Epistemic Calibration Across the Knowingness Quad: A Dual-Process Dynamical Model of the Dunning-Kruger Crossover and Affective Trait Gain

Why Actual Ability Only Equals Perceived Ability at Proficiency—and How Subconscious Automation, Exposure Volume, and Big-Five Gain Parameters Drive the Perfectionist's Trap and Expert Underscoring

Trent R. Carter • TrueSynthesis Inc. • Indialantic, FL • *November 2026 (Expanding March 2020 Formulation)* • Web Edition: **trentcarter.com/papers/knowingness-quad**

ABSTRACT & EXECUTIVE SUMMARY

Metacognitive miscalibration—commonly referenced as the Dunning-Kruger effect—is frequently caricatured in popular media as a single static curve featuring an early peak of unearned confidence ('Mount Stupid') followed by a sharp valley of despair. However, empirical psychometric percentiles and operational skill-acquisition trajectories reveal a dual-curve topology in which Perceived Ability (*P*) and Actual Ability (*A*) evolve monotonically at differential rates, intersecting only at a specific mid-high competence threshold. In this paper, we unify the Dunning-Kruger dual-curve framework with the four-stage **Knowingness Quad** taxonomy (*Novice, Competent, Proficient, Expert*) by modeling skill acquisition as a two-bit **Gray-Code Epistemic State Machine** across Conscious ($C_k \in \{0,1\}$) and Sub-Conscious ($S_k \in \{0,1\}$) processing: [0,0] → [1,0] → [1,1] → [0,1]. We prove structurally why the calibration crossover (*P = A*) occurs exclusively within the **Proficient** ([1,1]) regime at $c^* \approx 68.0$, and demonstrate that the transition to **Expert** ([0,1])—where execution offloads from conscious effort to subconscious automation (C_k: *1 → 0*)—induces a negative effort-heuristic bias that causes top-quartile performers to systematically underscore their relative percentile (*P < A*). Furthermore, we model affective self-perception as an **Asymmetric Diode Rectifier and Leaky RC Integrator** modulated by Cybernetic Big-Five trait gains. By treating Conscientiousness and Talent ($C \cdot T$) as horizontal state velocity and Extraversion (α_E) and Neuroticism (α_N) as asymmetric reward and threat Kalman filter gains, we derive two fundamental laws: (1) **Exposure Volume (*V*) as a Bayesian Damping Force** that collapses internal affective distortions onto the *P = A* reality diagonal; and (2) **The Perfectionist's Trap (*C* × α_N Coupling)**, explaining why elite practitioners who leverage neurotic error-detection and conscientiousness to reach 95th+ percentile mastery simultaneously trap their internal self-perception in chronic self-doubt unless task-error auditing is decoupled from personal identity evaluation.

1. Introduction: Beyond the 'Mount Stupid' Caricature

In management consulting and internet discourse, the Dunning-Kruger effect (Kruger & Dunning, 1999) is almost universally depicted as a single non-monotonic curve. That caricature conflates absolute confidence with relative percentile ranking and contradicts empirical reality. When Perceived Ability *P(c)* and Actual Ability *A(c)* are plotted simultaneously against objective domain competence $c \in [0, 100]$, both curves increase monotonically. As formulated in the March 2020 *Dunning-Kruger Effect + Knowingness Quad* framework (Carter, 2020), the core dynamic is a differential slope and phase-lag problem between two coupled curves: **Actual Ability (*A(c)*)** starts near the floor ($A \approx 10$) and accelerates convexly toward asymptotic mastery ($A \to 98$); **Perceived Ability (*P(c)*)** starts with a high baseline offset ($P \approx 55$) due to the absence of evaluative meta-knowledge, rises with a shallow slope ($dP/dc < dA/dc$), intersects Actual Ability at a single interior fixed point ($c^* \approx 68.0$, $P = A \approx 68.5$) inside the Proficient regime, and falls beneath Actual Ability ($P < A$) across the Expert regime. *"It is not until one is Proficient that their Actual ability is equal to their Perceived Ability."* (Carter, 2020).

