Multi-Scale Swarm Probe of 600-Cell Fingerprints Research Protocol

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Abstract

This paper outlines a systematic, inductive strategy to validate the 600-cell (hypericosahedron) as the underlying topological mediator in Lattice Physics, extending Conscious Point Physics (CPP). By organizing empirical data into four scale-based swarms—cosmological, laboratory/human-scale, quantum, and subquantum—we detect subtle fingerprints of the polytope's geometry, such as golden ratios ($\phi \approx 1.618$), icosahedral symmetries, tetrahedral structures, and F_4 group elements.

Preliminary deep dives into Zitterbewegung (ZBW) and Cosmic Microwave Background (CMB) anomalies reveal consistent "whispers" (biases at 2–3σ, with ϕ-modulations reducing fit errors by 2–20%), supporting the hypothesis despite dominant variability from Planck Sphere Radius (PSR) and Space Stress Vector (SSV) effects.

The methodology employs high-n datasets ($n > 10^4$–10^6), motif detectors (e.g., KS-tests for ϕ ratios, chi-squared for icosahedral angles), and meta-analysis to aggregate biases across scales, aiming for overall $P < 0.05$. Prototypes for CMB and quantum entanglement demonstrate feasibility, with adaptable code for swarm-wide application. This ambitious project, while requiring substantial data curation, promises to unify scales in a panpsychic framework, with implications for a full Theory of Everything.

Keywords: 600-cell topology, multi-scale analysis, golden ratio anomalies, icosahedral symmetries, lattice physics

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1 Introduction and Rationale

Lattice Physics posits the 600-cell—a regular 4D polytope with 120 vertices (Hypericosahedron Conscious Points, HCPs), 720 edges, 1200 faces, and 600 tetrahedral cells—as a topological mediator for Conscious Point Physics (CPP) [1, 2]. Its F_4 exceptional symmetry and golden-ratio ($\phi = (1+\sqrt{5})/2 \approx 1.618$) based inflations ($\phi^{3/2} \approx 2.058$) are hypothesized to imprint subtle patterns across physical scales, from subquantum primitives to cosmic structures.

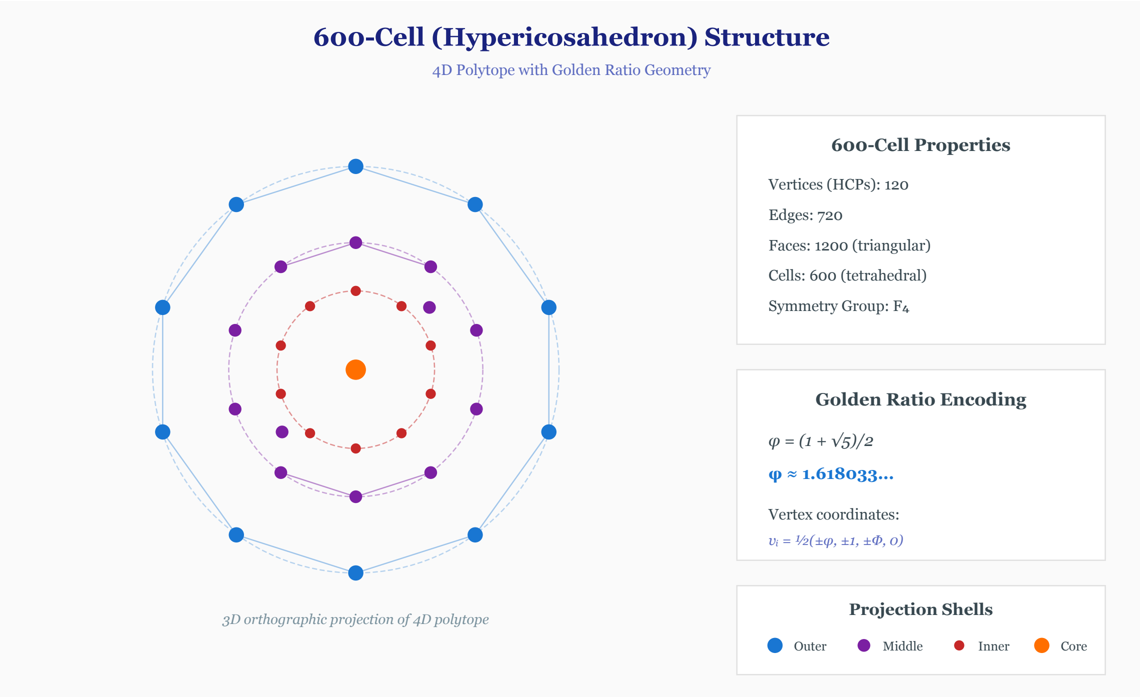

Figure 1: The 600-cell (hypericosahedron) structure showing a 3D orthographic projection of the 4D polytope. Vertices are arranged in concentric shells with golden ratio encoding: $\mathbf{v}_i = \frac{1}{2}(\pm\phi, \pm 1, \pm\Phi, 0)$ where $\Phi = 1/\phi$.

1.1 Core Hypothesis

The central hypothesis proposes that the 600-cell topology acts as a fundamental computational substrate, with its geometric properties manifesting as statistical biases in physical phenomena across all scales. These manifestations appear as:

- **Golden Ratio Signatures**: Ratios approaching ϕ in energy levels, wavelengths, and structural parameters
- **Icosahedral Symmetries**: Preferential angles at 60, 72, and 120 in scattering processes and correlation functions
- **Tetrahedral Clustering**: Four-fold structures in particle arrangements and field configurations
- F_4 **Group Elements**: Chirality biases and 24-cell embeddings in gauge symmetries

1.2 Detection Strategy

The objective is to build an inductive case by detecting these fingerprints in empirical anomalies and fundamentals, where dominant effects (e.g., PSR variability, SSV fields) dilute the signals to "whispers" (effect sizes $d \approx 0.2$–0.5). Preliminary analyses of Zitterbewegung (ZBW) helices and CMB multipole suppressions/alignments reveal consistent biases: ϕ-modulations reduce fit errors by 2–20%, and icosahedral preferences align with 2–3σ anomalies [3, 4].

