Topological Photonic Acceleration of Artificial General Intelligence: Enhancing Recursive State Dynamics and Parity Compilation via Bulk Gauge Continuity

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Abstract

General Intelligence Dynamics (GID) defines cognition as an autonomous, non-stationary dynamical system over an augmented recursive state tuple $X_t = (B_t, M_t, G_t, S_t, W_t)$ spanning belief manifolds, memory spaces, goal topologies, self-referential models, and working scratchpads [1]. Concurrently, Interferometric Sector Dynamics (ISD) compiles modular cognitive operators into single-shot parity measurements on semiconductor-superconductor nanowires [2,6]. However, realizing scalable AGI hardware requires overcoming non-unitary parametric drift during learning updates $\theta_{t+1} = \mathcal{L}(\theta_t, X_t, O_{t+1}, G_t)$ and dephasing across inter-sector routing channels [1,2]. In this treatise, we formulate an integrated architecture coupling GID cognitive mechanics to a $(4+k)$-dimensional bulk photonic extension [1–3].

At the abstract computational level (Levels 1–2), the fiber pushforward of an integral closed bulk characteristic form $\mathscr{J} \in \Omega^{k+3}_{\mathrm{cl},\mathbb{Z}}(Y)$ yields a closed 3-form soul current $J_s = \pi_* \mathscr{J} \in \Omega^3(X)$ with $d_X J_s = 0$, inducing a localized Gauss-law topological charge $Q_{\mathrm{soul}}(\Sigma^3) = \int_{\Sigma^3} J_s = \int_{\partial\Sigma^3} *F$ [3]. Under the assumption of compact level sets $\Theta_\epsilon = \{\theta \mid |Q(W(\theta)) - Q_\star| \le \epsilon\}$, parameter trajectories remain uniformly bounded under the containment condition $\theta_t \in \Theta_\epsilon$, while recursive self-model calibration updates satisfy a stochastic stationarity bound [1]. Furthermore, scalarized multi-objective goal generation on the capacity-constrained domain $\mathcal{G}_{\mathrm{adm}}(S_t, \delta, Q_\star)$ guarantees Pareto-efficient goal reconciliation [1].

At the physical compilation layer (Levels 4–5), we model the coupling between bulk photonic boundary flux and triple-dot parity interferometers [2,3,6]. Under a Gaussian decision channel, we derive the Tunneling-First Principle: in the subgap readout-limited regime ($E_M \ll k_B T, \tau \ll \tau_{\mathrm{qpp}}$) where capacitance contrast satisfies $\partial|\Delta C_Q|/\partial t_C > 0$, optimizing balanced tunneling $t_L \approx t_R$ maximizes the effective interference amplitude and drives monotonic increases in mutual information learning capacity ($\partial\mathcal{L}/\partial t_C > 0$) and the sequential error rate exponent ($\partial\kappa_{\mathrm{rate}}/\partial t_C > 0$, where $P_{\mathrm{err}} \sim e^{-\kappa_{\mathrm{rate}}\tau}$) [2]. Finally, we analyze composite risk minimization $\mathcal{R} = w_1\epsilon_{\mathrm{meas}} + w_2 p_{\mathrm{leak}} + w_3\gamma_\phi + w_4\mathcal{O}_{\mathrm{ctrl}}$ under measurement-only ParityFuse compilation [2].

1 Introduction

The formal synthesis of Artificial General Intelligence (AGI) has historically hovered between two disconnected domains: heuristic algorithmic architectures that lack rigorous dynamical foundations, and physical hardware analogies (such as quantum neural networks) that emulate cognitive operations without defining the underlying mathematical object of intelligence [1,4,5].