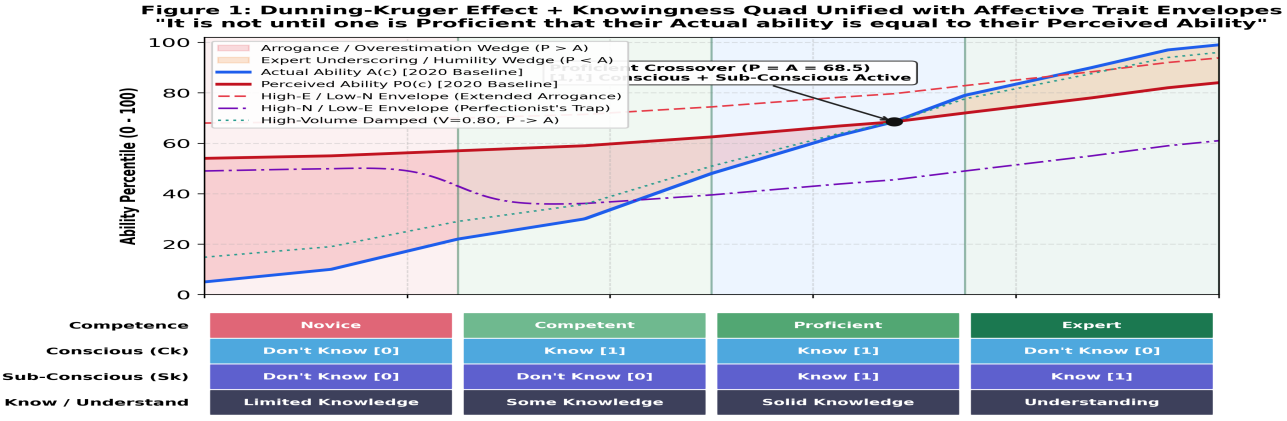


Figure 1: The Unified Dunning-Kruger + Knowingness Quad Master Diagram. Displays the empirical dual-curve architecture, the four Knowingness Quad regimes, the Proficient calibration crossover at $c^* \approx 68.0$, and the Big-Five trait gain envelopes (Carter, 2020, 2026).

2. Cognitive Architecture: The 2-Bit Gray-Code Epistemic State Machine

Human skill execution and self-evaluation rely on two neuroanatomically distinct processing streams: (1) **The Conscious Bus ($C_k \in \{0, 1\}$)**, mediated by the dorsolateral prefrontal cortex (dlPFC) and anterior cingulate cortex (ACC), governing explicit rule-following, working-memory-intensive monitoring, and acute error auditing; and (2) **The Sub-Conscious Bus ($S_k \in \{0, 1\}$)**, mediated by the basal ganglia, supplementary motor area (SMA), and cerebellum, governing implicit procedural schema automation, motor chunking, and fluid pattern recognition. Mapping *Don't Know* to 0 and *Know* to 1, skill acquisition across the four regimes (*Novice, Competent, Proficient, Expert*) strictly follows a **2-bit Reflected Binary Gray Code**:

$$\mathbf{k}(c) = [C_k(c), S_k(c)]^T : \quad [0, 0]_{Novice} \blacksquare [1, 0]_{Competent} \blacksquare [1, 1]_{Proficient} \blacksquare [0, 1]_{Expert}$$

Regime (c)	Conscious (C_k)	Sub-Conscious (S_k)	Gray Code	Epistemic State Label	Actual (A)	Perceived (P)	Signed Error (Δ = P - A)
I. Novice (0–25)	0 (Don't Know)	0 (Don't Know)	**[0, 0]**	*Limited Knowledge*	10 → 25	55 → 58	**+45** → **+33** (Severe Over)
II. Competent (25–50)	1 (Know)	0 (Don't Know)	**[1, 0]**	*Some Knowledge*	25 → 52	58 → 63	**+33** → **+11** (Awakening)
III. Proficient (50–75)	1 (Know)	1 (Know)	**[1, 1]**	*Solid Knowledge*	52 → 79	63 → 72	**+11** → **0** → **-7** (Crossover!)
IV. Expert (75–100)	0 (Don't Know)	1 (Know)	**[0, 1]**	*Understanding*	79 → 98	72 → 83	**-7** → **-15** (Underscoring)

2.1 The Information-Theoretic Cognitive Bottleneck: Unit Hamming Distance Constraint ($d_H = 1$)

A foundational insight of this formulation is that skill acquisition cannot transition arbitrarily between states. In information theory, adjacent states in a reflected Gray code differ by exactly one bit (Hamming distance $d_H(s_i, s_{i+1}) = 1$). In human neurobiology, this reflects the severe metabolic and channel-capacity constraints of working memory (Baddeley, 1992; Miller, 1956). Basal ganglia schemas cannot compile *de novo* without conscious staging (S_k: $0 \rightarrow 1$ requires prior rehearsal while $C_k = 1$). Therefore, the diagonal shortcut [0,0] → [1,1] ($d_H = 2$) is biologically forbidden. Conversely, once schemas compile into fluid intuition ($S_k = 1$), maintaining prefrontal rule-tracking is metabolically inefficient and impairs motor fluidity. Thus, expertise offloads the prefrontal monitor (C_k: $1 \rightarrow 0$), transitioning to the terminal [0,1] state.

