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Article

The SSD Method and the Algorithmic Economy of Reality: A Universal Interpreter, Latent Twin, and Experimental Test of Deviations from the Born Rule

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Abstract

This paper develops an integrated theoretical framework unifying three complementary approaches: the Universal Interpreter (UI), the Latent Twin (LT), and the Symbolic Structures of Differences (SSD) method. The central thesis is that reality is not determined by ontological necessity but by minimal informational cost—the history that can be consistently described with the least algorithmic effort enjoys a selection advantage. On this basis, the paper introduces Postulate P5, which predicts a systematic deviation from the standard Born rule: the probability of a quantum outcome depends not only on the amplitude but also on the algorithmic complexity of the outcome itself, $P_{UI}(i) = Z \cdot P_{Born}(i) \cdot 2^{-\lambda s^*(i)}$, where $s^*(i)$ is the SSD complexity index and $\lambda > 0$ is an informational stringency parameter. Section 9 provides a formal motivation for this step through a decomposition of the Kolmogorov complexity of the wave function—without claiming a complete derivation, but with precisely stated assumptions. The experimental framework for testing P5 is based on analyzing the correlation between the empirical frequency of multi-bit quantum measurement outcomes and their algorithmic complexity. The SSD index s^* serves as a computable proxy for Kolmogorov complexity, complemented by Lempel–Ziv and `zlib` compression for robustness. A pilot simulation confirms that the proposed statistical test reliably recovers an injected parameter λ under controlled conditions—but does not confirm that nature follows P5. Empirical validation of the SSD method on numerical sequences, images, and text confirms its reliability as a measure of global structural complexity, with clearly defined limitations in detecting fine semantic differences.

Keywords: Symbolic Structures of Differences; SSD entropy; Universal Interpreter; latent twin; Kolmogorov complexity; algorithmic economy; Born rule; quantum experiment

1. Introduction

Understanding the relationship between mathematical structure, informational cost, and physical reality is one of the foundational challenges of modern theoretical physics and the philosophy of science. Kolmogorov complexity $K(x)$ —the minimum length of a program required to generate sequence x on a universal Turing machine—provides an objective, representation-independent measure of the structural organization of data [5]. Its application to physical systems remains an open methodological question because K is uncomputable.

Symbolic Structures of Differences (SSD), developed for symbolic analysis of time series, provide a computable proxy for K by encoding the local geometry of sequences rather than the statistical amplitude distributions alone. Connections to permutation entropy [4] and invariance under affine transformations are elaborated in prior work by the author [1,3].

This paper integrates the SSD approach with two complementary frameworks—the Universal Interpreter (UI) and the Latent Twin (LT)—into a coherent system. The central contribution is Postulate P5, which derives a testable hypothesis regarding a correction to the Born rule from the principle of minimal algorithmic action. Unlike existing motivations of the Born rule grounded in symmetries,

rationality, or decoherence, the present approach introduces algorithmic complexity as an independent selection criterion, opening the possibility of principled, empirically testable corrections.

1.1. Three Pillars of the Integrated Framework

Each component makes a specific contribution:

- **Universal Interpreter (UI)**—focus on *selection*: how perceived reality emerges from the space of all possible histories via the principle of minimal algorithmic action.
- **Latent Twin (LT)**—focus on *retrieval*: how, for a given real configuration, a structurally equivalent entity can be constructed within the mathematically complete space of variations.
- **SSD Method**—focus on *measurement*: how the informational cost of configurations is operationalized through analysis of local sequence geometry using computable approximations of K .

1.2. Common Thesis

Reality = the economically cheapest coherent description.

This thesis pervades all three components: UI selects the history H that minimizes algorithmic cost $K(H)$; every real configuration X has a latent twin Q^* sharing the same structural signature; SSD measures the informational cost of local geometric patterns as a computable proxy for K .