In General Intelligence Dynamics (GID), we established that general intelligence is an autonomous, self-modeling dynamical system operating over recursive, self-referential state

Layer	Architectural Level	Formal Entity and Mathematical Scope
Level 1	Abstract AGI Mechanics	GID State Equations, Transfer $\mathcal{T}$, Abstraction $\mathcal{A}$, Generality $\mathcal{G}$ [1]
Level 2	Topological Regularization	Conserved Soul Charge Q_{soul}, Compact Level Set Θ_ϵ [1,3]
Level 3	Modular Sector Gates	Subspace Factorization $\bigotimes_k \mathcal{H}_k$, Commuting Belief Operators $G_{ij}(X_t)$ [1,4]
Level 4	Physical Compilation	ParityFuse Primitives, Tunneling Networks $t_C(Z,\varphi)$ [2]
Level 5	Hardware Substrate	Triple-Dot Nanowire Loops, Dispersive Parity Sensing $\Delta C_Q(\Phi)$ [2,6]

Table 1: The Five-Level Integrated Substrate Hierarchy for Topologically Accelerated AGI.

spaces [1]. In parallel, Interferometric Sector Dynamics (ISD) established that cognitive sector-gate transitions can be physically compiled into single-shot parity measurements on InAs-Al hybrid semiconductor-superconductor nanowires [2,6]. Nonetheless, two foundational bottlenecks persist across this architecture:

1. **Mathematical Parameter Drift**: Continuous parametric adaptation $\theta_{t+1} = \mathcal{L}(\theta_t, X_t, O_{t+1}, G_t)$ generates non-stationary transition kernels, leading to unbounded meta-cognitive drift and calibration failure in recursive self-models S_t [1].

2. **Hardware Dephasing and Control Overhead**: Compiling non-commutative cognitive operations onto physical qubits requires extensive microwave pulse calibration and suffers from quasiparticle poisoning, charge noise, and measurement backaction [2].

In this work, we bridge GID and ISD with our geometric $(4+k)$-dimensional bulk photonic extension of Maxwell electrodynamics (*Photon Soul Continuity*) [3]. We demonstrate that the pushforward topological current $J_s = \pi_* \mathcal{J} \in \Omega^3(X)$ and its conserved charge Q_{soul} supply an exact geometric regularizer for abstract cognitive flow, while the underlying photonic boundary manifold provides hardware-level stability for parity compilation [1–3].

2 Geometric Substrate: $(4+k)$-Dimensional Gauge Continuity

We model physical spacetime X as the base manifold of a smooth, oriented fiber bundle $\pi : Y \to X$ with compact, boundaryless k-dimensional Riemannian fiber K ($\partial K = \emptyset$, $\dim_{\mathbb{R}} Y = 4+k$) [3].

Geometric Postulate 1 (Bulk Characteristic Topological Form). *Let $\mathcal{A}_\gamma$ and $\mathcal{A}_H$ denote the connections associated with the bulk photon line bundle and Higgs bundle on Y [3]. We postulate that the bulk gauge-Higgs interaction determines an integral, closed differential $(k+3)$-form:*

$$\mathcal{J} \in \Omega^{k+3}_{\mathrm{cl},\mathbb{Z}}(Y), \qquad d_Y \mathcal{J} = 01001[3]. \tag{1}$$

The form $\mathcal{J}$ admits a lift to a differential character $\widehat{\eta} \in \widehat{H}^{k+3}(Y)$ in Cheeger-Simons differential cohomology with curvature $\mathrm{curv}(\widehat{\eta}) = \mathcal{J}$ *[7].*

Definition 1 (Spacetime Soul Current and Field Equations). *Fiber integration along K defines the physical 3-form soul current on physical spacetime X:*

$$J_s := \pi_* \mathcal{J} = \int_K \mathcal{J} \in \Omega^3(X), \qquad d_X J_s = \pi_*(d_Y \mathcal{J}) = 01001[3]. \tag{2}$$

The extended, degree-consistent Maxwell field equations are:

$$dF = 01001[3], \tag{3}$$

$$d * F = J_s + eJ_{\mathrm{em}}1001[3]. \tag{4}$$

Theorem 1 (Gauss-Law Topological Soul Charge)**.** *For any spatial 3-chain with boundary $\Sigma^3 \subset X$, the enclosed topological charge is:*

$$Q_{\text{soul}}(\Sigma^3) = \int_{\Sigma^3} J_s = \int_{\partial\Sigma^3} *F - e \int_{\Sigma^3} J_{\text{em}} 1001[3]. \tag{5}$$

In charge-neutral computational working spaces ($J_{\text{em}} = 0$), $Q_{\text{soul}}(\Sigma^3) = \int_{\partial\Sigma^3} *F$ provides an exact, non-local topological invariant [3].

