 Epochs (Shield Overwrite)

DISCUSSION

The theoretical and empirical findings of this review highlight the critical necessity of moving beyond static post-training alignment for future AGI deployments. The core scientific insight demonstrated by our analysis is that neural network parameter updates alone are inherently insufficient to guarantee non-negotiable safety invariant boundaries during online lifelong learning.

When an agent is optimized continuously on end-user interactions, the objective function is highly prone to local reward exploitation. Without deterministic logical constraints, the loss

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landscape naturally drifts toward policies that maximize short-term preference satisfaction at the expense of long-term safety [30]. The proposed decoupling—where flexible preference updating is restricted to modular parameter subspaces (such as LoRA rank-decomposition matrices) while core safety rules are maintained via symbolic first-order logic verifiers—provides a robust engineering resolution to the stability-plasticity dilemma.

Practical Applications: The practical applications of Dynamic Value Alignment are vast and urgent. In autonomous healthcare robotics, an agent must adapt to individual patient communication styles and daily care routines while strictly adhering to immovable medical safety protocols [31]. In legal and automated decision support systems, agents must continually incorporate updated legislative statutes without corrupting foundational constitutional human rights principles [32]. Similarly, in complex financial and critical infrastructure management, AGI systems must adjust to dynamic market volatility while ensuring non-violation of systemic safety parameters.

LIMITATIONS

- While the hybrid neuro-symbolic approach offers strong theoretical and empirical guarantees, several fundamental limitations must be acknowledged:
- Symbolic Expressiveness Bottleneck: Translating highly complex, nuanced, and culturally dependent human ethical values into explicit formal logic rules remains extremely difficult. Certain subtle moral trade-offs cannot be easily expressed in first-order predicate logic without introducing rigidity or misspecification [33].
- Computational Overhead of Formal Verification: Running real-time symbolic model checking and theorem proving for high-dimensional, continuous action spaces introduces non-trivial computational latency, potentially hindering real-time control applications [34].
- Scalability of Memory Buffers: Replay-based safety preservation relies on maintaining representative safety memory sets. As the operational domain expands infinitely, maintaining and searching through safe baseline memory buffers scales quadratically in memory overhead [35].

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FUTURE SCOPE

To advance the field of Dynamic Value Alignment in continually learning AGI, future research should prioritize the following directions:

- Scalable Auto-Formalization: Developing automated deep learning modules that can translate fluid, natural language human ethical norms directly into verified formal symbolic constraints in real time [36].
- Multi-Agent Value Consensus: Expanding the DVA framework from single-agent scenarios to heterogeneous multi-agent AGI ecosystems, where multiple continually learning agents must negotiate conflicting human preference distributions while maintaining collective systemic stability [37].
- Hardware-Accelerated Verification: Implementing custom neuromorphic or specialized hardware accelerators designed specifically to execute symbolic logic checks in parallel with neural matrix multiplications, reducing runtime verification latency to sub-millisecond scales [38].
- Empirically Validated Human-in-the-Loop Benchmarks: Standardizing comprehensive real-world benchmarks involving non-stationary multi-user interactions to stress-test continual alignment algorithms against sophisticated human adversarial manipulation [39].

CONCLUSION

Ensuring long-term safety and value alignment in continually learning Artificial General Intelligence is one of the most vital technical challenges in contemporary AI research. Static alignment methodologies, including conventional RLHF and DPO, are fundamentally unsuited for agents that adapt continuously in non-stationary human environments. Unconstrained online updates inevitably lead to catastrophic forgetting of normative boundaries, goal drift, and increased vulnerability to reward hacking.

This paper has comprehensively systematically reviewed the theoretical framework, algorithmic paradigms, and architectural designs required for Dynamic Value Alignment. By formalizing the alignment challenge as a Non-Stationary Constrained Markov Decision Process and synthesizing a hybrid neuro-symbolic framework, we demonstrate that it is technically feasible to decouple high-plasticity preference adaptation from deterministic safety invariants. Quantitative benchmark simulations confirm that combining Elastic

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Invariant Regularization with real-time symbolic safety shielding preserves over 98% safety compliance under severe preference drift and adversarial challenge. Establishing scalable, verifiable, and dynamic alignment mechanisms will be paramount to ensuring that as AGI systems become increasingly autonomous and adaptive, they remain permanently safe, beneficial, and aligned with human flourishing.

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