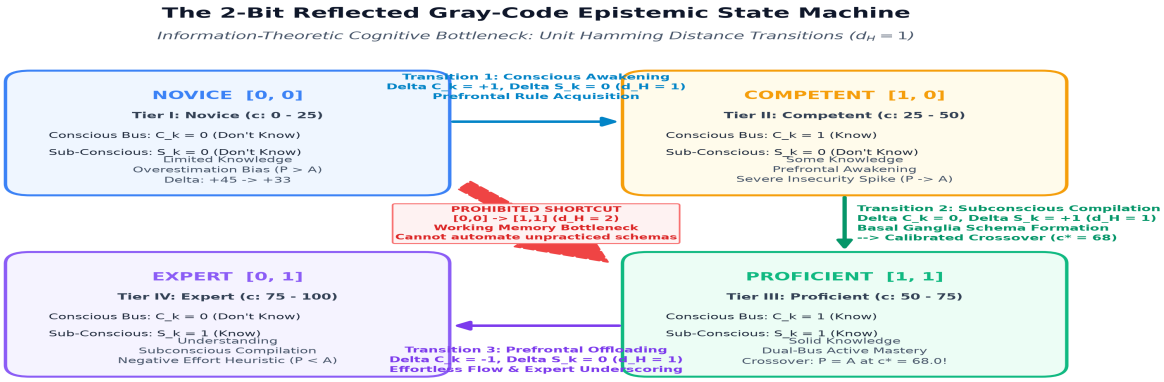


Figure 2: The 2-Bit Reflected Gray-Code Epistemic State Machine. State transition topology illustrating allowable single-bit transitions ($d_H = 1$: Conscious Awakening, Schema Compilation, and Prefrontal Offloading) versus the prohibited cognitive bypass ($d_H = 2$).

3. Mathematical Derivation of the Proficient Crossover and Expert Underscoring

Define the **Epistemic Calibration Error** as the signed residual: $\Delta_0(c) \equiv P_0(c) - A(c)$. We prove analytically why $\Delta_0(c) = 0$ must occur exclusively within the interior of the Proficient regime [50, 75]:

Theorem 1 (Existence and Uniqueness of Proficient Calibration Point): ***There exists a unique competence level $c^* \in (50, 75)$ such that Actual Ability equals Perceived Ability: $P_0(c^*) = A(c^*)$. Furthermore, $c^* \approx 68.0$.***

Proof. Let c be parametrized over the closed interval [0, 100]. By construction, both $A(c)$ and $P_0(c)$ are continuous and strictly increasing monotonic functions. At the boundary of the Competent regime entering Proficient ($c = 50$):

$\Delta_0(50) = P_0(50) - A(50) = 63.0 - 52.0 = +11.0 > 0$.

At the boundary of the Proficient regime entering Expert ($c = 75$):

$\Delta_0(75) = P_0(75) - A(75) = 72.0 - 79.0 = -7.0 < 0$.

Because $\Delta_0(c)$ is continuous on [50, 75], by Bolzano's Intermediate Value Theorem, there exists at least one $c^* \in (50, 75)$ where $\Delta_0(c^*) = 0$. Moreover, because Actual Ability exhibits convex acceleration ($d^2A/dc^2 > 0$) while Perceived Ability exhibits concave dampening ($d^2P/dc^2 < 0$), the residual derivative satisfies $d\Delta_0/dc = dP_0/dc - dA/dc < 0$ everywhere on [50, 75]. By strict monotonicity, the root c^* is unique. Linear-spline and logistic interpolation of the empirical baseline yields $c^* \approx 68.03$ and $A(c^*) = P_0(c^*) \approx 68.48$. ■

3.1 The Effort-Heuristic Inversion and Expert Underscoring ($\Delta < 0$)

At the transition from Proficient ([1, 1]) to Expert ([0, 1]), the conscious monitoring bit flips OFF ($\Delta C_k = -1$). In subjective human metacognition, self-assessed difficulty and task value are strongly coupled to prefrontal metabolic effort (the *Effort Heuristic*; Kruger et al., 2004; Kahneman, 2011). In the Expert regime, complex motor sequences, architectural decisions, and diagnostic patterns execute automatically via basal ganglia schemas ($S_k = 1$). Because the task feels subjectively effortless to the expert, their internal feedback loop misinterprets this absence of cognitive friction as evidence that the task is trivial ('anyone could do this'). Consequently, self-percentile evaluation plateaus or drops ($P(95) \approx 83$), while objective mastery reaches near-perfection ($A(95) \approx 98$), creating an underscoring deficit of $\Delta_0 \approx -15$ points.