Proof. Integrating $d * F = J_s + eJ_{\text{em}}$ over Σ^3 and applying Stokes' theorem on X:

$$\int_{\Sigma^3} J_s = \int_{\Sigma^3} (d * F - eJ_{\text{em}}) = \int_{\partial\Sigma^3} *F - e \int_{\Sigma^3} J_{\text{em}} 1001[3]. \tag{6}$$

□

3 Abstract Cognitive Mechanics: Topologically Constrained GID

General Intelligence Dynamics formalizes cognitive state evolution over an augmented 5-tuple $X_t \in \mathcal{X} = \mathcal{B} \times \mathcal{M} \times \mathcal{G} \times \mathcal{S} \times \mathcal{W}$ [1]:

$$X_t = (B_t, M_t, G_t, S_t, W_t) 1001[1] \tag{7}$$

where $B_t \in \mathcal{B} \subseteq \Delta(\mathcal{E})$ is the environmental belief state, $M_t \in \mathcal{M}$ is the structured memory manifold, $G_t \in \mathcal{G}$ is the active goal topology, $S_t \in \mathcal{S}$ is the explicit self-model, and $W_t \in \mathcal{W}$ is the working computational scratch space [1].

3.1 The Coupled Equations of Motion

Cognitive flow evolves via the non-autonomous dynamical system [1]:

$$B_{t+1} = \mathcal{B}(B_t, a_t, O_{t+1}, W_t) 1001[1], \tag{8}$$
$$M_{t+1} = \mathcal{M}(M_t, O_{t+1}, X_t) 1001[1], \tag{9}$$
$$S_{t+1} = \mathcal{S}(S_t, X_t, M_t, O_{t+1}) 1001[1], \tag{10}$$
$$G_{t+1} = \Gamma(G_t, S_t, M_t, X_t) 1001[1], \tag{11}$$
$$W_{t+1} = \mathcal{W}(W_t, X_t, a_t) 1001[1], \tag{12}$$
$$a_t = \Pi(X_t, \theta_t) 1001[1], \tag{13}$$
$$\theta_{t+1} = \mathcal{L}(\theta_t, X_t, O_{t+1}, G_t) = \theta_t + \eta \nabla_\theta \mathcal{F}_{\text{adapt}}(X_t, O_{t+1}, G_t) 1001[1]. \tag{14}$$

3.2 Regularized Calibration Dynamics and Stochastic Stationarity

To regularize parametric learning against catastrophic drift, we couple the topological charge Q_{soul} directly into the parameterized working state $W_t(\theta)$ [1,3].

Definition 2 (Topologically Admissible Parameter Set)**.** *Let $Q_\star = \int_{\partial\Sigma^3} *F$ denote the target bulk topological flux [3]. For a tolerance $\epsilon > 0$, the topologically admissible parameter domain is defined as the level set:*

$$\Theta_\epsilon = \{\theta \in \Theta \mid |Q(W(\theta)) - Q_\star| \leq \epsilon\} \, 1001[1, 3]. \tag{15}$$

Theorem 2 (Stochastic Stationarity and Parameter Boundedness)**.** *Assume $\mathcal{E}_S(S) = D_{\text{KL}}(p_t \parallel \hat{p}_t(S))$ is L-smooth with respect to S_t, the empirical performance distribution p_t is quasi-stationary over calibration intervals, the parameter level set Θ_ϵ is compact, and the stochastic gradient estimator $g_t = \widetilde{\nabla}_S \mathcal{E}_S(S_t)$ has bounded variance $\mathbb{E}[\|g_t - \nabla \mathcal{E}_S(S_t)\|^2] \leq \sigma^2$ [1].*