2. Common Ontology: The Space of Variations

2.1. Combinatorial Completeness—Postulate P1

Let A be a finite alphabet (for numerical sequences $A = \{0, 1, \dots, 9\}$; for images $A = \{0, 1\}$), $S = A^*$ the set of all finite sequences, and $\Omega = A^{\mathbb{N}}$ the space of infinite histories. Every history $H \in \Omega$ is an address in a mathematically complete space of all possible descriptions. For images of resolution $n \times n$:

$$I_n = \{0, 1\}^{n \times n} \cong \{0, 1\}^{n^2}, \quad |I_n| = 2^{n^2}. \quad (1)$$

Hypothesis 1 (Combinatorial Completeness (P1)). *Every $X \in I_n$ is a point in the space of variations. This is not a trivial mathematical tautology but a methodological assumption: no external agent prohibits any configuration a priori. The choice among possible histories is made exclusively through the selection mechanism of Section 3, not through ontological prohibition. P1 yields no direct empirical consequences but enables the formal definition of the space over which selection operates.*

3. Universal Interpreter: The Principle of Reality Selection

3.1. Three-Layer Structure

The UI is organized through three conceptual layers:

- *Ontological layer*: Ω —the space of all formal configurations (P1).
- *Selective layer*: filters and algorithmic economy (P3, P4*).
- *Epistemological layer*: attribution of meaning to selected configurations (P2).

3.2. Selection Measure

The measure quantifying preference for compressible histories is:

$$dv(H) = \frac{1}{Z} \cdot 2^{-\lambda K(H)} \cdot d\mu(H), \quad (2)$$

where $K(H)$ is the Kolmogorov complexity, μ is a reference (uniform) measure, $\lambda > 0$ is the selection stringency parameter, and Z is a normalization constant. Histories with smaller K receive greater selection weight—economy of description, not ontological necessity, determines what becomes reality. Z is finite because $\sum 2^{-K(H)}$ converges by Kraft's inequality [5, Thm. 2.1.1].

3.3. Algorithmic Action

The algorithmic action of history H is defined as $S_{\text{alg}}(H) = K(H)$, i.e., the minimum description length. Observed reality is that history whose description requires the least informational effort, consistent with available observables. This principle is a heuristic framework—not an independently confirmed physical law—motivated by Solomonoff’s inductive theory [6] and Occam’s razor. Experimental verification is possible only indirectly, through testable consequences such as P5.

3.4. Postulates P2 and P3

Hypothesis 2 (Semantic Labeling (P2)). *There exists a function $\sigma: I_n \rightarrow \Sigma$ mapping to a finite label set Σ . Operationally, σ is approximated by the SSD descriptor and/or expert annotation.*

Hypothesis 3 (Bounded Diameter of Classes (P3)). *For each label $i \in \Sigma$ there exists $L_i(n)$ such that $\text{diam}(\sigma^{-1}(i)) \leq L_i(n)$ in the metric space (I_n, d) .*

P2 and P3 are assumptions enabling the formal definition of semantic classes. They are necessary for Lemma G and the latent twin construction but yield no direct empirical predictions outside this framework.

3.5. Postulate P5—Algorithmic Correction to the Born Rule

In standard quantum mechanics, the probability of outcome i is $|\langle i|\psi\rangle|^2$. Within the UI framework, every quantum outcome i (a bitstring of length n) is a history in Ω ; applying the selection filter from Section 3.2 gives:

$$P_{\text{UI}}(i) \propto P_{\text{Born}}(i) \cdot 2^{-\lambda K(i)}. \quad (3)$$

Because K is uncomputable, we introduce the operational approximation $s^*(i)$ (Section 4):

Hypothesis 4 (Algorithmic Correction to the Born Rule (P5)). *Let $P_{\text{Born}}(i)$ be the Born-rule probability and $s^*(i)$ the SSD complexity index of outcome i . Then:*

$$P_{\text{UI}}(i) = Z \cdot P_{\text{Born}}(i) \cdot 2^{-\lambda s^*(i)}, \quad (4)$$

where $\lambda > 0$ is the informational stringency parameter and Z is a normalization constant.

P5 is a testable hypothesis extending standard quantum mechanics; its status is *empirical*, not *a priori*. States with lower s^* have slightly increased probability relative to the Born rule; more complex states have slightly decreased probability. The effect is $O(\lambda)$ and requires high statistical precision. Key limitations: (1) replacing K with s^* is inexact (Section 10); (2) P5 must remain consistent with existing high-precision Born-rule tests (Section 7.7).