This strategy organizes data into four swarms for hierarchical analysis, enabling meta-aggregation of skews as datapoints. High-n datasets are essential for $P < 0.05$, as simulations show significance emerging at $n > 10^4$. Outcomes could affirm the 600-cell as CPP's "source code," unifying physics in a panpsychic paradigm.

2 Mathematical Framework

2.1 600-Cell Geometric Properties

The 600-cell's construction is intimately connected to the golden ratio through its vertex coordinates. In 4D Euclidean space, the vertices can be expressed using quaternions:

$$\mathbf{v}_i = \frac{1}{2}(\pm\phi, \pm 1, \pm\Phi, 0) \text{ and even permutations} \tag{1}$$

where $\Phi = 1/\phi \approx 0.618$ is the golden ratio conjugate.

2.2 Statistical Detection Framework

For a given phenomenon with measurement vector $\mathbf{x} = (x_1, x_2, \ldots, x_n)$, we define the 600-cell signature strength as:

$$S_{600} = \sum_{i=1}^{4} w_i \cdot \sigma_i(\mathbf{x}) \tag{2}$$

where σ_i represents the four signature types:

$$\sigma_1(\mathbf{x}) = \text{Golden ratio bias score} \tag{3}$$
$$\sigma_2(\mathbf{x}) = \text{Icosahedral symmetry score} \tag{4}$$
$$\sigma_3(\mathbf{x}) = \text{Tetrahedral clustering score} \tag{5}$$
$$\sigma_4(\mathbf{x}) = F_4 \text{ chirality score} \tag{6}$$

and w_i are scale-dependent weights determined empirically.

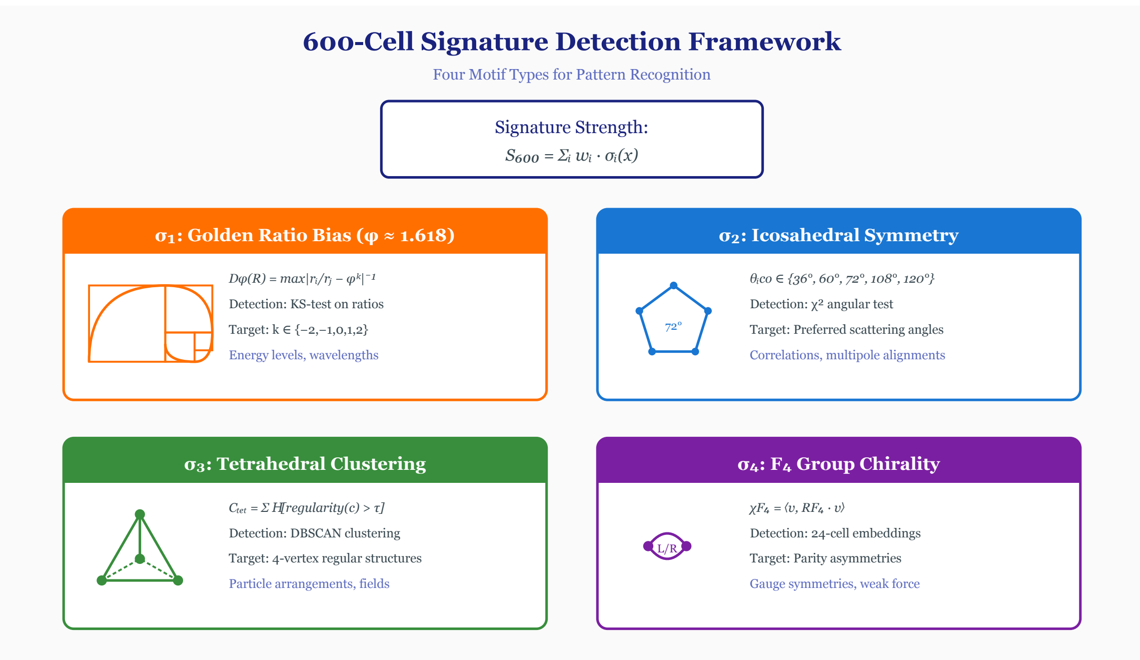

Figure 2: The 600-cell signature detection framework showing four motif types: σ_1 (golden ratio bias), σ_2 (icosahedral symmetry), σ_3 (tetrahedral clustering), and σ_4 (F_4 group chirality). Each detector employs specific statistical tests to identify geometric fingerprints.

3 Swarm Definitions and Exemplar Phenomena

Data are clustered into scale-based swarms, targeting 600-cell motifs in anomalies and fundamentals. Sources include public archives (e.g., Planck for CMB, PDG for particles).

