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Posted Date: 10 February 2026

doi: 10.20944/preprints202602.0699.v2

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Does Size Matter? Cross-Species Analysis of Intelligence and Brain Size

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Abstract

Brain size correlates weakly with intelligence within species yet strongly across species, and several taxa—from corvids to honeybees—exhibit cognitive abilities disproportionate to their brain mass. The Strong Electromagnetic Field Hypothesis (SEFH) proposes that higher cognition emerges from hierarchically nested electromagnetic (EM) field dynamics in neural tissue, generating predictions based on two variables: (i) *wattage density*—EM field production intensity per unit volume of integrative tissue, driven by neuron density—and (ii) *harmonic capacity*—the number of distinct geometric eigenmodes (resonant standing-wave patterns) that the field-permeable tissue can sustain. We test these predictions using comparative neuroscience datasets across primates, corvids, parrots, cetaceans, elephants, carnivores, rodents, and honeybees. After excluding cerebellar neurons, we find that SEFH predictions are confirmed across key comparisons: corvids and parrots achieve primate-rival cognition with 3–5× higher pallial wattage density than human cortex; honeybees achieve remarkable cognitive feats with ~960,000 neurons/mg; and elephants dramatically underperform even when cerebellar neurons are excluded. A preliminary two-variable regression of the form cognitive capacity ∝ wattage density × log(harmonic capacity) explains over 90% of cross-species cognitive variance ($R^2 = 0.918$), confirmed by leave-one-out cross-validation ($R^2 = 0.761$) and permutation testing ($p < 0.001$). The model's algebraic form—log(density^2 × volume)—yields a natural physical interpretation as total EM field energy in integrative tissue.

Keywords: electromagnetic field theory of consciousness; cross-frequency coupling; comparative neuroscience; neuron density; corvid cognition; honeybee cognition; isotropic fractionator; ephaptic coupling; Spectral Eigenmode Field Hypothesis; General Resonance Theory; geometric eigenmodes; harmonic brain modes

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1. Introduction

The observation that brain size correlates only weakly with intelligence within humans ($r \approx 0.24$, explaining approximately 6% of variance; Pietschnig et al., 2015) yet correlates substantially with cognitive ability across primate genera ($R^2 \approx 0.65$; Deaner et al., 2007) and across broader mammalian and avian taxa (Roth & Dicke, 2005) has generated a rich literature seeking the neural variables that best predict cognition. Total neuron count (Herculano-Houzel, 2017), encephalisation quotient (Jerison, 1973), cortical neuron density (Olkowicz et al., 2016), and processing speed (Roth & Dicke, 2005) have all been proposed as the critical variable. Each captures part of the pattern, but none provides a fully satisfying account.

The most striking challenges to brain-size explanations come from opposite ends of the animal kingdom. Corvids and parrots with brains weighing only 5–20 grams demonstrate cognitive abilities—tool manufacture, causal reasoning, mirror self-recognition, mental time travel—comparable to those of great apes with brains of approximately 400 grams (Emery & Clayton, 2004; Kabadayi & Osvath, 2017). More provocatively still, honeybees with fewer than one million neurons in a 1 mm^3 brain demonstrate counting, abstract concept learning, route optimization approaching solutions to the travelling salesman problem, and possibly play behaviour (Chittka, 2022; Dona et al., 2022). At the other extreme, the African elephant possesses 257 billion neurons—three times the human count—yet its cognitive abilities, while impressive, do not scale proportionally (Herculano-Houzel et al., 2014).

The Strong Electromagnetic Field Hypothesis (SEFH, Hunt 2026), building on General Resonance Theory (GRT; Hunt & Schooler, 2019) and earlier electromagnetic field theories of consciousness (McFadden, 2020; Pockett, 2000), offers a framework that may resolve these anomalies. The SEFH proposes that consciousness and higher cognition are constituted by hierarchically nested electromagnetic field dynamics in neural tissue, with neural firing serving primarily as an energy source and modulator for these fields. On this account, each neuron is not merely a computational unit but an EM field source, and cognition emerges from the structured interaction of these fields across spatial scales—from local ephaptic coupling between adjacent neurons, through mesoscale oscillatory dynamics, to global cross-frequency coupling (CFC) patterns. Ephaptic field effects propagate at electromagnetic speeds in neural tissue—orders of magnitude faster than action potential conduction (Ruffini et al., 2020)—suggesting that field dynamics, not spike patterns, may constitute the primary medium through which neural populations coordinate. The framework emphasises two variables: (i) EM field production *density* in associative tissue (watts per unit volume, determined by neurons per mg); and (ii) *harmonic capacity*—the number of distinct geometric eigenmodes (resonant standing-wave patterns) that the field-permeable tissue can sustain, determined by the geometry and spatial extent of the ephaptically coupled neural medium. Recent work in neural field theory demonstrates that brain geometry—rather than connectome topology—represents the fundamental constraint on neural dynamics (Pang et al., 2023), and that harmonic brain modes govern the spatiotemporal organisation of cognition and consciousness (Atasoy et al., 2016, 2018). These findings provide direct physical grounding for the SEFH's two-variable framework.

This paper asks: does the existing comparative neuroscience dataset discriminate between SEFH predictions and those of standard computational neuroscience? We systematically mine published data on cortical/pallial neuron counts, densities, myelination patterns, and cross-frequency coupling—spanning vertebrates and, for the first time in this framework, invertebrates—to identify where SEFH makes distinctive predictions and whether these are confirmed, challenged, or untestable with current data.

Table A provides a summary overview of key findings for each taxon examined in this paper.

Table A. Summary of key findings and SEFH predictions across major taxa.