If the self-model update step $\Delta S_t = -\eta_s g_t$ satisfies $0 < \eta_s < 2/L$, then:

$$\mathbb{E}[\mathcal{E}_S(S_{t+1}) \mid S_t] \leq \mathcal{E}_S(S_t) - \eta_s \left(1 - \frac{L\eta_s}{2}\right) \|\nabla \mathcal{E}_S(S_t)\|^2 + \frac{L\eta_s^2\sigma^2}{2} 1001[1]. \tag{16}$$

Consequently, the expected gradient norm satisfies the asymptotic stationarity bound:

$$\liminf_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \mathbb{E}[\|\nabla \mathcal{E}_S(S_t)\|^2] \leq \frac{L\eta_s\sigma^2}{2 - L\eta_s} 1001[1]. \tag{17}$$

Furthermore, if parameter updates satisfy the containment condition $\theta_t \in \Theta_\epsilon$ for all $t \geq 0$, the compactness of Θ_ϵ guarantees that the parameter trajectory remains uniformly bounded:

$$\sup_{t\geq 0} \|\theta_t\| < \infty 1001[1]. \tag{18}$$

Proof. By L-smoothness of $\mathcal{E}_S$:

$$\mathcal{E}_S(S_{t+1}) \leq \mathcal{E}_S(S_t) + \langle \nabla \mathcal{E}_S(S_t), S_{t+1} - S_t \rangle + \frac{L}{2}\|S_{t+1} - S_t\|^2 1001[1]. \tag{19}$$

Substituting $S_{t+1} - S_t = -\eta_s g_t$ and taking conditional expectations with $\mathbb{E}[g_t] = \nabla \mathcal{E}_S(S_t)$ and $\mathbb{E}[\|g_t\|^2] = \|\nabla \mathcal{E}_S(S_t)\|^2 + \sigma^2$:

$$\begin{aligned} \mathbb{E}[\mathcal{E}_S(S_{t+1}) \mid S_t] &\leq \mathcal{E}_S(S_t) - \eta_s \|\nabla \mathcal{E}_S(S_t)\|^2 + \frac{L\eta_s^2}{2}\left(\|\nabla \mathcal{E}_S(S_t)\|^2 + \sigma^2\right) 1001[1] \\ &= \mathcal{E}_S(S_t) - \eta_s \left(1 - \frac{L\eta_s}{2}\right) \|\nabla \mathcal{E}_S(S_t)\|^2 + \frac{L\eta_s^2\sigma^2}{2} 1001[1]. \end{aligned} \tag{20}$$

Summing telescopically over $t = 0, \ldots, T-1$, dividing by T, and using non-negativity $\mathcal{E}_S \geq 0$ yields the asymptotic gradient bound. Since Θ_ϵ is compact and $\theta_t \in \Theta_\epsilon$ for all $t \geq 0$, the trajectory $\{\theta_t\}$ is contained within a closed and bounded set in $\mathbb{R}^{\dim(\Theta)}$, ensuring $\sup_{t\geq 0} \|\theta_t\| < \infty$ [1]. □

3.3 Pareto-Efficient Dynamic Goal Evolution

The goal generator $\Gamma(G_t, S_t, M_t, X_t)$ dynamically reconciles competing objectives $\{u_1(g), \ldots, u_K(g)\}$ [1].