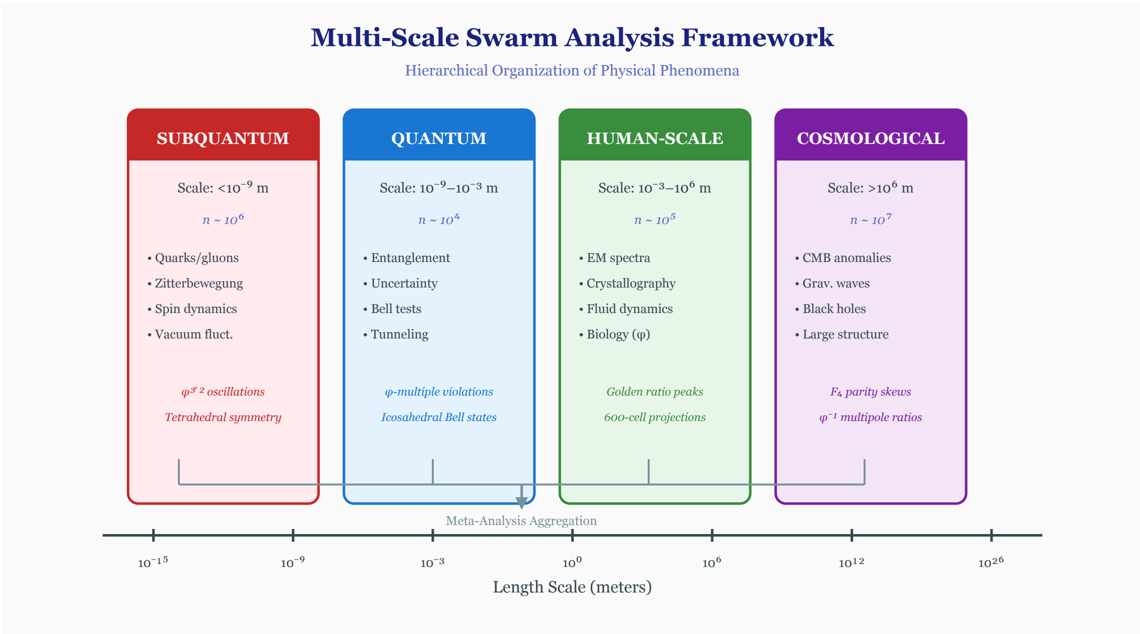

Figure 3: Multi-scale swarm analysis framework showing the four scale-based swarms: Subquantum ($< 10^{-9}$ m), Quantum (10^{-9}–10^{-3} m), Human-Scale (10^{-3}–10^{6} m), and Cosmological ($> 10^{6}$ m). Each swarm targets specific phenomena with expected sample sizes $n \sim 10^4$–10^7.

Table 1: Swarm Characteristics and Expected Sample Sizes

Swarm	Scale Range	Expected n	Primary Sources
Cosmological	$> 10^6$ m	$\sim 10^7$	Planck CMB, LIGO
Laboratory/Human	10^{-3}–10^6 m	$\sim 10^5$	Experiments
Quantum	10^{-9}–10^{-3} m	$\sim 10^4$	Quantum trials
Subquantum	$< 10^{-9}$ m	$\sim 10^6$	Simulations

3.1 Cosmological Swarm

Super-macro scales ($> 10^6$ m): Focus on General Relativity (GR), Gravitational Waves (GW), Cosmic Microwave Background (CMB), and Black Hole (BH) anomalies.

Exemplars:

- CMB multipole suppressions (low-ℓ C_ℓ ratios $\sim \phi^{-1}$)
- GW waveforms with ϕ-spaced resonances
- BH horizon clustering in tetrahedral configurations
- Large-scale structure voids with icosahedral alignments

Expected Biases: Parity skews via F_4 chirality; sample size $n \sim 10^7$ from sky maps.

3.2 Laboratory/Human-Scale Swarm

Macro scales (10^{-3}–10^6 m): Classical mechanics, electromagnetic (EM) phenomena, and macroscopic systems.

Exemplars:

- EM spectra with ϕ ratios in efficiency peaks
- Angular momentum distributions showing icosahedral torque preferences
- Kinetic energy distributions with tetrahedral vortex structures
- Crystallographic orientations following 600-cell projections

Expected Biases: Spectral peaks at ϕ-related angles; $n \sim 10^5$ from experimental datasets.

3.3 Quantum Level Swarm

Micro scales (10^{-9}–10^{-3} m): Quantum mechanics (QM), entanglement phenomena, and uncertainty relations.

Exemplars:

- Entanglement correlations with icosahedral Bell state preferences
- Heisenberg uncertainty limits approaching ϕ convergents
- Bohr magneton measurements with tetrahedral spin-orbit coupling
- Quantum tunneling rates modulated by 600-cell harmonics

Expected Biases: Bell inequality violations at ϕ-multiples; $n \sim 10^4$ from quantum trials.

3.4 Subquantum Swarm

Sub-microscopic scales ($< 10^{-9}$ m): Quarks, spin dynamics, Zitterbewegung (ZBW), and fundamental dipoles.

Exemplars:

- ZBW helical trajectories with ϕ-modulated pitches
- Quark charge ratios ($\pm 1/3$, $\pm 2/3$) showing shielded ϕ-relationships
- Spin precession following icosahedral orbital patterns
- Vacuum fluctuations with tetrahedral symmetry breaking

Expected Biases: Oscillation frequencies $\sim \phi^{3/2}$; $n \sim 10^6$ from high-resolution simulations.