Taxon	Wattage Density	Harmonic Capacity	Observed Cognition	SEFH Prediction	Outcome
Corvids/Parrots	Very high (133–278k n/mg)	Moderate	Primate-rival	High cognition from density	Strongly confirmed: density compensates for small brain
Honeybees	Extreme (~960k n/mg)	Very low	Domain-specific excellence	Limited by harmonic capacity	Confirmed: tiny drum, remarkable within narrow domains
Primates (human)	Moderate (~13k n/mg)	Very high	Highest general intelligence	Density × harmonic capacity	Confirmed: cathedral with moderate density
Elephants	Very low (~1.2k n/mg)	High (large cortex)	Below neuron-count prediction	Low density limits cognition	Supported but ambiguous: social cognition impressive
Cetaceans	Low (~3.6k n/mg)	Moderate–high	High social cognition	Low density + poor architecture	Challenging: social cognition exceeds density prediction

Galliforms	Moderate (~38k n/mg)	Low	Limited	Within-clade control for birds	Confirmed: lower density → lower cognition vs. corvids
Rodents	Moderate (~17.5k n/mg)	Low	Limited	Small harmonic capacity	Consistent: moderate density, tiny cortical surface area

2. Theoretical Framework: Core Claims of the SEFH Model

The SEFH builds on a growing body of work suggesting that endogenous EM fields play a functional role in neural computation (Anastassiou et al., 2011; McFadden, 2020; Pockett, 2000). It goes further than "weak" electromagnetic field hypotheses (WEFH), which view fields and spikes as equal partners in generating consciousness (Hunt, 2026), by proposing that neural firing may serve primarily as an energy source for the EM fields that constitute the actual substrate of consciousness and cognition. Three core claims generate the testable predictions examined in this paper.

An important terminological clarification is needed at the outset. The SEFH is fundamentally a hypothesis about *consciousness*—it proposes that EM field dynamics constitute the substrate of phenomenal experience. However, the cross-species evidence examined in this paper concerns *cognitive performance*: tool use, problem solving, flexible planning, and so on. We use cognitive capacity as a measurable proxy for the richness of conscious experience, on the reasonable but unproven assumption that higher-order cognition requiring flexible integration of information depends on richer and more complex conscious states. This assumption is standard in comparative consciousness research but should be kept in mind when interpreting the results.

2.1. Neurons as EM Field Sources

Herculano-Houzel (2011) demonstrated that the average metabolic cost per neuron is remarkably constant across mammalian species, varying only approximately 40% between rodents and primates: ~5.79×10^{-9} μmol glucose per minute per neuron. Because glucose metabolism generates electromagnetic fields through ionic currents and membrane potential fluctuations, this finding implies that each neuron contributes a roughly fixed quantity of EM field energy. Total brain EM field power is therefore approximately a linear function of neuron count. However, SEFH emphasises that what matters for cognition is not total power but power *density* in the tissue performing integrative computation—the cerebral cortex in mammals, the telencephalic pallium in birds, or the mushroom bodies and central complex in insects.

A crucial physical point deserves emphasis: the relationship between neuron density and macroscopic EM field strength is not merely additive. Incoherent firing by densely packed neurons would produce relatively weak macroscopic fields through destructive interference. However, dense packing strengthens ephaptic coupling between adjacent neurons—the very mechanism SEFH identifies as fundamental—and stronger ephaptic coupling promotes local synchronisation of neural populations. Synchronised populations produce coherent field summation, generating macroscopic fields far stronger than the sum of random individual contributions. Thus, density does not simply increase the number of field sources; it increases their tendency to synchronise, which in turn amplifies macroscopic field strength nonlinearly. This positive feedback loop—density → ephaptic coupling → synchronisation → coherent field production—is central to SEFH's prediction that wattage density, rather than total neuron count, drives cognitive capacity.

2.2. Myelination as Field Architecture

SEFH treats myelination not primarily as a mechanism for increasing conduction velocity (the standard account), but as an architectural element that shapes EM field hierarchies. Myelin sheaths act as insulation boundaries that channel fields, determining which neural populations are ephaptically coupled and which are isolated. This architectural role predicts that (i) the *pattern* of myelination matters more than its overall quantity; (ii) heavily myelinated pathways create EM field "trunks" that channel energy efficiently, while less myelinated associative regions remain open to flexible cross-field interaction; and (iii) species with thin or sparse myelination despite large brains (e.g., elephants, cetaceans) will show impaired field hierarchy formation—not merely slower conduction. In invertebrates, analogous architectural roles may be played by glial wrapping patterns and neuropil compartmentalisation.

2.3. Dynamic Harmonic Coupling and Information Bandwidth

SEFH posits that cross-frequency coupling (CFC)—the modulation of high-frequency oscillations by lower-frequency rhythms—reflects the dynamic engagement of nested EM field hierarchies. Critically, this coupling operates as a "gas pedal" (following Rodriguez-Larios & Alaerts, 2021; Klimesch, 2013): it is recruited on demand during cognitive tasks, not maintained tonically. This predicts that the relevant variable for intelligence is not the amount of resting-state CFC but the *dynamic range* of harmonic coupling—the system's capacity to rapidly transition between states of low and high cross-frequency engagement. Additionally, SEFH predicts that the absolute number of neurons in integrative tissue determines the *harmonic capacity*—the number of distinct geometric eigenmodes (resonant standing-wave patterns) the tissue can sustain, determined by its geometry and spatial extent. High density sets the quality of local field interactions; the harmonic capacity of the resonant medium sets the richness of standing-wave patterns that can coexist. This dual requirement explains why mouse cortex, despite higher density than human cortex, cannot support human-level cognition: insufficient harmonic capacity in its small cortical geometry.

3. Methods: Data Sources and Analytical Approach

3.1. Data Sources

We compiled neuron counts and densities from published isotropic fractionator and stereological studies spanning seven major clades. Primary data sources include: primates (Azevedo et al., 2009; Herculano-Houzel et al., 2007; Gabi et al., 2010); corvids and parrots (Olkowicz et al., 2016, encompassing 28 avian species); African elephant (Herculano-Houzel et al., 2014); cetaceans (Avelino-de-Souza et al., 2025; Mortensen et al., 2014); carnivores including dogs, cats, and raccoons (Jardim-Messeder et al., 2017); rodents (Herculano-Houzel et al., 2006); and Hymenoptera (Godfrey et al., 2021, adapting the isotropic fractionator for insect brains; Menzel, 2012). All data were drawn from peer-reviewed publications employing validated quantitative methods.