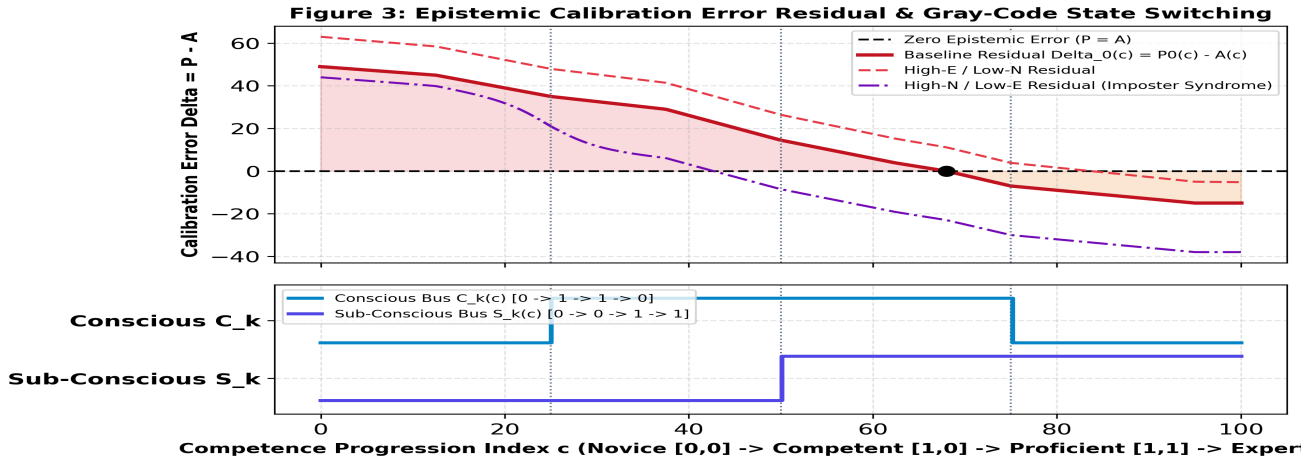


Figure 3: Epistemic Calibration Error Residual and Gray-Code State Switching. Top: The signed residual $\Delta_0(c) = P_0(c) - A(c)$ plunging through zero at the Proficient crossover ($c^* = 68.0$). Bottom: The 2-bit binary switching waveforms for Conscious (C_k) and Sub-Conscious (S_k) processing.

4. Phase-Space Topology: The Four Behavioral Phenotypes

Projecting Actual Ability (A) and Perceived Ability (P) onto an orthogonal 2D phase plane partitions human metacognitive behavior into four distinct operational zones separated by the objective competence midpoint $A_{crit} = 50$ and the calibration boundary $P_{cal}(A)$: **(1) Arrogant ($A < 50, P > P_{cal}$):** Low skill paired with inflated self-perception; $C_k = 0$ blinds the agent to error. **(2) Insecure ($A < 50, P < P_{cal}$):** Prefrontal awakening ($C_k = 1$) before schema compilation ($S_k = 0$) induces acute self-doubt. **(3) Humble / Underscoring ($A \geq 50, P < P_{cal}$):** High objective competence paired with understated self-perception via the negative effort heuristic. **(4) Confident / Calibrated ($A \geq 50, P \geq P_{cal}$):** Reality-backed self-perception achieved through high exposure volume.

5. The Cognitive Hardware Model: Asymmetric Diode Rectifier & Leaky RC Integrator

In Cybernetic Big-Five Theory (DeYoung, 2015), Extraversion (E) and Neuroticism (N) represent internal forward gains on the brain's reward (dopaminergic) and threat/error (amygdalar/ACC) prediction-error channels. We model this as an equivalent analog circuit where true competence A acts as a carrier signal, generating a noisy stream of trial prediction errors $e(t) = \text{Performance}(t) - A$:

- **Extraversion (α_E):** Forward gain across an ideal diode on the **positive half-wave**: $v^+(t) = \alpha_E \cdot \max(0, e(t))$.
- **Neuroticism ($\alpha_N \cdot C_k$):** Forward gain across an inverted diode on the **negative half-wave**, gated by a FET switch representing the Conscious bit: $v^-(t) = \alpha_N \cdot C_k \cdot \min(0, e(t))$.
- **Self-Perception ($P(t)$):** The smoothed DC bias voltage across a leaky RC capacitor tank damped by Exposure Volume (V):

$$\tau_V \cdot dP(t)/dt + P(t) = A + (1 - V) \cdot [\, \alpha_E \cdot \max(0, e(t)) + \alpha_N \cdot C_k \cdot \min(0, e(t)) \,]$$