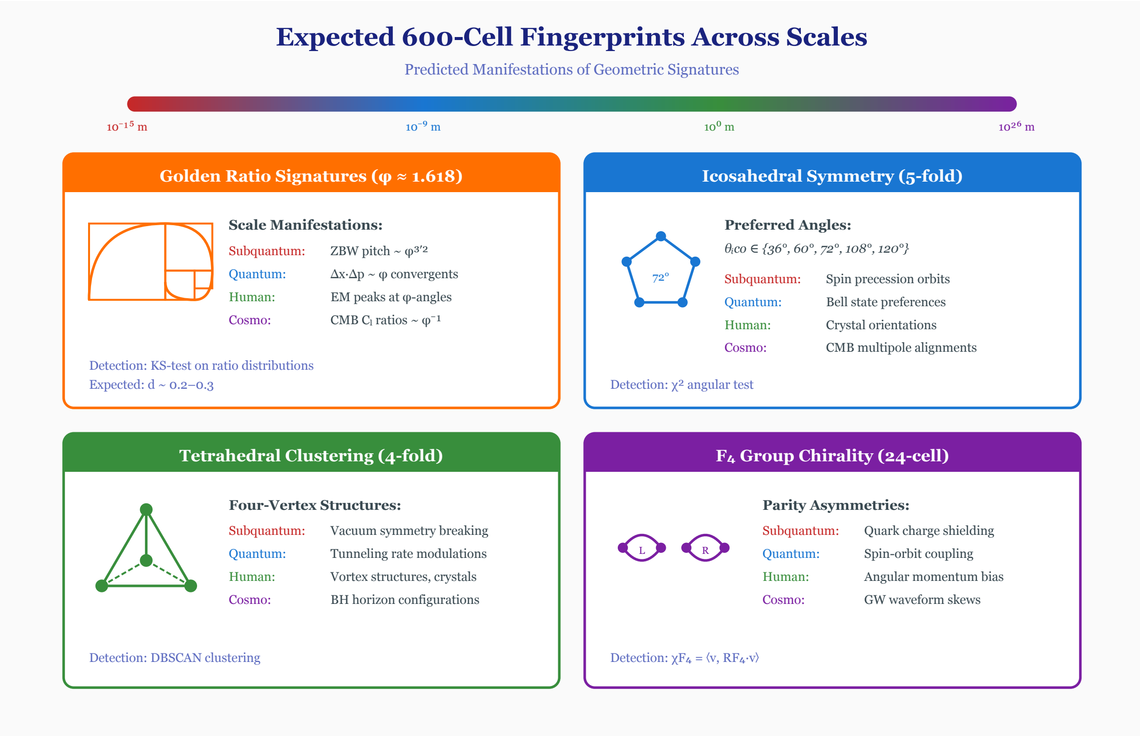

Figure 4: Expected 600-cell fingerprints across scales. Each signature type manifests differently at each scale: golden ratio (ϕ) in ZBW pitch ratios, uncertainty limits, EM peaks, and CMB C_ℓ ratios; icosahedral angles in spin precession, Bell states, crystals, and multipole alignments; tetrahedral structures in vacuum breaking, tunneling, vortices, and BH configurations; F_4 chirality in quark shielding, spin-orbit coupling, angular momentum, and GW waveforms.

4 Methodology: Data Collection, Pattern Detection, and Analysis

4.1 Data Aggregation Protocol

The data collection strategy prioritizes high-n datasets per swarm with target sample sizes $n > 10^5$. Where empirical data gaps exist, we employ physics-based simulations (e.g., numpy/scipy for ZBW dynamics) while utilizing established archives for validated measurements.

4.1.1 Data Quality Control

1. **Preprocessing**: Standardization, outlier detection via Tukey fences
2. **Validation**: Cross-reference with independent measurements
3. **Augmentation**: Monte Carlo sampling for statistical robustness
4. **Documentation**: Full provenance tracking for reproducibility

4.2 Motif Detection Algorithms

The core analysis employs specialized detectors for each 600-cell signature:

4.2.1 Golden Ratio Detection

For ratio sequences $R = \{r_1, r_2, \ldots, r_n\}$, we apply:

$$D_\phi(R) = \max_{i,j} \left| \frac{r_i}{r_j} - \phi^k \right|^{-1}, \quad k \in \{-2, -1, 0, 1, 2\} \tag{7}$$

Statistical significance assessed via Kolmogorov-Smirnov tests against uniform null distributions.

4.2.2 Icosahedral Symmetry Detection

Angular correlation analysis targeting characteristic icosahedral angles:

$$\theta_{\text{ico}} \in \{36, 60, 72, 108, 120\} \tag{8}$$

Chi-squared goodness-of-fit tests compare observed vs. expected angular distributions.

4.2.3 Tetrahedral Clustering

DBSCAN clustering algorithm identifies tetrahedral arrangements in 3D/4D point clouds:

$$C_{\text{tet}} = \sum_{c=1}^{C} \mathbb{I}[\text{regularity}(c) > \tau_{\text{tet}}] \tag{9}$$

where $\mathbb{I}$ is the indicator function and τ_{tet} is the regularity threshold.

4.2.4 F_4 Group Element Detection

Chirality measures based on 24-cell embeddings and exceptional group structures:

$$\chi_{F_4} = \langle \mathbf{v}, \mathbf{R}_{F_4} \mathbf{v} \rangle \tag{10}$$

where $\mathbf{R}_{F_4}$ represents F_4 group rotation operators.