4. SSD Method: Formal Framework

4.1. Definition of Symbolic Structures

For a numerical sequence $X = (x_0, x_1, \dots, x_{N-1})$, define sliding triplets $S_k = (x_k, x_{k+1}, x_{k+2})$, $k = 0, \dots, N-3$, with differences:

$$\begin{aligned} \Delta_1^1 &= x_k - x_{k+1} \quad (\text{first transition}), \\ \Delta_2^1 &= x_{k+1} - x_{k+2} \quad (\text{second transition}), \\ \Delta_1^2 &= |\Delta_1^1| - |\Delta_2^1| \quad (\text{geometric acceleration}). \end{aligned} \quad (5)$$

The symbolic structure of a triplet is determined by the signs of these three quantities:

$$\sigma_k = (\text{sgn}(\Delta_1^1), \text{sgn}(\Delta_2^1), \text{sgn}(\Delta_1^2)), \quad \text{sgn} \in \{<, =, >\}, \quad (6)$$

generating $3^3 = 27$ possible local geometries. Each maps to a code $c \in [0, 26]$ via base-3 indexing:

$$c(\sigma_k) = \text{val}(s_1) \cdot 9 + \text{val}(s_2) \cdot 3 + \text{val}(s_3), \quad \text{val}(<) = 0, \text{val}(>) = 1, \text{val}(=) = 2. \quad (7)$$

4.2. SSD Metrics

From the empirical distribution $p_s = N_s / (N - 2)$:

- **SSD entropy:** $E_{\text{SSD}} = -\sum_s p_s \log_2 p_s$ (diversity of local geometries).
- **Symbolic space activity:** $\kappa = |\{s : p_s > 0\}| / 27$ (fraction of activated symbolic states).
- **Transition entropy ε :** normalized entropy of the transition matrix between consecutive symbolic states, $\varepsilon \in [0, 1]$.
- **Composite index:** $s^*(H) = [\kappa(H) + \varepsilon(H)] / 2$. Lower values indicate more structured (compressible) configurations; higher values indicate randomness.

s^* is a computable proxy for K , exhibiting monotonic correlation with K on standard sequence classes. Its limitations are discussed in Section 10.

4.3. SSD Descriptor and Pseudometric

The SSD descriptor of configuration X is the frequency vector of the 27 symbols:

$$\mathbf{S}_{\text{SSD}}(X) = (f_0, f_1, \dots, f_{26}) \in \Delta^{26}. \quad (8)$$

The SSD pseudometric is the L^1 norm of the difference of descriptors:

$$d_{\text{SSD}}(X, Y) = \|\mathbf{S}_{\text{SSD}}(X) - \mathbf{S}_{\text{SSD}}(Y)\|_1. \quad (9)$$

5. Latent Twin: Formal Framework

5.1. Definition and Acceptance Criteria

Let $X \in I$ be a real configuration, Q a candidate set, and $\Phi: I \rightarrow L$ a coding map (SSD descriptor, AE/VAE/CLIP encoder, or their fusion). The latent twin is:

$$Q^* = \arg \min_{Z \in Q} D(\Phi(X), \Phi(Z)). \quad (10)$$

Candidate Q^* is accepted as the latent twin of X if there exists a symmetry transformation $g \in G$ such that:

$$d_{\text{SSD}}(\mathbf{S}_{\text{SSD}}(X), \mathbf{S}_{\text{SSD}}(g \cdot Q^*)) \leq \varepsilon \quad (\text{structural condition}), \quad (11)$$

$$d_{\text{perc}}(X, g \cdot Q^*) < \tau \quad (\text{perceptual condition}), \quad (12)$$

where ε and τ are calibratable thresholds and G is the group of meaning-preserving symmetries (flips, 90° rotations, mild photometric corrections).

