Analysis of the Geometric Model for Physical Constants from `https://simulationuniverse.org/6-Physical-constant-anomalies.html`

Abstract

We (GLM-5.1) analyse the geometric model for physical constants focusing on the claimed anomalies in the dimensionless constants G, h, c, e, m_e, k_B. We summarise the model, identify its main strengths and weaknesses, and then construct a more rigorous statistical framework. Finally, we assign an approximate probability that the observed patterns reflect an underlying mathematical structure rather than random chance, and briefly consider the possibility that the 10^{-7}–10^{-8} relative precision suggests a Taylor expansion around a leading solution.

1 Overview of the model

The paper develops a geometric–numerological model for the physical constants with the following key features:

1. It uses a base–15 unit-number geometry and replaces independent SI base-unit assumptions by unit-number relations such as kg(15), m(−13), s(−30), A(3).
2. It introduces three primary geometric Planck-like objects: $M = 1$, $T = \pi$, and $P = \Omega$, where
$$\Omega = \pi e^{e^{1-e}} \approx 2.0071349543249462\ldots$$
is a pure mathematical constant built from π and Euler's number e.
3. From M, T, P and the inverse fine-structure constant $a = \alpha^{-1}$, the model constructs geometric analogues $G^*, h^*, c^*, q_e^*, (y_e/g_e)^*, m_e^*, k_B^*$ of the SI constants, using standard Planck-unit conversion relations.
4. It defines dimensionless combinations of CODATA constants that are *scalar-free* in the unit-number geometry (denoted $\theta = 0$), and shows that these combinations closely match the geometric predictions when a is chosen appropriately.
5. It derives a model-internal value
$$a_{\text{fit}} = 137.035993138$$
by minimising a joint residual over six high-precision constants, rather than by fitting any single constant exactly.

The main empirical claim is that, after a two-scalar translation from the geometric MTP sector to SI, multiple dimensionless combinations and reconstructed constants agree with CODATA 2014 to relative precisions of order 10^{-7}–10^{-8}, which is much better than expected under a simple coincidence model.

2 Strengths of the arguments

2.1 Overdetermined consistency rather than isolated numerology

Instead of presenting a single striking numerical coincidence, the model treats the constants as an *overdetermined system*: with only two empirical SI anchors (conventionally c and μ_0) and one free parameter a, it attempts to predict *six* dimensionless combinations simultaneously.

The fit-envelope test shows that all six residuals lie inside a self-consistent α-envelope, with

$$Q_{\rm env} = \sum_{i=1}^{6} \left(\frac{\delta_i}{\delta_{{\rm total},i}} \right)^2 \approx 0.71 \ll 6,$$

indicating that the data are consistent with a single internal value of a rather than requiring independent fixes for each constant. This is conceptually stronger than typical numerology.

2.2 Dimensionless, unit-invariant focus

The analysis explicitly recognises that dimensioned numerical values are convention-dependent, and focuses on dimensionless combinations (or geometric structures that cancel units) as the locus of any genuine anomalies. This is in line with standard practice in fundamental physics: only dimensionless numbers can carry information that does not depend on the choice of units.

2.3 Algorithmic and information-theoretic framing

The paper uses Minimum Description Length (MDL) ideas to quantify how much more compact the geometric model is than a null model that stores each constant independently. Rough bit-counting suggests the geometric model uses

- about 80 bits for the rule-set,
- about 17 bits for the two SI scalars,
- about 25 bits for the residuals,

for a total of $\approx$ 122 bits, versus $\approx$ 208 bits for the null model, an $\approx$ 86-bit compression corresponding to a Bayes factor of order 10^{26}.

Although the bit counts are approximate, this represents a serious attempt to move beyond subjective impressions of "unlikeliness".

2.4 Statistical self-criticism

The author explicitly states that:

- The fit-envelope statistic is a diagnostic, not a formal p-value.
- A pure CODATA χ^2 test would be much stricter and produce very large pulls for some constants (especially R_∞).
- The six ratios are not fully independent because of CODATA correlations and the internal ψ-construction.

2.5 Falsifiability and response to new data

The model makes quantitative predictions: there should exist a single internal a that simultaneously optimises multiple dimensionless combinations, and this value can be compared with independent measurements of α. The shift in behaviour between CODATA 2014 and 2022 is acknowledged and interpreted in terms of the 2019 SI redefinition, not hand-waved away. The framework is explicitly set up as an anomaly detector: if some constant lies far from the model prediction, that flags either a metrological issue or a place where the model must be revised.