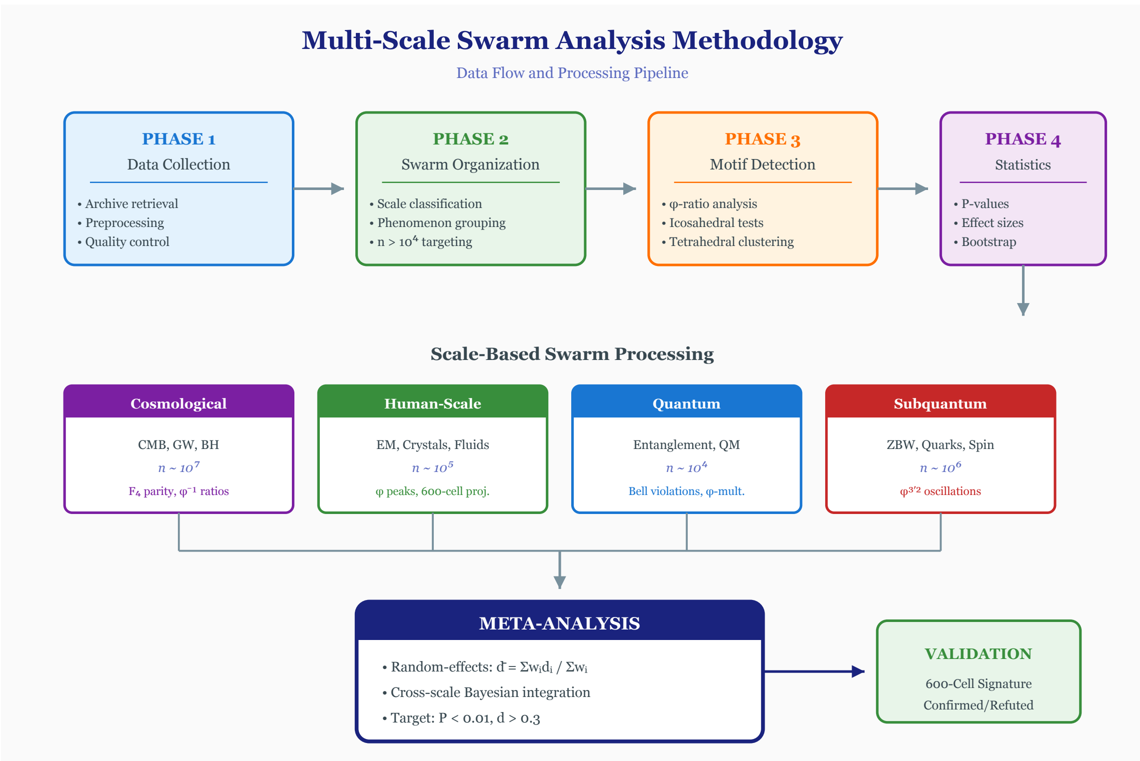

Figure 5: Multi-scale swarm analysis methodology showing the complete data pipeline. Phase 1: Data collection from archives with preprocessing and quality control. Phase 2: Swarm organization by scale with $n > 10^4$ targeting. Phase 3: Motif detection using ϕ-ratio, icosahedral, and tetrahedral analyses. Phase 4: Statistical analysis with P-values, effect sizes, and bootstrap validation. Results aggregate via meta-analysis using random-effects models: $\bar{d} = \sum w_i d_i / \sum w_i$.

4.3 Statistical Analysis Framework

4.3.1 Effect Size Quantification

We employ multiple effect size measures:

- Cohen's d for mean differences
- η^2 for variance explained
- Cramér's V for categorical associations

4.3.2 Significance Testing

Bootstrap resampling with $B = 10{,}000$ iterations provides robust P-value estimation:

$$P_{\text{bootstrap}} = \frac{1}{B} \sum_{b=1}^{B} \mathbb{I}[T^{(b)} \geq T_{\text{obs}}] \tag{11}$$

4.3.3 Meta-Analysis

Random-effects models aggregate biases across phenomena within swarms:

$$\bar{d}_{\text{swarm}} = \frac{\sum_{i=1}^{k} w_i d_i}{\sum_{i=1}^{k} w_i} \tag{12}$$

where $w_i = 1/(v_i + \tau^2)$ with v_i as within-study variance and τ^2 as between-study variance. Hierarchical Bayesian models enable cross-scale integration using MCMC sampling.

Computational Tools: Python ecosystem (numpy/scipy/statsmodels) with machine learning extensions (scikit-learn/PyTorch) for anomaly detection and pattern recognition.