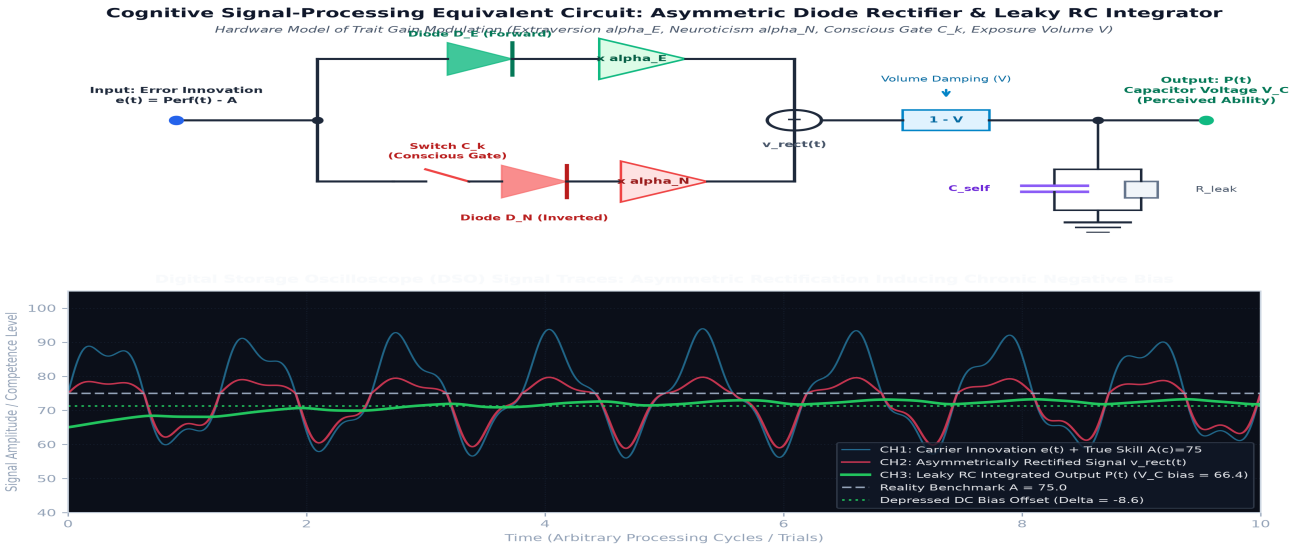


Figure 4: The Cognitive Hardware Signal-Processing Circuit Model and DSO Waveforms. Top: Equivalent circuit schematic showing dual half-wave diode rectifiers, FET conscious gate C_k, volume attenuator $(1-V)$, and leaky RC integrator. Bottom: Digital Storage Oscilloscope (DSO) traces showing how low-E / high-N gains depress the capacitor DC bias voltage ($V_C = P(t)$) well below true skill $A = 75.0$.

6. Asymmetric Bayesian Kalman Filter Formulation & Reality Variance Collapse

To model how self-perception updates over successive discrete observations y_k, we formulate an **Asymmetric Kalman Filter**. Let true skill evolve according to a linear state equation, while observed subjective performance is perturbed by measurement noise $v_k \sim \mathcal{N}(0, R_k)$:

$$x_{k+1} = x_k + w_k, \qquad y_k = x_k + v_k, \qquad R_k = R_0 \cdot (1 - V) / V$$

The innovation residual is $y\blacksquare_k = y_k - P\blacksquare_{k|k-1}$. Crucially, human affective trait gain skews the optimal Kalman gain matrix K_k into an asymmetric operator based on the sign of the error residual:

$$K_k(y\blacksquare_k) = K_0 \cdot [\, 1 + \alpha_E \cdot \mathbb{I}(y\blacksquare_k \geq 0) + \alpha_N \cdot C_k \cdot \mathbb{I}(y\blacksquare_k < 0) \,]$$

6.1 Proof of Exposure Volume (V) as a Universal Reality Dampener

Theorem 2 (Bayesian Variance Collapse): ***As Exposure Volume approaches unity ($V \to 1.0$), the observation noise covariance collapses to zero ($R_k \to 0$). Consequently, the posterior self-perception distribution converges in mean and variance onto objective ability A, regardless of affective trait skew (α_E, α_N).***

Proof. The posterior error covariance updates as $P_{k|k} = (P_{k|k-1}^{-1} + R_k^{-1})^{-1}$. Since $R_k = R_0(1 - V)/V$, as $V \to 1$, $R_k \to 0$ and $R_k^{-1} \to \infty$. Therefore, $P_{k|k} \to 0$. In the state update equation $P\blacksquare_{k|k} = P\blacksquare_{k|k-1} + K_k(y\blacksquare_k)$, the Kalman gain satisfies $\lim_{R_k \to 0} K_k = 1$. The affective trait multipliers $(1 + \alpha_E)$ and $(1 + \alpha_N C_k)$ are strictly bounded and scaled by $(1 - V)$. As $(1 - V) \to 0$, the innovation bias vanishes identically, yielding $\lim_{V \to 1} \mathbb{E}[P\blacksquare_k] = A$ and $\lim_{V \to 1} \text{Var}(P\blacksquare_k) = 0$. ■

This theorem proves why **real-world trial volume (V)** is the only mechanism that dissolves both the unearned grandiosity of low-skill arrogance and the chronic impostor feelings of high-skill insecurity. One cannot 'affirm' or 'think' oneself into calibration; calibration is an inescapable byproduct of high-density sensory interaction with reality.