5.2. SSD Isomorphism and Equivalence Classes

X and Q are *SSD-isomorphic* to tolerance ε ($X \sim_{\text{SSD}}^\varepsilon Q$) if $\exists g \in G$ such that $d_{\text{SSD}}(\mathbf{S}_{\text{SSD}}(X), \mathbf{S}_{\text{SSD}}(g \cdot Q)) \leq \varepsilon$. This is an equivalence relation for fixed ε and closed G ; its classes define structural types in the space of variations.

5.3. Postulate P4*—Local Density

Hypothesis 5 (Local Density (P4*)). *There exist $\rho_i \in (0, 1]$ and $r^* \geq 1/N_n$ such that for every $X \in \sigma^{-1}(i)$:*

$$\frac{|B_{r^*}(X) \cap \sigma^{-1}(i)|}{|B_{r^*}(X)|} \geq \rho_i. \quad (13)$$

Near every configuration of class i there are sufficiently many other configurations of the same class—this assumption of local cohesion of semantic classes is necessary for finding a latent twin.

P4* is a technical assumption enabling Lemma G. No subsequent experimental test depends directly on it; it serves solely for internal consistency.

6. Local Clustering Lemma (Lemma G)

Theorem 1 (Lemma G—Discrete Version). *Under Postulates P1–P4*(i), for every $X \in \sigma^{-1}(i)$ there exists $Y \in \sigma^{-1}(i)$, $Y \neq X$, such that $0 < d(X, Y) \leq r^*$.*

Theorem 2 (Lemma G—Asymptotic Version). *Under Postulates P1–P3 and P4*(ii), for every $\varepsilon > 0$ there exists n_0 such that for all $n \geq n_0$ and every $X \in \sigma^{-1}(i)$ there exists $Y \neq X$ with $\bar{d}_n(X, Y) < \varepsilon$.*

Proof of Lemma G (Discrete Version). Suppose the contrary: all $Y \in B_{r^*}(X)$ satisfy $\sigma(Y) \neq i$ except X itself, giving $|B_{r^*}(X) \cap \sigma^{-1}(i)| = 1$. Since $r^* \geq 1/N_n > 0$, the ball contains at least one Hamming neighbor, so $|B_{r^*}(X)| \geq 2$, and therefore $1/|B_{r^*}(X)| \leq 1/2 < \rho_i$ (for $\rho_i > 1/2$), which contradicts P4*(i). $\square$

Interpretation. In the space of variations, no configuration is structurally isolated within its semantic class. A structurally close alternative realization always exists, guaranteeing the existence of latent twins. The role of Lemma G in this paper is purely structural—ensuring internal consistency of the latent twin construction—with no direct empirical implications.

7. Experimental Test of Postulate P5: Design and Methodology

7.1. Objective

P5 predicts $P_{\text{UI}}(i) = Z \cdot P_{\text{Born}}(i) \cdot 2^{-\lambda s^*(i)}$. The experiment tests whether the distribution of quantum measurement outcomes correlates with their algorithmic complexity—a deviation from standard quantum mechanics, which predicts that probability depends solely on amplitude.

7.2. Operational Formulation of the Test

P5 is tested as follows:

1. Prepare quantum state $|\psi\rangle$.
2. Perform N_{shots} measurements; collect outcomes $i \in \{0, 1\}^n$.
3. Compute $s^*(i)$ for each distinct outcome.
4. Test the correlation between empirical frequency $P(i)$ and complexity $s^*(i)$.

Key test (for a uniform state): $P(i) \propto 2^{-\lambda s^*(i)}$.

7.3. Choice of Quantum State

The minimal test uses a uniform superposition:

$$|\psi\rangle = \frac{1}{\sqrt{2^n}} \sum_i |i\rangle, \quad (14)$$

with $P_{\text{Born}}(i) = 1/2^n$ for all i . Standard theory predicts a uniform distribution; any systematic deviation is in principle detectable. For $n \leq 3$, all outcomes have similar complexity and the effect is undetectable; $n \geq 10$ (preferably 20–50) is needed for meaningful s^* variation among outcomes.

7.4. Measurement and Data Collection

Required: $N_{\text{shots}} \sim 10^6\text{--}10^9$. For each outcome i : occurrence count O_i and empirical probability $P(i) = O_i/N_{\text{shots}}$.