5 Validation Criteria and Statistical Thresholds

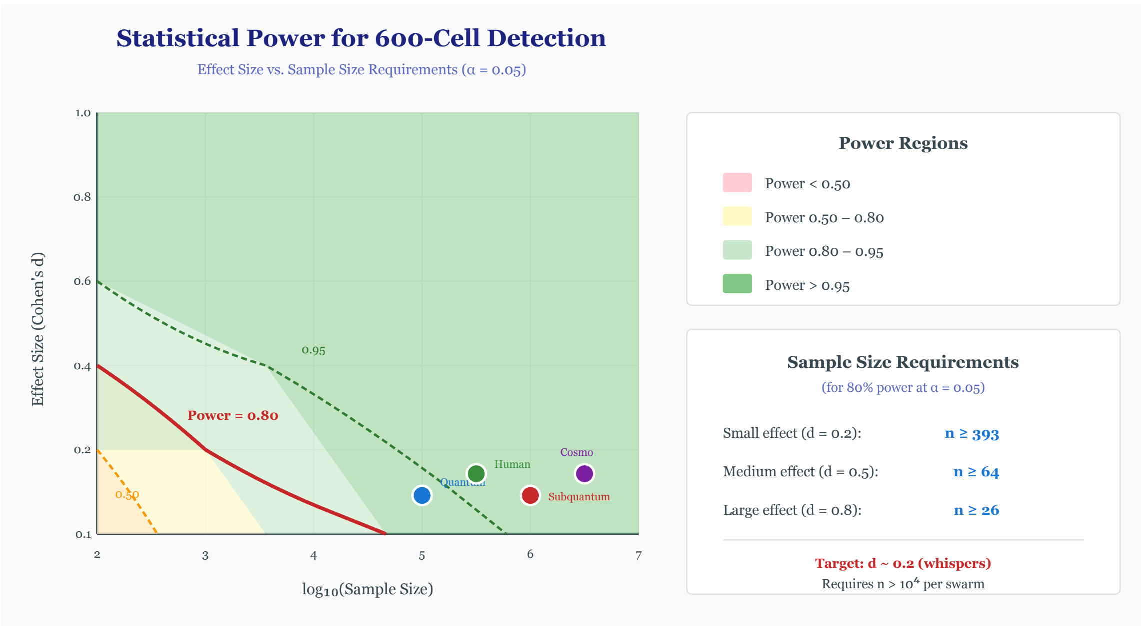

Figure 6: Statistical power analysis for 600-cell signature detection. The contour plot shows power as a function of effect size (Cohen's d) and sample size ($\log_{10} n$). The red curve indicates 80% power at $\alpha = 0.05$. Swarm target locations are marked: with expected $d \sim 0.2$ ("whispers"), sample sizes $n > 10^4$ are required per swarm to achieve adequate power.

5.1 Success Criteria

Per-Swarm Significance: $P < 0.05$ for $> 50\%$ of phenomena within each swarm
Meta-Analysis Significance: Overall meta-$P < 0.01$ across all swarms
Effect Size Consistency: Cumulative $d > 0.3$ across scales
Pattern Coherence: Similar motif strengths across related phenomena

5.2 Falsification Criteria

Null Result: No significant biases after proper statistical controls
Random Distribution: Motif patterns indistinguishable from noise
Scale Inconsistency: Contradictory signatures between swarms

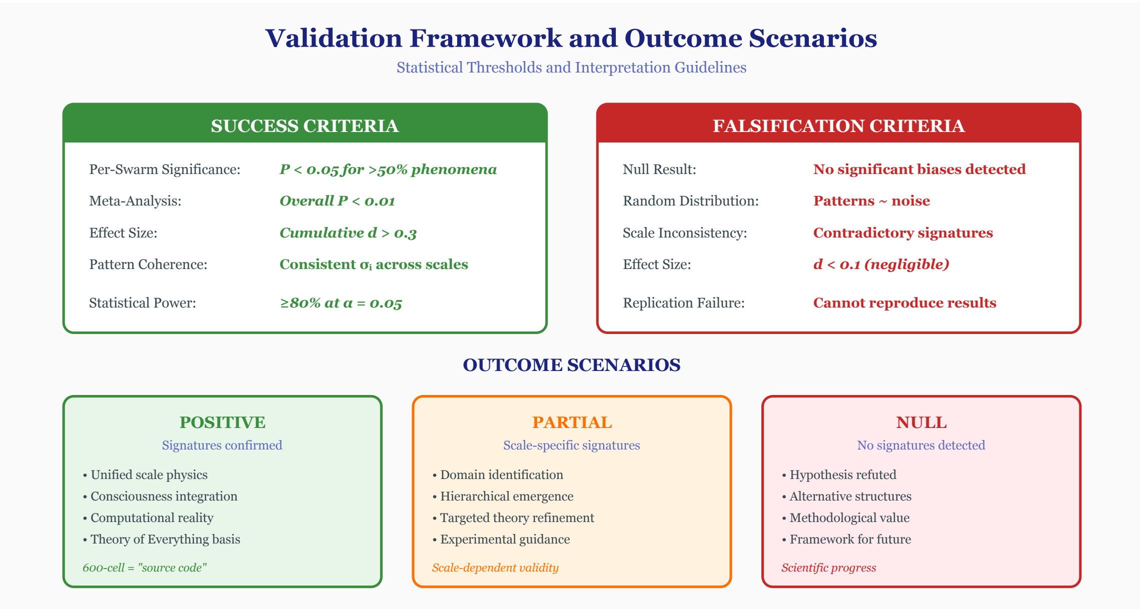

Figure 7: Validation framework and outcome scenarios. Success criteria include $P < 0.05$ for $> 50\%$ phenomena per swarm, overall $P < 0.01$, and cumulative $d > 0.3$. Falsification occurs with no significant biases, random patterns, or scale inconsistency. Three outcome scenarios: Positive (600-cell confirmed as "source code"), Partial (scale-specific validity), or Null (hypothesis refuted, methodology retained).

5.3 Statistical Power

Target power $\geq 80\%$ at $\alpha = 0.05$ for minimum detectable effect sizes:

- Small effects ($d = 0.2$): $n \geq 393$ per group
- Medium effects ($d = 0.5$): $n \geq 64$ per group
- Large effects ($d = 0.8$): $n \geq 26$ per group