3.2. Cerebellar Exclusion

A critical methodological decision, motivated directly by the SEFH framework, was the exclusion of cerebellar neurons from all vertebrate analyses. The cerebellum typically contains approximately 80% of all brain neurons in mammals (Herculano-Houzel, 2010) and is primarily involved in motor coordination, timing, and procedural learning—not the integrative consciousness and higher cognition that SEFH addresses. This exclusion dramatically alters the comparative landscape: the African elephant's neuron count drops from 257 billion (whole brain) to 5.6 billion (cortex only)—approximately one-third of the human cortical count, rather than three times the human total. For insects, no analogous exclusion is necessary; the mushroom bodies and central complex function as integrative centres without a separate motor-dominated cerebellar structure.

3.3. Wattage Density Estimation

We estimated EM field production density for integrative neural tissue using the following procedure. First, neuron counts in integrative tissue were converted to estimated metabolic power using Herculano-Houzel's (2011) fixed energy-per-neuron constant (~5.67 × 10^{-10} watts per neuron, assuming ~20% thermodynamic efficiency from glucose oxidation). Second, total watts were divided by tissue mass to yield milliwatts per gram (mW/g). Third, mW/g was converted to mW/cm³ using tissue-specific gravity. We acknowledge that the per-neuron energy cost may differ between vertebrate and invertebrate neurons; insect neuron energy budgets remain poorly characterised. However, because SEFH predicts *relative* differences in wattage density across taxa, the absolute calibration is less critical than the rank ordering.

3.4. Cognitive Assessment and Anthropocentric Bias

Assessing cognitive capacity across species is fraught with methodological challenges. Standard comparative cognition batteries—object permanence, mirror recognition, means-end reasoning, delayed gratification—are designed around human cognitive priorities and privilege visual-manual manipulation (Schubiger et al., 2020; Mikhalevich & Powell, 2020). The Primate Cognition Test Battery (PCTB; Herrmann et al., 2007) has been adapted for corvids (Pika et al., 2020), parrots (Krasheninnikova et al., 2019), monkeys (Schmitt et al., 2012), and lemurs (Fichtel et al., 2020), but results reveal systematic apparatus bias rather than cognitive differences (see Section 5). Species that solve ecological problems through non-visual modalities are systematically disadvantaged. We flag this anthropocentric bias throughout our analyses and note where it may affect SEFH evaluation.

4. Results: SEFH Predictions Against Comparative Data

We organise our results around seven specific tests of SEFH predictions, spanning vertebrates and invertebrates. Table 1 provides the neural data underlying these comparisons.

Table 1. Integrative neural tissue data across major taxa. Vertebrate data use cortical/pallial neurons only (cerebellum excluded). Wattage density estimated using Herculano-Houzel (2011) energy constant.

Taxon	Brain Mass (g)	Integrative Neurons	Tissue Mass	Density (neurons/mg)	Est. Wattage Density (mW/cm³)	Cognitive Highlights
Human	1,400	16.3B (cortex)	1,233 g	~13,200	~7.8	Language, abstract reasoning, long-range planning
Raven	15	1.2B (pallium)	~5 g	~240,000	~140	Tool mfg, causal reasoning, mental time travel
Macaw	20	1.6B (pallium)	~8 g	~200,000	~115	Tool innovation, vocal learning, stat. inference
Honeybee	0.001	~960K (whole brain)	~1 mg	~960,000	~545*	Counting, concept learning, route optimisation
Chimp	400	6.2B (cortex)	~310 g	~12,000–15,000	~7–9	Tool use, social learning, limited planning
Raccoon	39	453M (cortex)	~19 g	~23,800	~14	Lock-picking, >3yr memory, manual dexterity
Chicken	3.5	77M (pallium)	~1.5 g	~51,000	~29	Basic spatial memory, social hierarchy

Mouse	0.42	14M (cortex)	~0.17 g	~15,000–20,000	~9–11	Spatial nav., olfactory discrim., limited flexibility
Elephant	4,780	5.6B (cortex)	~4,660 g	~1,200	~0.7	Social memory, cooperation, possible mourning
Dog	95	627M (cortex)	~60 g	~6,600	~3.8	Social cognition, olfactory tracking (untested)
Cetaceans (minke whale)	2,700	~3.2B (cortex, revised)	~2,100 g	~2,400	~1.4	Vocal learning, alliances, cooperative hunting

**Honeybee wattage density is estimated assuming similar per-neuron energy costs to vertebrates; actual insect neuron energy budgets may differ. Value shown for comparative purposes.*

4.1. Test 1: Corvids and Parrots — The Density Prediction

SEFH predicts that species with high neuron density in integrative tissue should achieve cognitive capacities disproportionate to their brain size, because denser neuron packing produces stronger local EM fields and more opportunities for ephaptic coupling.

The avian data strongly confirm this prediction. Corvid and parrot pallial neuron densities range from 133,000 to 278,000 neurons per milligram of tissue (Olkowicz et al., 2016)—approximately 10–20× higher than human cortex (~13,200 neurons/mg) and 100–230× higher than elephant cortex (~1,200 neurons/mg). These species demonstrate tool manufacture and use (New Caledonian crows; Hunt, 1996), causal reasoning (Jelbert et al., 2014), planning for future needs (Kabadayi & Osvath, 2017), and possibly mirror self-recognition (Prior et al., 2008)—cognitive capacities broadly comparable to those of great apes, achieved with brains weighing 5–20 grams.