7.5. Complexity Proxies

Three proxies are applied in parallel, all normalized to $[0, 1]$:

1. SSD index $s^*(i) = [\kappa(i) + \varepsilon(i)]/2$.
2. Lempel–Ziv complexity.
3. zlib compression ratio.

Consistency across proxies controls for artefacts specific to any single approximant.

7.6. Statistical Test

Model tested: $\log P(i) = -\lambda s^*(i) + C$.

Hypotheses: $H_0: \lambda = 0$ (standard quantum mechanics); $H_1: \lambda \neq 0$ (algorithmic correction).

Procedure: group outcomes by complexity bins, compute mean probability per bin, perform linear regression with $\log P(i)$ as the dependent variable and $s^*(i)$ as the independent variable.

7.7. Consistency with Existing Experiments

The Born rule has been confirmed to precision $\lesssim 10^{-6}$ (spectroscopy) and $\lesssim 10^{-4}$ (direct quantum optical tests). For P5 to be consistent, we need:

$$\lambda \cdot \Delta s_{\text{max}}^* \lesssim 10^{-4}, \quad (15)$$

where Δs_{max}^* is the maximum complexity difference between outcomes. For a 10-qubit system with $s^* \in [0.02, 0.42]$, this gives $\lambda \lesssim 2.5 \times 10^{-4}$.

7.8. Control of Systematic Errors

Key error sources: quantum hardware noise, readout bias, imperfect superposition. Controls:

1. Readout matrix calibration.
2. Ideal-case simulation (Qiskit Aer) as a reference.
3. Cross-device comparison (IBM Q, IonQ, Rigetti).
4. Randomization of measurement order.

7.9. Methodological Verification of the Statistical Test

Note on status: The simulation below confirms only that the test correctly recovers injected λ from synthetic data. It does *not* confirm that nature follows P5.

A simulation was run on all 1,024 possible 10-bit outcomes of a uniform superposition (Aer ideal simulator), with injected $\lambda = 0.01$: $P_{\text{sim}}(i) \propto 2^{-10} \cdot 2^{-0.01 \cdot s^*(i)}$. The SSD index s^* ranges from 0.0185 (periodic/all-zeros) to 0.4188 (most random). Linear regression returned: slope = -0.010000 ; recovered $\lambda \approx 0.010000$; $r^2 = 1.000000$. The value $r^2 = 1$ is expected because data were generated exactly without noise. In a real experiment, r^2 will be substantially lower due to statistical noise and hardware imperfections.

Statistical power estimate. For realistic parameters ($n = 10\text{--}20$, $\lambda \sim 10^{-4}$, $N_{\text{shots}} = 10^8\text{--}10^9$), expected statistical power is approximately 0.6–0.8, requiring careful experimental planning.

7.10. Interpretation of Possible Outcomes

- $\lambda \approx 0$: consistent with the Born rule; sets an upper bound on λ .
- Weak correlation: indication of an effect; requires independent replication.
- Clear correlation: potential fundamental deviation from standard quantum mechanics.

8. Empirical Validation of the SSD Method

8.1. Decimal Sequences: π , PRNG, QRNG

Table 1 reports SSD metrics for three classes of numerical sequences.

Table 1. SSD metrics for numerical sequences.

Source	Active Codes	E_{SSD}	κ	ϵ	s^*
Theory	17	3.83281	—	—	—
π	17	3.83233	0.512	1.000	0.756
PRNG	17	3.83190	0.512	0.999	0.756
QRNG	17	3.83479	0.518	1.001	0.759

Finding 1. The SSD method is completely blind to the ontological origin of the sequence—deterministic (π , PRNG) and quantum (QRNG) sources yield virtually identical structural complexity metrics. SSD measures informational structure, not the data-generation mechanism.

8.2. Images and Textual Data

Table 2 summarizes SSD performance across domains (binary 30×30 images; corpora of Python code, Shakespeare, and random text).

Table 2. SSD performance across application domains.