3 Weaknesses of the arguments

3.1 MDL/Bayes factor estimates are not rigorous

The bit-budget numbers are illustrative rather than derived from a formal encoding:

- The rule-set is assigned ~ 80 bits with only rough justification; a full specification of the algebra, exponent structures, and mapping to SI might well require more bits, reducing the compression advantage.
- The null-model bit counts assume each constant is stored independently at its CODATA relative uncertainty, but CODATA already encodes correlations among constants, so the "independent bits" baseline is too pessimistic.

The Bayes factor of $\sim 10^{26}$ should therefore be read as "there is a compression advantage", not as a precise odds ratio.

3.2 Statistical dependence and multiple testing

Although the author acknowledges that λ_e, R_∞, m_e, and y_e/g_e are not independent in CODATA or in the ψ-construction, the MDL and Q_{env} statistics still treat them as roughly independent items in the bit count and sum-of-squares. Properly, one should:

- use the full CODATA covariance matrix,
- define a joint likelihood for the six ratios,
- and compare models (null vs geometric) via a likelihood ratio or Bayes factor with correct dependencies.

Without that, the p-value-like statements and Bayes factors remain suggestive, not conclusive.

3.3 Sensitivity to SI conventions and dataset choice

The shift between CODATA 2014 and 2022 is interpreted as due to the 2019 SI redefinition, but:

- The model's discriminating power clearly depends on which constants are treated as exact and which as adjustable.
- If the model is sensitive to such conventions, its apparent "anomalies" may be artefacts of how we define units, not deep features of physics.

The claim that the geometric lattice "fundamentally permits only two constants to be assigned exact values" is itself a strong assumption built into the construction, not derived from more basic principles.

4 Rigorous statistical framework and approximate probability

Because the 2019 SI revision broke the clean "wait for the next CODATA update" test, we must adopt a probabilistic, model-comparison approach. Below is a simplified but explicit Bayesian calculation.

4.1 Data and notation

Let R_i^{CODATA} be the six dimensionless combinations $R_1, \dots, R_6$ defined in the paper, and let $R_i^{\mathrm{geom}}(a)$ be the geometric predictions as functions of $a = \alpha^{-1}$. Define the fractional deviations

$$\delta_i(a) \;=\; \frac{R_i^{\mathrm{CODATA}} - R_i^{\mathrm{geom}}(a)}{R_i^{\mathrm{CODATA}}}.$$

At the best-fit value a_{fit}, the observed relative deviations are of order 10^{-7}–10^{-8}.

4.2 Hypotheses

H_0 **(random/unstructured)** The δ_i are drawn independently from a zero-mean broad distribution with scale σ_0, e.g. $\delta_i \mid H_0 \sim \mathcal{N}(0, \sigma_0^2)$. There is no underlying geometric relation; any apparent pattern is accidental.

H_1 **(geometric lattice)** There exists a single a such that $R_i^{\mathrm{CODATA}} \approx R_i^{\mathrm{geom}}(a)$ up to small residuals. Conditional on a, $\varepsilon_i \equiv \delta_i(a) \sim \mathcal{N}(0, \sigma_1^2)$ with $\sigma_1 \ll \sigma_0$. We then marginalise over a with a prior that encodes the allowed spread from Table 4 of the paper, roughly $\Delta a \approx 4.8 \times 10^{-6}$.

4.3 Approximate Bayes factor from the fit envelope

Under H_1, treat the fit-envelope uncertainties $\delta_{\mathrm{total},i}$ as standard deviations of the residuals. Then, approximately,

$$P(\delta \mid H_1) \;\propto\; \prod_{i=1}^{6} \frac{1}{\delta_{\mathrm{total},i}} \exp\!\left(-\frac{\delta_i^2}{2\,\delta_{\mathrm{total},i}^2}\right).$$

Because $\sum(\delta_i/\delta_{\mathrm{total},i})^2 \approx 0.71$, the exponential factor is roughly $e^{-0.355} \approx 0.70$.

Under H_0, choose σ_0 comparable to the typical observed $|\delta_i|$, say $\sigma_0 \sim 10^{-7}$. Then

$$P(\delta \mid H_0) \;\propto\; \prod_{i=1}^{6} \frac{1}{\sigma_0} \exp\!\left(-\frac{\delta_i^2}{2\sigma_0^2}\right).$$

Since $\sigma_0 \gg \delta_{\mathrm{total},i}$, the exponents strongly favour H_1, and the prefactor ratio $(\sigma_0/\langle\delta_{\mathrm{total}}\rangle)^6$ is huge.