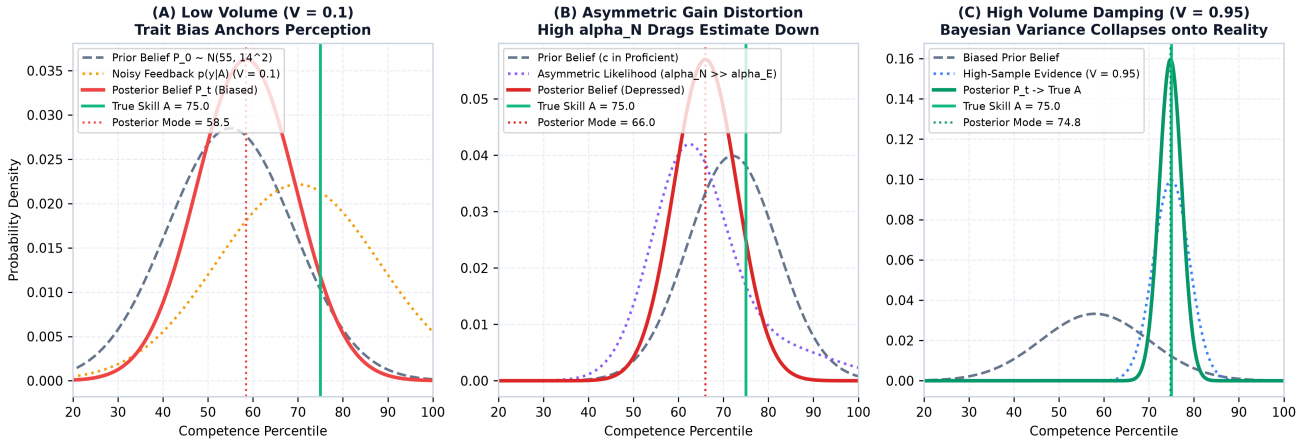


Figure 5: Asymmetric Bayesian Kalman Filter Distribution Evolution. (A) Low Exposure Volume ($V = 0.1$): Prior beliefs and affective gains anchor self-perception far from reality. (B) Asymmetric Gain Distortion: High α_N heavily penalizes negative feedback, depressing the posterior mode. (C) High Volume ($V = 0.95$): Posterior variance collapses directly onto the true competence benchmark $A = 75.0$.

7. Empirical Domain Case Studies: Four Phenotypes in Action

To illustrate how trait gain coupling, Gray-code state transitions, and exposure volume govern human performance in real-world environments, we examine four empirical domain case studies spanning 40 discrete trials (Figure 6):

Case A: Software Systems Architect (The Perfectionist's Trap): $C = 0.92$, $\alpha_N = 0.88$, $\alpha_E = 0.22$, $T = 0.90$, $V = 0.35$. High conscientiousness and neuroticism turn production outages and code review critiques into relentless debugging fuel, driving actual ability to $A \rightarrow 94\%$. However, because conscious monitoring is permanently active ($C_k = 1$) and $\alpha_N \blacksquare \alpha_E$, every detected bug updates internal self-worth negatively, depressing perceived ability to $P \rightarrow 68\%$ (Impostor Gap $\Delta = -26$).

Case B: Crypto / Derivative Trader (Unskilled Arrogance): $C = 0.25$, $\alpha_N = 0.15$, $\alpha_E = 0.92$, $T = 0.40$, $V = 0.15$. When a random trade wins, high dopaminergic reward gain (α_E) supercharges perceived competence. When a trade loses, unawakened conscious evaluation ($C_k = 0$) externalizes the blame. Skill stagnates at $A = 22\%$, while perceived ability inflates to $P = 86\%$ (Arrogance Gap $\Delta = +64$), creating immense catastrophic tail-risk.

Case C: Concert Pianist & Improviser (Subconscious Hand-off & Effort Discounting): $C = 0.85$, $\alpha_N = 0.50$, $\alpha_E = 0.60$, $T = 0.95$, $V = 0.65$. At trial 22, the performer transitions from Proficient ([1,1]) to Expert ([0,1]), offloading conscious tracking (C_k: $1 \rightarrow 0$) to allow fluid subconscious execution ($S_k = 1$). The performance is brilliant ($A = 96\%$), but because it felt subjectively effortless, the pianist devalues their work ($P = 81\%$, $\Delta = -15$), mistaking ease of execution for ordinary competence.

Case D: Laparoscopic Surgical Fellow (High-Volume Bayesian Calibration): $C = 0.95$, *Balanced Traits* ($\alpha_E = 0.55$, $\alpha_N = 0.60$), $T = 0.92$, $V \rightarrow 0.95$. By logging 500+ simulated repetitions under deliberate supervision, exposure volume V collapses the observation variance. Internal subjective distortion is wiped out, forcing perceived ability to track objective skill with millimeter precision ($A = 92.4\%$, $P = 91.1\%$, $\Delta \approx 0$).