Critically, this result discriminates between SEFH and simpler “neuron count” models. A raven has approximately 1.2 billion pallial neurons versus a human’s 16.3 billion—only 7% of the human count—yet achieves a substantial fraction of human-like cognitive performance. SEFH accounts for this by emphasising that the raven’s pallial neurons are packed into a volume roughly 100× smaller, generating far denser EM fields per unit tissue. Standard computational models, which treat neurons as discrete processing units, cannot readily explain why density per se should matter.

4.2. Test 2: Honeybees — The Invertebrate Extreme

The honeybee (*Apis mellifera*) presents perhaps the most extraordinary case in comparative cognition: remarkable cognitive abilities achieved with fewer than one million neurons in approximately $1\ \text{mm}^3$ of neural tissue. As documented comprehensively by Chittka (2022), individual honeybees demonstrate: counting up to 4–5 items; understanding zero as a quantity less than one; learning abstract relational concepts (“same” vs. “different” applied to novel stimuli); route optimisation approaching solutions to the travelling salesman problem; contextual learning adjusted by time and location; individual recognition of human faces; and what appears to be play behaviour in bumblebees (rolling wooden balls with no food reward; Dona et al., 2022).

These are the achievements of individual bees, not the hive—a distinction Chittka (2022) emphasises. The mushroom body, functionally analogous to the vertebrate hippocampus and cortex, receives multimodal sensory input and supports associative learning through neuroplastic changes at hundreds of thousands of synaptic connections (Menzel, 2012). A single identified neuron (VUMmx1) mediates reward-based learning in a manner functionally similar to mammalian dopamine neurons.

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The neural density data are striking. With approximately 960,000 neurons in ~1 mg of tissue, honeybee brain density is approximately 960,000 neurons/mg—three to four times higher than the densest vertebrate neural tissue (corvid associative pallium at ~280,000 neurons/mg) and roughly 70× higher than human cortex. Some Hymenoptera are even denser: the metallic green sweat bee (*Augochlorella*) reaches approximately 2,000,000 neurons/mg (Godfrey et al., 2021)—the highest neural density measured in any animal.

Table 2. Neural density comparison across major clades, highlighting the extraordinary density gradient from elephants to bees.

Taxon	Integrative Tissue Density (neurons/mg)	Ratio to Human Cortex	Cognitive Level
Sweat bee (Augochlorella)	~2,000,000	151×	Unknown (unstudied)
Honeybee	~960,000	73×	Counting, concepts, route optimisation
Goldcrest	~278,000	21×	Vocal learning; limited flexibility
Raven	~240,000	18×	Primate-rival (tools, planning)
Macaw/Cockatoo	~133,000–208,000	10–16×	Primate-rival (tools, stat. inference)
Raccoon	~23,800	1.8×	Exceptional for carnivore
Mouse	~15,000–20,000	1.1–1.5×	Spatial nav., limited flexibility
Human	~13,200	1× (reference)	Language, abstract reasoning
Great Apes	~12,000–15,000	0.9–1.1×	Tool use, social learning
Dog	~6,600	0.5×	Social cog.; olfactory unknown
Cetaceans	~2,400	0.18×	Social cog., vocal learning
Elephant	~1,200	0.09×	Social memory, cooperation

What does the honeybee case mean for SEFH? On a pure wattage-density model, bees should be the smartest animals on the planet—they are clearly not. However, bee cognition dramatically outperforms what their total neuron count would predict. With fewer than one million neurons, bees accomplish feats that animals with 10–100× more neurons (but lower density) cannot. Ants, with comparable brain mass but substantially lower neuron density (down to ~400,000 neurons/mg in some species; Godfrey et al., 2021), show correspondingly limited cognitive flexibility. Flying Hymenoptera consistently show higher neural densities than non-flying relatives, and this correlates with richer behavioural repertoires—though the confound with flight-related sensory processing demands cannot yet be separated from cognitive density effects.

Critically, bees are remarkable *within narrow domains* but do not show the open-ended, flexibly transferable cognition that characterises corvids and primates. They solve the travelling salesman problem for flowers but cannot transfer that optimisation strategy to a novel domain. This pattern is exactly what SEFH's dual-requirement model predicts: extraordinary density enables powerful local field interactions and efficient information processing *within* circuits, but with fewer than one million neurons packed into approximately one cubic millimetre, the harmonic capacity—the number of distinct geometric eigenmodes the tissue can sustain—is severely constrained. Pang et al. (2023) demonstrated that brain dynamics are fundamentally shaped by geometric eigenmodes: the resonant standing-wave patterns of the tissue's physical shape. A honeybee's mushroom body is an exquisitely tuned tiny drum—it produces remarkably pure tones (domain-specific cognitive excellence from a handful of harmonic modes), but it cannot produce the harmonic complexity of a cathedral, whose vast reverberant geometry sustains thousands of simultaneous resonant modes in structured coordination.

4.3. Test 3: The Elephant Paradox — Architecture vs. Raw Power

The African elephant provides the clearest test of SEFH's architectural prediction. With 257 billion total neurons, the elephant brain generates an estimated 146 watts of total metabolic power—substantially more than the human brain (~49 watts). However, 97.5% of elephant neurons reside in the cerebellum (Herculano-Houzel et al., 2014). The cerebral cortex contains only 5.6 billion neurons at a density of approximately 1,200 neurons per milligram—roughly one-eleventh of human cortical density.

SEFH predicts that this low cortical density, combined with thin myelin sheaths and large interneuronal distances (Cozzi et al., 2001), should produce EM fields that are diffuse and poorly structured—high in total power but low in hierarchical organisation. The elephant's cognitive profile is consistent with this prediction: impressive social cognition, long-term memory, cooperative problem-solving, and possible mourning behaviour (Plotnik et al., 2006; McComb et al., 2006), but falling substantially short of what 257 billion neurons would predict if total neuron count were the critical variable.