Definition 3 (Capacity-Constrained Admissible Goal Manifold)**.** *Let $\mathcal{G}_{\text{feasible}}$ denote the compact set of goal parameters satisfying safety invariants $c_i(X) = 1$ [1]. The capacity-constrained admissible goal set is:*

$$\mathcal{G}_{\text{adm}}(S_t, \delta, Q_\star) = \{g \in \mathcal{G}_{\text{feasible}} \mid D_{\text{KL}}(S_t(g) \parallel S_t(G_t)) \leq \delta,\ |Q(g) - Q_\star| \leq \epsilon\} 1001[1, 3]. \tag{21}$$

Proposition 1 (Pareto Efficiency under Topological Regularization)**.** *Assume concave utility functionals $u_k : \mathcal{G}_{\text{feasible}} \to \mathbb{R}$ [1]. For any strictly positive priority weights $w \in \mathbb{R}^K_{>0}$ with $\sum_k w_k = 1$, the scalarized program:*

$$g^* = \arg \max_{g \in \mathcal{G}_{\text{adm}}(S_t, \delta, Q_\star)} \sum_{k=1}^{K} w_k u_k(g) 1001[1] \tag{22}$$

is Pareto-efficient on the admissible manifold $\mathcal{G}_{\text{adm}}$, ensuring $g^* \in \mathcal{P}(\mathcal{G}_{\text{adm}})$ [1].

Proof. Suppose g^* is not Pareto-efficient. Then there exists $g' \in \mathcal{G}_{\text{adm}}$ such that $u_k(g') \geq u_k(g^*)$ for all $k \in \{1, \ldots, K\}$ and $u_j(g') > u_j(g^*)$ for some j [1]. Because $w_k > 0$ for all k:

$$\sum_{k=1}^{K} w_k u_k(g') = w_j u_j(g') + \sum_{k\neq j} w_k u_k(g') > w_j u_j(g^*) + \sum_{k\neq j} w_k u_k(g^*) = \sum_{k=1}^{K} w_k u_k(g^*) 1001[1] \tag{23}$$

contradicting the maximality of g^*. Hence $g^* \in \mathcal{P}(\mathcal{G}_{\text{adm}})$ [1]. □

4 Modular Sector Gates and Algebraic Commutation

At Level 3, the cognitive state space is factorized into modular functional sectors [1, 4]:

$$\mathcal{H}_{\text{AGI}} = \bigotimes_{k=1}^{N} \mathcal{H}_k = \mathcal{H}_{\text{perception}} \otimes \mathcal{H}_{\text{reasoning}} \otimes \mathcal{H}_{\text{memory}} \otimes \mathcal{H}_{\text{self}} \otimes \mathcal{H}_{\text{goal}} 1001[1,\ 4]. \tag{24}$$

Inter-sector routing operators $G_{ij}(X_t) : \mathcal{H}_i \to \mathcal{H}_j$ are parameterized dynamically by the full cognitive state tuple X_t [1]:

$$G_{ij}(X_t) = \exp\left(-i \sum_m \theta_m(X_t) \hat{A}_{ij}^{(m)}\right), \qquad \hat{A}_{ij}^{(m)} = \hat{P}_i^{(m)} \otimes \hat{Q}_j^{(m)} 1001[1]. \tag{25}$$

Proposition 2 (Sufficient Condition for Dynamic Gate Commutation). *Let $U = G_{jk}(X_t)G_{ij}(X_t)$ and $V = G_{ij}(X_t)G_{jk}(X_t)$ act across sectors (i, j, k) [1, 4]. If the generator algebra satisfies:*

$$[\hat{A}_{ij}^{(m)}, \hat{A}_{jk}^{(n)}] = 0 \quad \forall m, n 1001[1,\ 4] \tag{26}$$

then $[U, V] = 0$ holds identically for all parameter trajectories $\theta(X_t)$, guaranteeing that belief-directed routing executes deterministically independent of gate scheduling [1, 4].

Proof. When generator operators commute pairwise, the Lie algebra elements span an abelian subalgebra. By the Baker-Campbell-Hausdorff formula:

$$\exp(-i\theta_A \hat{A}) \exp(-i\theta_B \hat{B}) = \exp(-i\theta_A \hat{A} - i\theta_B \hat{B}) = \exp(-i\theta_B \hat{B}) \exp(-i\theta_A \hat{A}) 1001[4]. \tag{27}$$

Hence $[U, V] = 0$ dynamically [1, 4]. □

5 Physical Compilation: Parity Readout and the Tunneling-First Principle

At Levels 4–5, abstract sector transitions compile into measurement-first parity fusions on InAs-Al hybrid semiconductor-superconductor nanowires [2, 6].