A rough Bayes factor is therefore

$$B \;=\; \frac{P(\delta \mid H_1)}{P(\delta \mid H_0)} \;\sim\; \left(\frac{\sigma_0}{\langle\delta_{\mathrm{total}}\rangle}\right)^6 \exp\!\left[-\frac{1}{2}\sum_i \delta_i^2 \left(\frac{1}{\delta_{\mathrm{total},i}^2} - \frac{1}{\sigma_0^2}\right)\right].$$

Even with conservative choices, B is easily in the range 10^4–10^6; the author's MDL accounting suggests $B \sim 10^{26}$ (86 bits of compression).

4.4 Approximate probability of an underlying mathematical structure

If we start with prior odds 1 : 1, the posterior probability for an underlying mathematical structure is

$$P(H_1 \mid \delta) \;=\; \frac{B}{1+B}.$$

For $B \sim 10^4$–10^6 this is > 0.9999; for $B \sim 10^{26}$ it is effectively $1 - 10^{-26}$.

Thus, under fairly conservative assumptions, the approximate probability that the observed pattern reflects an underlying mathematical relationship rather than random chance is

$$\boxed{P(H_1 \mid \delta) \;\gtrsim\; 0.9999}$$

and possibly much closer to 1, depending on how one counts degrees of freedom and model variants.

This probability is conditional on the model class and the statistical approximations, and it does not account for possible "fishing expeditions" over many similar geometric constructions.

5 Taylor-series interpretation of the 10^{-7}–10^{-8} precision

The relative deviations between the geometric model and CODATA 2014 are typically of order 10^{-7}–10^{-8}:

- e: $\delta \approx +1.92 \times 10^{-8}$
- λ_e: $\delta \approx 0$
- R_∞: $\delta \approx +8.75 \times 10^{-8}$
- h: $\delta \approx -5.34 \times 10^{-9}$
- y_e: $\delta \approx +2.44 \times 10^{-8}$
- m_e: $\delta \approx -5.60 \times 10^{-9}$

This level of precision suggests that the geometric formulas may be viewed as leading-order terms in a Taylor expansion around a zeroth-order solution.

5.1 Sketch of the expansion idea

Suppose the true physics depends on a small dimensionless parameter ϵ (for example, a correction from a more fundamental theory). Write

$$a \;=\; a_0 + \epsilon\, a_1 + \epsilon^2\, a_2 + \cdots ,$$

where a_0 is the leading-order value (close to 137.035993), and similarly for other constants in the geometric expressions. Then each dimensionless combination R_i admits an expansion

$$R_i^{\text{true}} \;=\; R_i^{\text{geom}}(a_0) + \epsilon\, r_{i1} + \epsilon^2\, r_{i2} + \cdots .$$

If the geometric model corresponds to the leading-order approximation, the residuals δ_i should scale as ϵ:

$$\delta_i \;\sim\; \epsilon.$$

The observed $|\delta_i| \lesssim 10^{-7}$ then suggests $\epsilon \lesssim 10^{-7}$.

Conversely, if future CODATA improvements tighten the agreement to 10^{-9} or better, that would indicate either:

- the geometric model is exact to all orders (unlikely but logically possible), or
- additional structure (higher-order terms, symmetries, or discrete corrections) is at work, which one might try to parametrise as a Taylor or Fourier series in a small parameter.

A concrete toy model is:

$$a \; = \; 137.035993138 \; + \; \epsilon \sum_k c_k \cos(k\phi),$$

with $\epsilon \sim 10^{-7}$ and phases ϕ linked to other fundamental numbers. Then the deviations δ_i become *functions* of ϕ, and one could in principle fit the c_k and ϕ to the data. If such a Fourier–Taylor expansion significantly improves the fit without excessive overfitting, that would be evidence for a structured hierarchy of corrections rather than uncorrelated noise.

At present, the data are consistent with a single leading-order geometric structure plus small residuals, but the precision is not yet sufficient to resolve detailed substructure. Future CODATA adjustments, especially if accompanied by explicit covariance matrices, may allow one to test whether the residuals behave like a smooth Taylor series or instead like uncorrelated metrological noise.