We note, however, that the elephant case is not unambiguously supportive. The degree of social and cooperative cognition elephants display is arguably more than their cortical wattage density and harmonic capacity "should" produce under strict SEFH predictions. Two factors complicate interpretation: first, elephant cognition in olfactory and infrasound domains—which may involve substantial cortical integration—is largely untested by standard batteries (Bates et al., 2008); second, the extent to which cerebellar circuits contribute to non-motor cognitive functions remains debated (Buckner, 2013).

4.4. Test 4: Within-Clade Controls — Galliforms vs. Corvids

An informative within-clade comparison is available in birds. Galliforms (chickens, emus) and corvids share the same basic avian brain architecture—nuclear (non-laminar) pallium, absence of a layered cortex—yet differ dramatically in pallial neuron counts and densities. Chickens have approximately 77 million pallial neurons; emus approximately 193 million. By contrast, jackdaws pack 510 million and ravens 1.2 billion pallial neurons into brains of comparable or smaller mass (Olkowicz et al., 2016). Because architecture is held roughly constant within the avian pallial bauplan, this comparison isolates the density variable. SEFH predicts exactly this outcome: higher neuron density in associative tissue → higher EM field source density → stronger ephaptic coupling → richer field interactions → greater cognitive capacity.

4.5. Test 5: Cross-Frequency Coupling as Dynamic Range

SEFH posits that cross-frequency coupling reflects the dynamic engagement of nested EM field hierarchies, and predicts that the *dynamic range* of CFC—not its tonic level—should predict cognitive capacity. Within humans, this prediction is supported by converging evidence. Pahor and Jaušovec (2014) found that resting-state theta–gamma CFC negatively correlated with IQ scores—smarter individuals showed *less* coupling at rest—but that task-dependent CFC increases were greater in higher-IQ participants. This pattern—low resting coupling, high task-dependent coupling—maps directly onto SEFH's "gas pedal" metaphor: a well-tuned system idles low but deploys harmonic resonance with precision when needed. Cross-species CFC data are limited: theta–gamma coupling has been well documented in rodent hippocampus during spatial tasks (Tort et al., 2009), confirming that harmonic resonance is a genuine neural mechanism, but comparative CFC recordings in corvids, parrots, elephants, and cetaceans during cognitive tasks are essentially absent. This represents the single most important data gap for testing SEFH.

4.6. Test 6: Myelination as Field Sculpting

SEFH predicts that the *pattern* of myelination, not its total quantity, should predict cognitive capacity by determining the geometry of EM field channelling. Within humans, neurite density rather than cortical myelination mediates the link between genetic variation and general intelligence (Stammen et al., 2025)—a finding paradoxical under standard accounts but predicted by SEFH. Humans display uniquely prolonged myelination relative to other primates, with maturation continuing into the third decade (Miller et al., 2012). Cetaceans and elephants—the taxa that most underperform their neuron counts—are characterised by thin myelin sheaths (Cozzi et al., 2001; Manger, 2006). Under SEFH, this thin myelination produces EM fields that are diffuse rather than hierarchically channelled, regardless of total brain wattage.

4.7. Test 7: Cetaceans — The Hardest Case

Cetaceans present a genuine tension for the SEFH model in its current form. Dolphins and whales demonstrate vocal learning, cultural transmission, signature whistles functioning as individual names, complex alliance formation, and cooperative hunting strategies involving role differentiation and real-time coordination (Connor, 2007; Rendell & Whitehead, 2001; Pitman & Durban, 2012). This level of social cognition is difficult to reconcile with the low cortical wattage density (~3,600 neurons/mg) and relatively poor field architecture that SEFH predicts should limit cognitive capacity.

Several factors partially mitigate this challenge. Recent data from Avelino-de-Souza et al. (2025), using the isotropic fractionator on a northern minke whale, found only 3.2 billion cortical neurons—dramatically fewer than the 37.2 billion estimated for long-finned pilot whales by Mortensen et al. (2014) using stereology—suggesting that some earlier estimates may have been inflated. Unihemispheric sleep suggests hemispheric independence rather than tight cross-hemispheric integration, and echolocation may rely substantially on dedicated subcortical circuits. Nevertheless, we do not consider these explanations fully satisfactory. Cetacean social cognition represents the clearest case where the two-variable model, as currently formulated, underestimates observed cognitive performance. This may indicate unmeasured field architectural features that enhance cetacean cortical field dynamics, cognitive specialisations that operate through mechanisms not well captured by the wattage density × harmonic capacity framework, or genuine limitations of the current model that will require theoretical refinement.

5. The Measurement Problem: Anthropocentric Bias in Cognitive Assessment

Any attempt to correlate neural substrate with cognitive capacity across species must contend with the problem of anthropocentric bias. The Primate Cognition Test Battery (PCTB; Herrmann et al., 2007), the only standardised cross-taxon cognitive instrument, reveals systematic apparatus bias when administered across taxa. Ravens matched chimps and orangutans, reaching adult performance by 4 months (Pika et al., 2020). Old World monkeys matched great apes (Schmitt et al., 2012). Lemurs matched haplorhines in social cognition despite smaller brains (Fichtel et al., 2020). But parrots—species independently validated as cognitively sophisticated—scored at chance level across the entire PCTB (Krasheninnikova et al., 2019).

The parrot result is diagnostic: these species demonstrate tool innovation (Goffin's cockatoos), statistical inference (kea), and Stage 6 object permanence (African greys) in other paradigms. Their PCTB failure reflects apparatus incompatibility—parrot beaks are precision tools for cracking and gripping, not for the reach-and-choose paradigm the PCTB requires—not cognitive limitation. If the PCTB fails for parrots, it cannot be trusted for any species departing from the primate/corvid visual-manual paradigm.

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Critically, no cognitive batteries exist for non-visual modalities. There is no Olfactory Cognition Test Battery for dogs (despite their unique olfactory-to-occipital white matter pathway; Johnson et al., 2022), no Echolocation Integration Battery for cetaceans, and no Infrasound Communication Battery for elephants. The entire edifice of cross-species cognitive comparison rests on visual-manual tasks. Even in humans, olfactory working memory shows fundamentally different properties from visual/auditory WM (recency without primacy effects, independent factor structure).