Domain	Performance	Conclusion
Structured vs. noise	$> 95\%$	Reliably distinguishes order from randomness
Textual structure	$s^* \in [0.55, 0.75]$	Lower s^* = more structured (code < language < random)
Fine semantic differences	$< 30\%$	Does not substitute for deep learning

Finding 2. SSD is an effective measure of global structural complexity but not of fine semantic distinctions. This precisely defines its domain of application within the integrated model.

9. Theoretical Implications

9.1. Motivating the Born Rule in the UI Framework

The goal is not to claim a complete derivation of the Born rule—that would require resolving the quantum measurement problem, which remains open. The goal is to show that squaring the amplitude is not *a priori* unexpected within algorithmic economy, and that P5 represents a natural extension.

Explicit acknowledgment. The UI framework does not derive the Born rule; it is consistent with it at leading order. The following argument provides motivation, not deduction.

Decomposition of informational channels. Within the UI framework, the wave function $|\psi\rangle = \sum_i c_i|i\rangle$ is interpreted as a compressed record of the pair (G, Φ) , where G represents structural density (geometric pattern in the space of variations) and Φ the set of phase relations among components. This interpretation is non-standard; it is an additional assumption of the UI framework. Assuming G and Φ are informationally independent channels:

$$K(|\psi\rangle) = K(G) + K(\Phi) + O(1), \quad \nu(i) \propto 2^{-K(G_i)} \cdot 2^{-K(\Phi_i)}.$$

(16)

If $|c_i|^2 \sim 2^{-(K(G_i)+K(\Phi_i))}$, then squaring the amplitude follows from algorithmic economy rather than being an arbitrary axiom. However, this relation is heuristic, not exact; alternative forms $|c_i|^\alpha$ for $\alpha \neq 2$ are not excluded by this argument.

Conclusion on motivation. This argument provides a consistent motivation for squaring the amplitude within the UI framework, but not a unique derivation. The Born rule appears as the leading-order term of algorithmic economy; P5 is the corrective term that is in principle testable.

Open problem. A formal proof that $\alpha = 2$ is the only value consistent with the UI framework remains explicitly open.

9.2. Categorical Framework

A functor $U: \mathbf{Img} \rightarrow \mathbf{Sem}$ maps structural signatures to semantic classes, where **Img** has configurations (or SSD-equivalence quotients) as objects and **Sem** has semantic classes $\sigma^{-1}(i)$ as objects. Empirically, U is partially faithful: it distinguishes a portrait from noise but not ‘3’ from ‘5’ in MNIST, precisely defining where U is sufficient.

10. Limitations and Open Problems

10.1. The Epistemic Gap Between K and s^* —Central Methodological Problem

P5 is formulated in terms of $K(i)$ but the experiment measures $s^*(i)$. Formal reasons why s^* cannot uniformly approximate K :

- 1. K is uncomputable; any computable approximation has non-uniform limitations.
- 2. Pathological sequences exist with low K but high s^* (globally simple, locally chaotic) and vice versa; $|K(X) - s^*(X)|$ can be arbitrarily large.
- 3. SSD analyzes only triplets; structures requiring longer windows are invisible.

Epistemic consequence. If the experiment finds $\lambda = 0$ using s^* , a non-zero λ in terms of K is not excluded. Conversely, finding $\lambda \neq 0$ using s^* is a strong signal because pathological sequences do not form systematic patterns in outcomes from a uniform superposition.

Recommended control. Consistency across s^* , Lempel–Ziv, and `zlib` substantially reduces the probability that any observed effect is a method-specific artefact.

10.2. SSD Performance Profile

Table 3. SSD performance profile by application domain.

Task	Performance	Explanation
Structured vs. noise (images)	> 95%	Global entropy and compressibility
Geometrically simple vs. complex	70–90%	Activity sum as transition measure
Digits (MNIST)	30–50%	Meta-structure partially helpful
Fine semantic distinctions	< 30%	Requires spatially aware representations

10.3. Open Problems

- 1. Formal proof that $\alpha = 2$ is the unique value consistent with the UI framework.
- 2. An upper bound on λ derived from a comprehensive analysis of existing high-precision quantum experiments.
- 3. Extension of SSD to windows of length $k > 3$ for detection of long-range correlations.
- 4. Relationship between selection parameter λ and empirically measurable constants (e.g., Planck’s constant or the dimensionality of the state space).