5.1 Effective Hamiltonian and Boundary Flux Coupling

We formulate the physical substrate via the 3+1 Hamiltonian:

$$H_{\text{eff}} = H_{\text{wire}} + H_{\text{Maxwell}} + H_{\text{int}} \tag{28}$$

where $H_{\text{wire}} = i \sum_j \epsilon_{ij} \gamma_i \gamma_j$ models low-energy subgap states in the nanowire [2], $H_{\text{Maxwell}} = \frac{1}{2} \int_{\Sigma^3} (\mathbf{E}^2 + \mathbf{B}^2)\, d^3x$ is the physical electromagnetic Hamiltonian on spatial slices [3], and the interaction between boundary photonic flux and the nanowire loop is modeled via the phenomenological boundary coupling ansatz:

$$H_{\text{int}} = g \int_{\partial\Sigma^3} A \wedge *J_s 1001[2,\ 3]. \tag{29}$$

This induces an effective magnetic flux $\varphi = 2\pi\Phi/\Phi_0 + \frac{e}{\hbar} \oint_{\partial\Sigma^2} A$ through the interferometer loop [2, 6].

5.2 Interferometric Parity Readout

A triple-dot loop coupled to left and right nanowire segments exhibits flux-dependent interferometric tunneling [2, 6]:

$$t_C(Z, \varphi) = \sqrt{t_L^2 + t_R^2 + 2t_L t_R \sin\varphi\, Z}1001[2] \tag{30}$$

where $Z \in \{-1, +1\}$ denotes the total fermion parity, and $\Phi_0 = h/e$ is the superconducting flux quantum [2,6]. Under Condition 1 and fixed total tunneling strength $t_L^2 + t_R^2$, balanced coupling ($t_L \approx t_R$) maximizes the effective interference amplitude and is therefore adopted as the optimal operating configuration for parity discrimination [2]. The dispersive quantum capacitance shift is:

$$\Delta C_Q(\Phi) = C_Q(Z = +1, \Phi) - C_Q(Z = -1, \Phi) \propto \frac{\partial^2 E}{\partial V_{\mathrm{QD}}^2}[t_C(+1, \varphi)] - \frac{\partial^2 E}{\partial V_{\mathrm{QD}}^2}[t_C(-1, \varphi)]1001[2, 6]. \tag{31}$$

Recent experiments by Aghaee et al. [6] have demonstrated single-shot interferometric parity readout in InAs-Al hybrid devices with quantum capacitance shifts up to 1 fF and SNR = 1 within 3.6 μs, while cautioning that parity readout alone does not definitively establish the topological nature of the underlying zero modes.

5.3 Derivation of the Tunneling-First Principle

Single-shot parity measurement operates via dispersive reflectometry, modeled as a binary symmetric Gaussian channel:

$$y \sim \mathcal{N}\big(\pm\Delta C_Q(\Phi), \sigma_m^2\big), \qquad \sigma_m^2 = \frac{S_N}{2\tau}1001[2, 6] \tag{32}$$

with signal-to-noise ratio $\mathrm{SNR} = \frac{2|\Delta C_Q|}{\sigma_m} = 2|\Delta C_Q|\sqrt{\frac{2\tau}{S_N}}$ [2,6].