Table 3. Cross-species results on the Primate Cognition Test Battery (PCTB) and adaptations, illustrating measurement bias.

Taxon	Performance vs. Great Apes	Brain Mass / Density	Interpretation
Ravens (CCTB)	Matched chimps and orangutans	15g brain; ~240K neurons/mg	Clean match: both visual foragers. Adult performance by 4 months vs. years in primates.
Old World Monkeys	Matched great apes	~95g brain; ~12K neurons/mg	Expected brain-size gradient absent. Questions brain-size–cognition link.
Lemurs	Matched in social cognition	~24g brain; moderate density	Dramatically smaller brains; social cognition matches larger-brained taxa.
Parrots (4 species)	Chance level (floor effect)	10–20g brain; ~133–208K n/mg	Known to be cognitively sophisticated from other paradigms. Apparatus bias, not cognitive deficit.

For SEFH testing, the implication is clear: the cleanest tests are those where the cognitive assessment modality matches both species' ecological toolkit. Corvids vs. primates (both visual foragers), corvids vs. galliforms (same bauplan, same sensory ecology), and within-human CFC–IQ data provide the most interpretable comparisons. For taxa whose cognitive strengths lie in untested modalities—dogs, elephants, cetaceans—SEFH evaluation is *indeterminate* rather than "challenging."

6. Summary: Cross-Taxon Evidence Assessment

Table 4 summarises the alignment of published data with SEFH predictions for each major taxon examined. Ratings reflect the degree to which existing evidence supports or challenges the model, with caveats noted.

Table 4. Summary of SEFH evidence alignment across taxa. Cortical/pallial neurons only for vertebrates; whole brain for insects. Cerebellum excluded.

Taxon	SEFH Alignment	Key Finding and Caveats
Corvids	Strong support	Highest vertebrate integrative density (140–280K/mg); primate-rival cognition in walnut-sized brains. Cleanest SEFH confirmation.
Parrots	Strong support	Same density pattern as corvids; cognitive output far exceeds brain size. PCTB failure reflects apparatus bias, not cognitive limits.
Honeybee	Strong support	Highest density of any animal (~960K/mg); remarkable cognition from <1M neurons. Outperforms insects with more neurons but lower density. Confirms density matters; limited flexibility confirms harmonic capacity constraint.
Human	Strong support	Moderate density + uniquely prolonged myelination + documented dynamic CFC predicting IQ. Enormous cortical geometry provides vast harmonic capacity for open-ended cognition.

Great Apes	Moderate support	Good density, good architecture, shorter myelination window. Cognition likely underestimated by human-designed tests.
Raccoon	Moderate support	High density for carnivore (~23,800/mg); exceptional problem-solving within clade. Fits density → cognition prediction.
Galliforms vs. Corvids	Moderate support	Same avian bauplan, lower pallial density → correspondingly weaker cognition. Clean within-clade control.
Within-human CFC–IQ	Moderate support	Resting CFC negatively correlates with IQ; task-dependent dynamic range predicts performance. Supports gas-pedal model.
Small Rodents	Mixed	High density (15–20K/mg) + confirmed CFC, but limited tested flexibility. Mouse denser than human yet less cognitively flexible → confirms harmonic capacity constraint. Olfactory cognition untested.
Songbirds	Mixed	Highest vertebrate whole-brain density (278K/mg) but tiny absolute count (74M). Vocal learning is genuinely integrative. Confirms density × harmonic capacity model.
Dogs	Indeterminate	Low cortical density (~6,600/mg). Olfactory integration via unique bulb-to-occipital pathway (Johnson et al., 2022) is wholly unmeasured. Cannot evaluate SEFH until olfactory cognition tested.
Elephant	Moderate challenge	Very low cortical density (~1,200/mg) + thin myelin = poor architecture. SEFH predicts underperformance vs. total neuron count, confirmed. But social cognition exceeds strict prediction. Olfactory/infrasound cognition untested.
Cetaceans	Moderate challenge	Low wattage density + limited harmonic capacity (low density despite large volume) but impressive social cognition. Revised neuron counts and modularity arguments reduce but don't eliminate the challenge. Echolocation may be subcortical.

7. Toward a Quantitative Predictive Model: Wattage Density × Harmonic Capacity

No single neural variable predicts cognitive capacity across all taxa (Table 5). Brain mass fails for corvids and elephants. Total neuron count fails for elephants and cannot explain corvid performance. Cortical neuron count improves matters but cannot explain why corvids with 7% of the human count match apes with 40–60%. Cortical neuron density works across many comparisons but cannot explain why mice (denser than human cortex) are not smarter than humans, or why bees (denser than any vertebrate) do not exceed all vertebrate cognition.

Table 5. Failure modes of single-variable predictive models. Each candidate predictor fails for at least one major comparison.

Candidate Predictor	Successes	Failures
Brain mass	Broad mammalian correlation; within-species human trend (weak)	Corvids (5–20g, primate cognition). Elephants (4.8kg, underperform). Bees (1mg, remarkable).
Total neuron count	Better than mass; primates generally scale	Elephants (257B, underperform). Corvids (1.2B = 7% of human, match apes).
Cortical/pallial neuron count	Corvids vs. galliforms; elephant underperformance; human supremacy	Corvids still only 7% of human count yet match apes (6–9B). Bees (<1M) exceed many vertebrates.

Neuron density in integrative tissue	Corvids > galliforms; bees > ants; raccoon > dog; elephant underperformance	Mouse cortex denser than human. Bees densest of all, not smartest overall.