11. Conclusions

This paper develops an integrated theoretical framework connecting the space of variations, the Universal Interpreter, the algorithmic economy of reality, the concept of the latent twin, and

the SSD measure into a coherent, operationally defined system. The central thesis—that reality is not determined by ontological necessity but by minimal informational cost—provides an alternative interpretive basis for understanding physical laws. Standard physical laws emerge as consistent with the principle of algorithmic economy; the Born rule receives motivation (though not a complete derivation) within this framework.

The SSD method is the key operational contribution of this work. Its applicability has been demonstrated on numerical sequences, images, and textual data, with clearly defined limitations: excellent for global structuredness vs. noise; insufficient for fine semantic distinctions.

Postulate P5 introduces a testable hypothesis about a correction to the Born rule based on the algorithmic complexity of outcomes. The experimental framework has been formulated with all methodological safeguards: the epistemic gap between K and s^* is explicitly addressed as the central problem (Section 10); the upper bound on λ from existing experiments is estimated (Section 7.7); and the methodological verification (Section 7) is clearly identified as a procedural check, not a confirmation of the hypothesis.

Lemma G formally ensures that no configuration is isolated within its semantic class, thereby guaranteeing the existence of latent twins and the stability of structural types.

The paper does not claim empirical confirmation of the algorithmic correction to quantum probabilities. It establishes a theoretical and experimental framework in which such a hypothesis is precisely formulated and testable. Although P5 is the central empirically testable consequence addressed here, the UI framework in principle generates a broader class of testable predictions through the introduction of algorithmic selection bias, the systematic investigation of which remains the subject of future work.

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Abbreviations

The following abbreviations are used in this manuscript:

SSD	Symbolic Structures of Differences
UI	Universal Interpreter
LT	Latent Twin
PRNG	Pseudo-random number generator
QRNG	Quantum random number generator
MNIST	Modified National Institute of Standards and Technology (digit database)

Appendix A. Formal Motivation of Postulate P5

Appendix A.1. Why Correct the Born Rule?

In standard quantum mechanics, $P_{\text{Born}}(i) = |\langle i|\psi\rangle|^2$ is an axiomatic postulate. Within the UI framework, every quantum outcome i (a bitstring of length n) is a point in Ω , and the same selection measure applies: $dv(H) = Z^{-1} \cdot 2^{-\lambda K(H)} \cdot d\mu(H)$.

Appendix A.2. Derivation from the Selection Measure

Applying the selection filter to outcome i : $P_{\text{UI}}(i) \propto P_{\text{Born}}(i) \cdot 2^{-\lambda K(i)}$. The Born amplitude is retained because it is consistent with the leading-order of algorithmic economy—it encodes the informational cost of phase relations and structural density already embedded in c_i . The additional factor $2^{-\lambda K(i)}$ penalizes configurations requiring a longer description. Replacing K with s^* :

$$P_{\text{UI}}(i) = Z \cdot P_{\text{Born}}(i) \cdot 2^{-\lambda s^*(i)}. \quad (\text{A1})$$

Appendix A.3. Intuitive Interpretation

Low $s^*(i)$ (periodic sequences, low Hamming weight) $\Rightarrow$ factor $\approx 1 \Rightarrow$ slightly increased probability. High $s^*(i)$ (random bitstrings) $\Rightarrow$ factor $< 1 \Rightarrow$ slightly decreased probability. The effect is $O(\lambda)$, but systematic and cumulative. For $\lambda \approx 0.001\text{--}0.01$ (consistent with the upper bound from Section 7.7), detection requires $10^8\text{--}10^9$ measurements on 10–20 qubits.

Appendix A.4. Experimental Testability

The test reduces to linear regression: $\log P_{\text{emp}}(i) = -\lambda s^*(i) + C$, with $H_0: \lambda = 0$ vs. $H_1: \lambda \neq 0$. Section 7 confirms the algebraic correctness of the procedure. A real quantum hardware experiment is required for a meaningful test of the hypothesis.

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