Operating Condition 1 (Dispersive Tunneling-Contrast Window)**.** *We operate in the subgap regime ($E_M \ll k_B T, \tau \ll \tau_{\mathrm{qpp}}$) where device parameters lie within the operating window $\mathcal{W}$ in which the effective capacitance contrast is monotonically increasing in balanced tunneling amplitude: $\partial|\Delta C_Q|/\partial t_C > 0$ [2].*

Theorem 3 (Tunneling-First Monotonicity in Readout-Limited Regimes)**.** *Let $\mathcal{L} = I(Z; Y)$ denote the mutual information capacity between the parity state Z and readout Y, and let $\kappa_{\mathrm{rate}} = \frac{1}{\tau}D_{\mathrm{KL}}(p_+ \parallel p_-)$ denote the sequential error exponent rate such that $P_{\mathrm{err}} \sim e^{-\kappa_{\mathrm{rate}}\tau}$ [2]. Under Condition 1:*

$$\frac{\partial\mathcal{L}}{\partial t_C} > 0, \qquad \frac{\partial\kappa_{\mathrm{rate}}}{\partial t_C} > 0 \quad \textit{for } t_C \in \mathcal{W}1001[2]. \tag{33}$$

Consequently, optimizing balanced tunneling networks ($t_L \approx t_R$) is prioritized before cognitive sector scaling ($N \to \infty$) in the engineering hierarchy [2].

Proof. For a binary symmetric Gaussian channel with prior $P(Z = \pm 1) = 1/2$, the mutual information $I(Z; Y)$ is a strictly increasing function of SNR, satisfying $\partial I(Z; Y)/\partial \mathrm{SNR} > 0$ [2]. Since $\mathrm{SNR} \propto |\Delta C_Q|$, applying the chain rule under Condition 1 yields:

$$\frac{\partial\mathcal{L}}{\partial t_C} = \frac{\partial I(Z; Y)}{\partial \mathrm{SNR}} \frac{\partial \mathrm{SNR}}{\partial|\Delta C_Q|} \frac{\partial|\Delta C_Q|}{\partial t_C} > 01001[2]. \tag{34}$$

For Gaussian branch distributions $p_\pm(y) = \mathcal{N}(\pm\Delta C_Q, \sigma_m^2)$, the Kullback-Leibler rate is:

$$\kappa_{\mathrm{rate}} = \frac{1}{\tau}D_{\mathrm{KL}}(p_+ \parallel p_-) = \frac{1}{\tau}\frac{(2\Delta C_Q)^2}{2\sigma_m^2} = \frac{4(\Delta C_Q)^2}{S_N}1001[2]. \tag{35}$$

Differentiating with respect to t_C:

$$\frac{\partial \kappa_{\text{rate}}}{\partial t_C} = \frac{8|\Delta C_Q|}{S_N} \frac{\partial |\Delta C_Q|}{\partial t_C} > 01001[2]. \tag{36}$$

Monotonicity holds throughout $\mathcal{W}$ until backaction-induced level splitting $E_M(t_C)$ enters the denominator of ΔC_Q [2]. $\square$

6 Composite Hardware Risk and Architecture Analysis

We define the composite execution risk functional for compiled cognitive operations [2]:

$$\mathcal{R} = w_1 \epsilon_{\text{meas}} + w_2 p_{\text{leak}} + w_3 \gamma_\phi + w_4 \mathcal{O}_{\text{ctrl}} 1001[2] \tag{37}$$

where $\epsilon_{\text{meas}} = \frac{1}{2}\operatorname{erfc}(\text{SNR}/\sqrt{8})$ is the single-shot assignment error, $p_{\text{leak}} \leq Ae^{-L/\xi}$ is subgap leakage, $\gamma_\phi \leq B n_{\text{qp}} e^{-\Delta/k_B T}$ is the dephasing rate, and $\mathcal{O}_{\text{ctrl}}$ is microwave control overhead [2].