7.1. Geometric Eigenmodes and the Physics of Harmonic Capacity

Recent work in neural field theory provides the physical foundation for resolving these failures. Pang et al. (2023) demonstrated that human brain function is more parsimoniously explained by geometric eigenmodes—the natural resonant modes of the brain's physical shape, derived from the Laplace–Beltrami operator on the cortical surface—than by modes derived from connectome topology. A simple wave equation on cortical geometry, with just one free parameter, outperformed complex neural mass models with fifteen parameters and a full connectome. Over 10,000 task-evoked brain maps were dominated by long-wavelength eigenmodes (>60 mm), and the spatial patterns of activity in subcortical structures (thalamus, striatum, hippocampus) showed near-perfect correspondence with their geometric eigenmodes ($r \geq 0.93$).

Independently, Atasoy et al. (2016, 2018) showed that human brain networks function in connectome-specific harmonic waves and that these harmonic brain modes provide a unifying framework linking space and time in brain dynamics. Critically, Atasoy et al. (2017) demonstrated that psychedelic-induced expansion of consciousness corresponds to an enlarged repertoire of harmonic brain modes, while loss of consciousness narrows the repertoire to low-frequency modes only—directly linking the number of available harmonic modes to the richness of conscious experience.

These findings converge on a principle that is fundamental to the SEFH: brain dynamics are shaped not by the topology of point-to-point axonal connections but by the geometry of the tissue through which EM fields propagate. The eigenmodes of this geometry—the resonant standing-wave patterns it can sustain—constitute the "building blocks" (Atasoy et al., 2019) of spatiotemporal brain dynamics. We propose the term *harmonic capacity* for the number of distinct geometric eigenmodes that a structure's field-permeable tissue can sustain.

7.2. The Two-Variable Model

The SEFH resolves the failures of single-variable models by proposing two variables, both native to field physics rather than to the spike-coding framework that, despite sophisticated modern variants (predictive coding, reservoir computing, neural mass models), continues to treat neurons as the fundamental computational units whose outputs carry information. These modern frameworks already incorporate continuous dynamics, population coding, and oscillatory processing—significant advances over McCulloch–Pitts logic gates—but they remain fundamentally tethered to the assumption that computation occurs *through* neurons rather than *in the fields neurons generate*. The SEFH's two variables derive from a different ontological commitment: that the EM field is the primary computational and experiential medium.

Wattage density (neurons per mg in integrative tissue) sets the intensity of local EM field production: ephaptic coupling strength, the richness of field interactions at each spatial scale, and the efficiency of energy transfer between neurons and the field medium. Higher density means more EM field sources per unit volume, creating stronger and more finely structured local field dynamics.

Harmonic capacity (the number of distinct geometric eigenmodes sustainable in the field-permeable tissue) determines how many resonant standing-wave patterns can coexist in the neural medium. This is set by the geometry and spatial extent of the ephaptically coupled tissue—its shape, volume, surface area, and curvature—following directly from the eigenvalue solutions of the Laplace–Beltrami operator ($\Delta\psi = -\lambda\psi$). A larger, more complexly folded cortical surface supports more eigenmodes with shorter wavelengths, enabling richer cross-frequency coupling between harmonic modes.

Gyrification plays a particularly important role in this framework that extends well beyond the standard account of packing more cortical surface into a fixed cranial volume. Ruffini et al. (2020), modelling mesoscopic ephaptic coupling across 401 human brains, demonstrated that cortical folding creates *ephaptic hotspots* along sulcal walls where adjacent gyri bring cortical surfaces into close physical proximity (often <2 mm apart). Their ephaptic modulation index (EMOD) correlates positively with gyrification, decreases with age as sulci widen, and tracks the spatial distribution of regions where non-synaptic, cross-sulcal field coupling is strongest. Crucially, neurons separated by a gyrus are more likely to be functionally connected than those separated by a sulcus—a finding more naturally explained by ephaptic field coupling across the narrow sulcal gap than by synaptic connectivity alone. Under the SEFH, this suggests that gyrification was selected not only for increased surface area but because folding creates ephaptic bridges between cortical populations that would otherwise require long-range axonal connections to communicate. The pattern of folding—which cortical regions are brought into proximity—may therefore be as important for cognitive capacity as the total surface area, and the eigenmode spectrum of a gyrified cortex is enriched not merely by having more area but by the complex boundary conditions that folding imposes on standing-wave patterns. In the cross-species regression below, we use total integrative neuron count as an approximate proxy for harmonic capacity. There is a physical justification for this proxy: each neuron occupies a characteristic spatial volume, so the total number of neurons constrains the minimum resolvable spatial wavelength of standing-wave patterns via a spatial Nyquist-type argument—more neurons packed into a given volume means finer spatial sampling and hence higher-order eigenmodes can be functionally resolved. Total neuron count thus captures both the volume of the resonant cavity and the spatial granularity of field sources within it. A more rigorous determination would require computing Laplace–Beltrami eigenmodes directly from 3D reconstructions of field-permeable tissue in each species, following the methodology of Pang et al. (2023), and would ideally incorporate ephaptic modulation mapping (following Ruffini et al., 2020) to identify cross-sulcal coupling zones.

Critically, what was previously treated as a third variable—field architecture (myelination patterns, neuropil organisation)—collapses into these two. Myelination reshapes the effective field-permeable geometry: myelin's lipid-rich sheaths act as high-resistance barriers that block ephaptic field propagation (Hunt, 2026), so the relevant geometry for harmonic capacity is not raw anatomical shape but the topology of the unmyelinated, ephaptically coupled tissue. The thalamocortical system's striking preservation of 73% unmyelinated tissue (despite myelination's clear advantages for long-range transmission) becomes, under this framework, the evolutionary preservation of a large resonant cavity optimised for harmonic richness. Similarly, neuropil density and dendritic arbor complexity determine local coupling efficiency between field sources—which is precisely what wattage density captures.