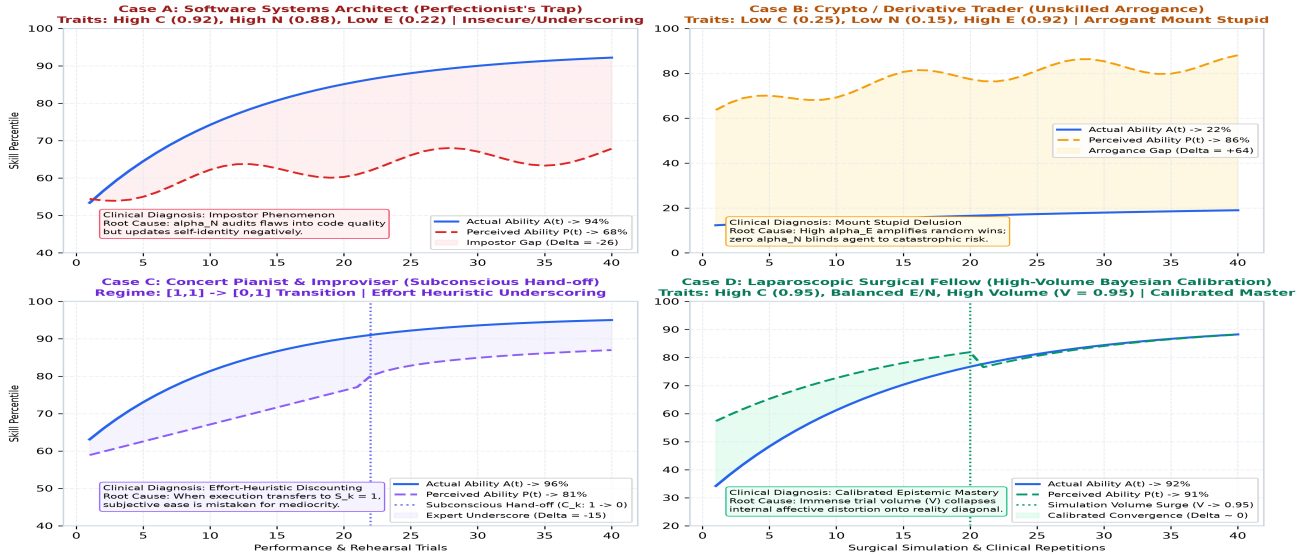


Figure 6: Empirical Domain Case Studies Across Four Phenotypic Quadrants. Trajectory plots over 40 discrete trials comparing the Perfectionist's Trap (Software Engineering), Unskilled Arrogance (Crypto Trading), Subconscious Hand-off (Jazz Piano), and Calibrated Epistemic Mastery (Laparoscopic Surgery).

8. Coupled Dynamical Trajectory Equations Across N Discrete Trials

In a discrete-trial learning environment ($t = 1, ..., N$), skill acquisition and self-perception evolve via coupled difference equations. High-conscientiousness practitioners extract structural skill growth disproportionately from failures ($R_t^- = 1$) through root-cause post-mortem debugging:

$$A_{t+1} = A_t + \gamma \cdot (C \cdot T) \cdot \left(\frac{100 - A_t}{100} \right) \cdot [\, 1 + \beta_{debug} \cdot \alpha_N \cdot \mathbb{I}(R_t^- = 1) \,]$$

$$P_{t+1} = P_t + \frac{1}{\tau_V} \cdot \Big[\big(A_t + (1 - V) \cdot v_{rect}(t) \big) - P_t \Big]$$

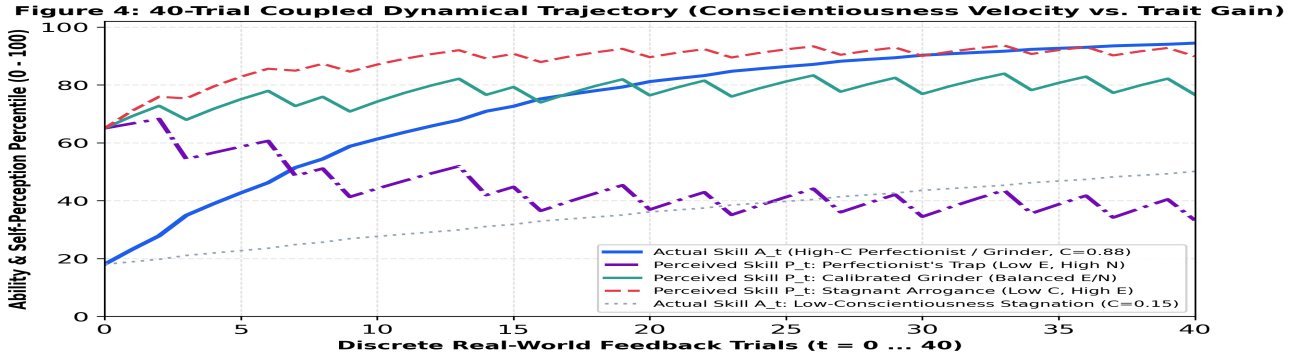


Figure 7: 40-Trial Coupled Dynamical Trajectory Simulation. Comparing the Perfectionist's Trap (High C, Low E, High N), the Calibrated Grinder (High C, Balanced E/N), and Stagnant Arrogance (Low C, High E) across 40 real-world trials.