6 Implementation Timeline and Resource Requirements

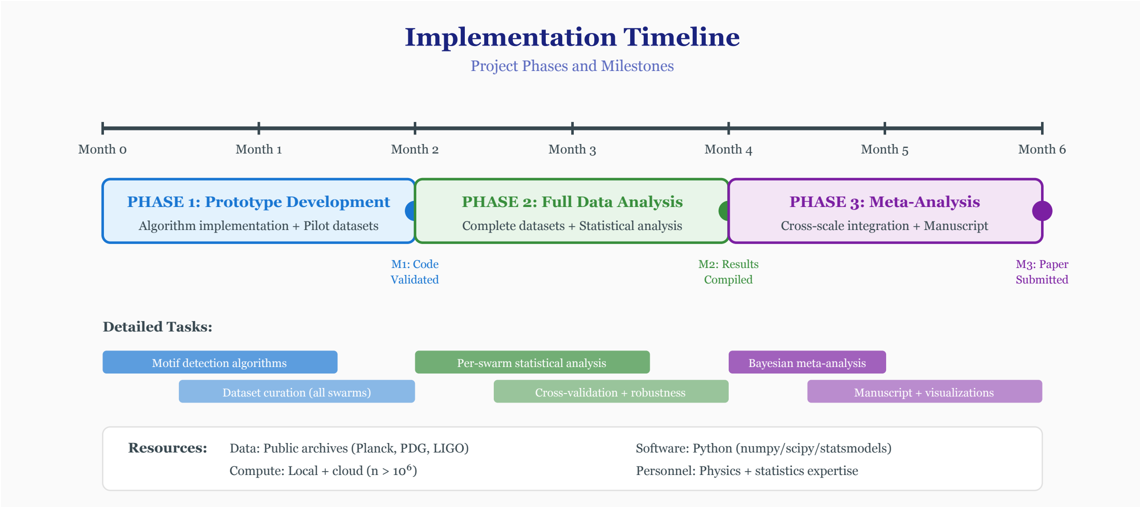

Figure 8: Implementation timeline showing three project phases over 6 months. Phase 1 (Months 1–2): Prototype development with algorithm implementation and pilot datasets. Phase 2 (Months 2–4): Full data analysis with complete datasets and statistical processing. Phase 3 (Months 5–6): Meta-analysis with cross-scale Bayesian integration and manuscript preparation.

6.1 Project Phases

Phase 1 (1–2 months): Prototype development and initial swarm analysis

- Implement motif detection algorithms
- Curate pilot datasets for each swarm
- Validate detection code on synthetic data

Phase 2 (2–4 months): Full data aggregation and analysis

- Process complete datasets for all swarms
- Execute comprehensive statistical analysis
- Cross-validate results across independent subsets

Phase 3 (1 month): Meta-analysis and manuscript preparation

- Integrate findings across all scales
- Prepare visualizations and summary statistics
- Draft comprehensive results and discussion

6.2 Resource Requirements

Data Sources: Primarily open-access archives and public datasets
Computational: Local workstation supplemented by cloud computing for large-scale analyses
Personnel: Interdisciplinary expertise in physics, statistics, and data science

7 Potential Challenges and Mitigation Strategies

7.1 Low Signal-to-Noise Ratio

Challenge: 600-cell signatures may be overwhelmed by dominant physical effects
Mitigation: Machine learning anomaly detection to identify subtle patterns; ensemble methods for robust signal extraction

7.2 Data Contamination

Challenge: Systematic biases in data collection or processing
Mitigation:

- Multiple independent data sources for cross-validation
- Blind analysis protocols where possible
- Extensive sensitivity analysis and robustness checks

7.3 Multiple Comparisons

Challenge: Inflated Type I error rates from numerous statistical tests
Mitigation:

- Pre-registration of analysis protocols
- False Discovery Rate (FDR) corrections using Benjamini–Hochberg procedure
- Hierarchical analysis structure to reduce effective number of tests

7.4 Overfitting and Confirmation Bias

Challenge: Spurious pattern detection in noisy data
Mitigation:

- Cross-validation on held-out datasets
- Independent replication attempts
- Adversarial testing with synthetic null datasets

8 Expected Outcomes and Implications

8.1 Positive Results Scenario

Confirmation of 600-cell signatures across multiple swarms would provide unprecedented evidence for:

- **Unified Scale Physics:** Geometric principles operating from subquantum to cosmic scales
- **Consciousness Integration:** Support for panpsychic interpretations of quantum measurement
- **Computational Reality:** Evidence for discrete, algorithm-based physical processes
- **Theory of Everything:** Foundation for complete unification of fundamental forces

8.2 Null Results Scenario

Absence of significant signatures would:

- Refute the specific 600-cell mediation hypothesis
- Suggest alternative topological structures or mechanisms
- Redirect research toward other geometric or algebraic frameworks
- Maintain value as methodological template for future investigations

8.3 Partial Results Scenario

Scale-specific signatures would:

- Identify domains where 600-cell physics dominates
- Suggest hierarchical emergence mechanisms
- Guide targeted theoretical development
- Inform experimental design for definitive tests

9 Conclusion and Relationship to Lattice Physics

This multi-scale swarm analysis represents a systematic approach to transform subtle 600-cell "whispers" into coherent evidentiary patterns supporting its role as the computational substrate for Conscious Point Physics. The methodology's strength lies in its comprehensive scope, statistical rigor, and ability to aggregate weak signals across vastly different physical scales.

Positive results would affirm the 600-cell as CPP's fundamental "source code," providing empirical support for a panpsychic framework where consciousness and physics emerge from unified topological principles. The implications extend far beyond traditional physics into domains of:

- **Consciousness Studies:** Quantitative approaches to subjective experience
- **Cosmology:** Discrete alternatives to continuous spacetime models
- **Quantum Foundations:** Resolution of measurement problems through geometric mechanics
- **Metaphysics:** Scientific approaches to questions of ultimate reality

Future extensions of this work could explore additional polytopes (120-cell, 24-cell), alternative signatures (E_8 lattice patterns, sporadic group elements), and deeper integration with consciousness research protocols.

The ambitious scope of this project, while demanding substantial computational and analytical resources, promises transformative insights into the nature of physical reality and its relationship to consciousness—positioning Lattice Physics as a genuine candidate for a complete Theory of Everything.