Compilation Hypothesis 1 (Risk Suppression under ParityFuse Compilation)**.** *Compiling sector-gate operators into repeat-until-success sequences of the measurement-only primitive* ParityFuse(L, R) *systematically suppresses* $\mathcal{R}$ *relative to transmon or quantum-dot gate architectures [2]:*

1. *Non-local* $\mathbb{Z}_2$ *parity encoding provides exponential suppression of leakage* $p_{\text{leak}} \sim e^{-L/\xi}$ *and charge-noise dephasing [2].*

2. *Measurement-only compilation replaces calibrated microwave rotation pulses with baseband gate sensing and topological parity projections, minimizing control overhead* $\mathcal{O}_{\text{ctrl}} \sim \mathcal{O}(1)$ *[2].*

7 Discussion and Theoretical Implications

Synthesizing GID mechanics with topological photonic continuity and parity compilation yields three primary insights:

1. **Decoupling Abstract Mechanics from Physical Substrates**: General intelligence is defined at Levels 1–2 as a mathematical dynamical system governing belief update $\mathcal{B}$, memory consolidation $\mathcal{M}$, goal revision Γ, and recursive self-modeling $\mathcal{S}$ [1]. Physical hardware acts strictly as an execution layer for these equations of motion [1].

2. **Topological Parameter Regularization**: The bulk topological current $J_s = \pi_* \mathcal{J}$ supplies an invariant reference channel Q_{soul}, restricting the admissible parameter domain to Θ_ϵ while calibration dynamics satisfy a rigorous stationarity bound and stabilize Pareto-efficient goal reconciliation [1,3].

3. **Engineering Prioritization**: The Tunneling-First Principle provides an actionable roadmap for quantum AGI hardware: engineer symmetric, high-contrast InAs-Al triple-dot junctions ($t_L \approx t_R$) before scaling sector dimensionality N [2,6].

8 Conclusion

We have presented an integrated theoretical framework unifying General Intelligence Dynamics (GID), Interferometric Sector Dynamics (ISD), and higher-dimensional gauge continuity [1–3]. At the abstract mathematical level, we proved that the topological constraint restricts the admissible parameter domain, while recursive calibration dynamics satisfy a stochastic stationarity bound and guarantee Pareto-efficient goal synthesis over capacity-constrained domains [1].

At the physical compilation layer, we derived the Tunneling-First Principle for parity-driven quantum substrates, demonstrating that balanced tunneling maximizes single-shot capacitance contrast ΔC_Q, mutual information learning capacity $\mathcal{L}$, and sequential error rate exponents κ_{rate} [2, 6]. This establishes a mathematically consistent and hardware-grounded paradigm for topologically accelerated Artificial General Intelligence [1, 2].

References

[1] P. De Ceuster, "Beyond Artificial Intelligence: The Mathematical Dynamics of General Intelligence — Recursive State-Space Dynamics, Self-Modeling, and Adaptive Goal Formation," Technical Monograph, August 2026.

[2] P. De Ceuster, "Interferometric Sector-Gate Quantum Dynamics for AGI: Parity-Driven Tunneling First and the Case for a Topological Core," Zenodo Technical Report, August 2025.

[3] P. De Ceuster, "Photon Soul Continuity: An Unobserved Extension of Maxwell's Equations," Technical Preprint, August 2025.

[4] P. De Ceuster, "Quantum Sector-Gate Dynamics for Artificial General Intelligence," Zenodo Preprint, doi:10.5281/zenodo.16968899, 2024.

[5] P. De Ceuster, "Quantum Eigenstate Dynamics for Artificial General Intelligence Synthesis," Zenodo Preprint, doi:10.5281/zenodo.16748240, 2024.

[6] M. Aghaee, A. Alcaraz Ramirez, Z. Alam, et al., "Interferometric single-shot parity measurement in InAs-Al hybrid devices," *Nature*, vol. 638, pp. 651–656, 2025.

[7] D. S. Freed, "Dirac charge quantization and generalized differential cohomology," *Surveys in Differential Geometry*, vol. 7, pp. 129–194, 2000.

[8] E. Witten, "Geometric Langlands and the equations of Nahm and Bogomolny," *arXiv preprint arXiv:1602.09021* [hep-th], 2016.

[9] M. E. Peskin and D. V. Schroeder, *An Introduction to Quantum Field Theory*, Addison-Wesley, Reading, MA, 1995.