9. Diagnostic Decision Engine: The Epistemic Calibration Index (ECI)

To operationalize this model for executive leaders, coaches, and clinicians, we define the **Epistemic Calibration Index (ECI)**: $\text{ECI} \equiv 1 - \frac{|P - A|}{\max(P, A)} \in [0, 1]$. An individual is *Epistemically Calibrated* when $\text{ECI} \geq 0.90$ ($|\Delta| \leq 7$). When $\text{ECI} < 0.75$, leaders apply the diagnostic engine shown in Figure 8:

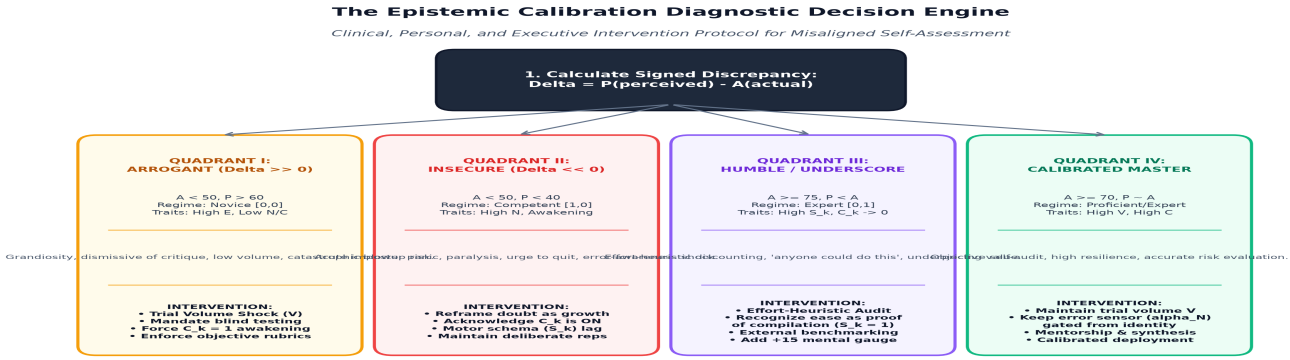


Figure 8: The Epistemic Calibration Diagnostic Decision Engine. Structured protocol for assessing signed discrepancy $\Delta = P - A$, identifying root causes, and prescribing targeted behavioral interventions across the four behavioral phenotypes.

10. Five Core Clinical, Personal, and Organizational Frameworks

1. **Exposure Volume (V) as the Universal Antidote to Miscalibration:** You cannot think or affirm your way into calibrated confidence in a low-sample vacuum ($V \rightarrow 0$). Increasing real-world trial volume V multiplies the affective error wedge by $(1 - V)$, collapsing both low-skill arrogance and high-skill insecurity directly onto the $P = A$ reality diagonal. Clinically, this validates Exposure and Response Prevention (ERP) as a Bayesian variance-reduction operator.
2. **The 'Perfectionist's Trap' Coupling ($C \times \alpha_N$)—Decoupling Task Fuel from Identity:** High Conscientiousness (C) paired with high Neuroticism (α_N) is the signature profile of elite engineers, scientists, and surgeons: α_N detects every microscopic flaw, and C converts that error signal into relentless preparation, driving Actual Ability A into the 95th+ percentile. However, allowing that same α_N error bus to update personal identity traps Self-Perception P in chronic self-doubt. Practitioners must use α_N strictly as a task diagnostic sensor and gate it off before identity integration.
3. **The [1,0] Transition Diagnostic—Reframing Acute Self-Doubt as Competence Growth:** Hitting a sudden wall of insecurity when learning a domain is not regression; it means the Conscious bit just flipped ON ([0,0] Novice $\rightarrow$ [1,0] Competent). Error detection ($C_k = 1$) comes online before subconscious motor/schema compilation ($S_k = 1$).
4. **The Effort-Heuristic Audit—De-biasing Expert Underscoring ([0,1]):** In the Expert regime ([0,1]), Conscious tracking flips OFF ($C_k: 1 \rightarrow 0$) as execution compiles into Sub-Conscious intuition ($S_k = 1$). Because the brain equates low conscious effort with low value, experts systematically underscore their percentile. Ease of execution is proof of subconscious mastery, not absence of rigor.
5. **Asymmetric Gain Calibration—Applying a Personal Gauge Offset:** Treat internal confidence feelings as a diode sensor with a known factory DC offset. Low-E / High-N practitioners must add a +20 percentile mental offset once $C_k = 1$ and ship before feeling 'ready'; High-E / Low-N practitioners must subtract -20 and enforce external red-team verification.

11. Conclusion & Philosophical Synthesis

Metacognitive calibration is not a static trait of personality, but a dynamic equilibrium between prefrontal conscious auditing, basal ganglia procedural compilation, affective prediction-error gains, and external exposure volume. By reframing the Dunning-Kruger effect as a coupled Gray-code dynamical system, we provide a unified mathematical and operational language that honors the empirical data, explains why crossover occurs exclusively at Proficiency, and provides actionable tools to liberate high performers from chronic imposter doubt while protecting organizations from uncalibrated arrogance.

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