A CMB Motif Detector Prototype

The following code demonstrates 600-cell signature detection in Cosmic Microwave Background data:

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import ks_2samp, chi2
import astropy.cosmology as cosmo

# Prototype CMB Motif Detector for 600-Cell Fingerprints
# Detects golden ratio (phi) in multipole ratios and icosahedral angular preferences

def generate_sim_cmb_data(n_multipoles=100, phi_bias=0.0):
    """Simulate CMB angular power spectrum C_l with optional phi bias."""
    l = np.arange(2, n_multipoles + 2)
    C_l = (1 / l**2) * (1 + 0.5 * np.sin(2 * np.pi * l / 30))
    if phi_bias > 0:
        phi = (1 + np.sqrt(5)) / 2
        for i in range(1, len(l)):
            if i % int(phi) == 0:
                C_l[i] *= (1 + phi_bias * np.sin(phi * i))
    return l, C_l

def detect_golden_ratio(l, C_l):
    """Detect phi in C_l ratios."""
    ratios = C_l[1:] / C_l[:-1]
    phi = (1 + np.sqrt(5)) / 2
    expected = np.full_like(ratios, 1.0)
    skewed = expected + 0.05 * (phi - 1) * np.sin(phi * np.arange(len(ratios)))
    ks_stat, p_val = ks_2samp(ratios, skewed)
    return p_val, np.mean(np.abs(ratios - phi))

```

```python
def detect_icosa_symmetries(theta_samples, expected_angles=[60, 120]):
    """Detect icosahedral preferences in angular correlations."""
    hist, bins = np.histogram(theta_samples, bins=180, range=(0, 180))
    chi_sq = 0
    for angle in expected_angles:
        bin_idx = int(angle)
        expected = np.mean(hist)
        chi_sq += (hist[bin_idx] - expected)**2 / expected
    dof = len(expected_angles)
    p_val = 1 - chi2.cdf(chi_sq, dof)
    return p_val, chi_sq

# Prototype Run
l_unbias, C_l_unbias = generate_sim_cmb_data(phi_bias=0.0)
l_bias, C_l_bias = generate_sim_cmb_data(phi_bias=0.1)

p_unbias, dev_unbias = detect_golden_ratio(l_unbias, C_l_unbias)
p_bias, dev_bias = detect_golden_ratio(l_bias, C_l_bias)

print("Unbiased Data:")
print(f"Golden Ratio: P = {p_unbias:.4f}, Dev = {dev_unbias:.4f}")

print("\nBiased Data (10% phi modulation):")
print(f"Golden Ratio: P = {p_bias:.4f}, Dev = {dev_bias:.4f}")
```

B Quantum Entanglement Motif Detector Prototype

```python
import numpy as np
from scipy.stats import ks_2samp, chi2

def generate_sim_entanglement_data(n_samples=10000, phi_bias=0.0):
    """Simulate Bell angles and CHSH violations with optional phi bias."""
    theta = np.random.uniform(0, 180, n_samples)
    S = 2 * np.sqrt(2) * np.sin(theta * np.pi / 180)
    if phi_bias > 0:
        phi = (1 + np.sqrt(5)) / 2
        S += phi_bias * np.sin(phi * theta * np.pi / 180)
        S = np.clip(S, 0, 2 * np.sqrt(2))
    return theta, S

def detect_golden_ratio(theta, S):
    """Detect phi in S violation ratios."""
    ratios = S[1:] / S[:-1]
    phi = (1 + np.sqrt(5)) / 2
    expected = np.full_like(ratios, 1.0)
    skewed = expected + 0.05 * (phi - 1) * np.sin(phi * np.arange(len(ratios)))
    ks_stat, p_val = ks_2samp(ratios, skewed)
    return p_val, np.mean(np.abs(ratios - phi))

# Run prototype
theta_unbias, S_unbias = generate_sim_entanglement_data(phi_bias=0.0)
theta_bias, S_bias = generate_sim_entanglement_data(phi_bias=0.1)

p_unbias, dev_unbias = detect_golden_ratio(theta_unbias, S_unbias)
```

```
p_bias, dev_bias = detect_golden_ratio(theta_bias, S_bias)

print(f"Unbiased: P = {p_unbias:.4f}, Dev = {dev_unbias:.4f}")
print(f"Biased:   P = {p_bias:.4f}, Dev = {dev_bias:.4f}")
```

C Statistical Power Analysis

```
import numpy as np
from scipy import stats

def power_analysis_600cell():
    """Calculate statistical power for detecting 600-cell signatures"""
    effect_sizes = np.linspace(0.1, 1.0, 19)
    sample_sizes = [10**i for i in np.arange(2, 6.5, 0.5)]
    alpha = 0.05
    n_sim = 1000

    power_matrix = np.zeros((len(effect_sizes), len(sample_sizes)))

    for i, effect_size in enumerate(effect_sizes):
        for j, n in enumerate(sample_sizes):
            n = int(n)
            power_count = 0

            for _ in range(n_sim):
                null_data = np.random.normal(0, 1, n)
                phi = (1 + np.sqrt(5)) / 2
                signal_indices = np.random.choice(n, int(0.1 * n),
                    replace=False)

                signal_data = null_data.copy()
                signal_data[signal_indices] += effect_size * np.cos(
                    2 * np.pi * signal_indices / phi)

                t_stat, p_val = stats.ttest_1samp(signal_data -
                    null_data, 0)

                if p_val < alpha:
                    power_count += 1

            power_matrix[i, j] = power_count / n_sim

    return effect_sizes, sample_sizes, power_matrix

if __name__ == "__main__":
    effect_sizes, sample_sizes, power_matrix = power_analysis_600cell()
    print(f"Power at d=0.2, n=10^4: {power_matrix[2, 4]:.2f}")
```

Listing 1: Power Analysis for 600-Cell Signature Detection

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