Under the SEFH's two-variable model, neither wattage density nor harmonic capacity alone determines cognitive capacity—their interaction does. The honeybee's mushroom body has extraordinary wattage density (~960,000 neurons/mg) but a severely limited resonant cavity (~1 mm^3), restricting it to domain-specific excellence from a handful of harmonic modes. The human cortex has moderate wattage density (~13,000 neurons/mg) spread across ~2,500 cm^2 of highly folded, predominantly unmyelinated cortical surface, sustaining thousands of geometric eigenmodes in structured cross-frequency coordination. Corvid pallium occupies an intermediate position: extreme wattage density (~40,000 neurons/mg) compensates for a smaller resonant cavity, producing a surprisingly rich harmonic repertoire from a walnut-sized brain.

This model explains the full cross-species pattern. Corvids succeed through extreme wattage density compensating for moderate harmonic capacity. Humans succeed through enormous harmonic capacity (vast cortical geometry) at moderate density. Bees succeed through extraordinary density sufficient for domain-specific excellence but are harmonic-capacity-limited by the tiny volume of field-permeable tissue. Mice are dense but harmonic-capacity-limited by small cortical area. Elephants have a large cortex but catastrophically low wattage density (~1,200 neurons/mg), yielding a resonant cavity that is vast but energetically feeble—a cathedral with barely a whisper echoing through it.

A preliminary quantitative formulation: *Cognitive capacity* $\propto$ *Wattage density* × *log(Harmonic capacity)*, where harmonic capacity is the number of geometric eigenmodes sustainable in the field-permeable integrative tissue. The logarithmic term captures diminishing returns: each additional hierarchical level of harmonic organisation requires exponentially more eigenmodes (consistent with eigenvalue spacing in the Laplace–Beltrami spectrum), and the observation that corvids achieve disproportionate cognitive returns from relatively few ultra-dense neurons. We emphasise that this formulation is intended to generate testable predictions rather than to serve as a validated model, and that empirical determination of harmonic capacity across species will require detailed geometric characterisation of field-permeable tissue architecture.

As a preliminary test, we fitted a multiple regression of the form log(density) + log(integrative neuron count) to ordinal cognitive rankings across our ten focal taxa (using integrative neuron count as a proxy for harmonic capacity, since the number of resolvable eigenmodes in neural tissue scales with the number of spatially distinct field sources). Cognitive rankings were assigned on the basis of published comparative cognition literature, weighting flexible problem-solving, tool use, causal reasoning, and planning ability (drawing on Emery & Clayton, 2004; Chittka, 2022; Herculano-Houzel, 2017; and the PCTB results in Table 3). Rankings were assigned prior to fitting the model and represent our best assessment of the comparative literature; we acknowledge that these rankings involve subjective judgement and examine their sensitivity below.

This two-variable model explains $R^2 = 91.8\%$ (adjusted $R^2 = 89.4\%$) of cross-species cognitive variance, with Spearman $\rho = 0.976$ ($p < 0.00001$). For comparison, log(brain mass) alone explains 39.2%, log(integrative neuron count) alone explains 64.8%, and log(neuron density) alone explains less than 1%. Both coefficients are positive and approximately equal (β_density = 0.94, β_neurons = 1.09), indicating that wattage density and harmonic capacity contribute roughly equally and independently to cognitive capacity.

Given the small sample ($n = 10$, $k = 2$), we subjected this result to three robustness tests. First, leave-one-out cross-validation yields $R^2 = 0.761$ with Spearman $\rho = 0.952$ ($p = 0.00002$), confirming that the model generalises beyond the training data. The two largest LOO prediction errors are honeybee (+2.88) and elephant (+1.63), precisely the taxa that Section 5 identifies as most likely to be underestimated by anthropocentric testing batteries—the model predicts they should rank higher than our current data allow us to place them. Second, a permutation test (10,000 iterations of randomly shuffled cognitive rankings) produces $p < 0.0001$: no random ranking achieved $R^2 \geq 0.918$ (mean permuted $R^2 = 0.223$; 99th percentile = 0.741). Third, bootstrap resampling (10,000 iterations) yields a 95% confidence interval of [0.806, 0.995] for R^2.

We also tested sensitivity to the cognitive rankings themselves. Under plausible alternative rankings—moving elephants up to tie with chimpanzees, down to raccoon level, adjusting bees or dogs by one rank position—R^2 ranges from 0.872 to 0.949, with Spearman ρ remaining above 0.96 in all variants. Adding uniform random noise of ±1 rank position across all taxa yields a mean R^2 of 0.886 (95% CI: [0.804, 0.952]). The result is robust to reasonable disagreements about cognitive rankings.

A reflexive concern deserves explicit acknowledgement. Section 5 argues that anthropocentric bias systematically underestimates certain taxa's cognitive capacities; but if we genuinely cannot measure elephant or cetacean cognition, then we cannot confidently rank them—and the regression depends on those rankings. Our response is twofold. First, the rankings represent *currently measurable* cognition, which we argue is a lower bound for some taxa. The model's residuals are consistent with this: the two taxa most likely to be underestimated (elephant and honeybee) are both predicted to be cognitively richer than their current rankings suggest. A fully corrected ranking would likely produce equal or stronger model fit. Second, the sensitivity analysis demonstrates that the result is robust to substantial ranking perturbations, indicating that the model captures genuine structure in the data rather than depending on precise ordinal placements.

Finally, we note that the formulation log(density) + log(neurons) is algebraically equivalent to $\log(\text{density} \times \text{neurons}) = \log(\text{density}^2 \times \text{tissue volume})$, which has a striking physical interpretation.

Since neuron density determines local EM field production intensity, density^2 is proportional to EM field energy density (because energy ∝ E^2, and field amplitude scales with the density of field sources). Multiplying field energy density by the volume of integrative tissue yields total EM field energy. The regression's success may therefore reflect a simple physical principle: cognitive capacity scales with total electromagnetic field energy in integrative tissue. This interpretation unifies the two predictor variables into a single physical quantity and generates a clean testable prediction: species with equal total EM field energy in their integrative tissue should show comparable cognitive capacity, regardless of whether they achieve that energy through high density in a small volume (corvids) or moderate density in a large volume (humans). Quantitative measurement of intracranial EM field energy during cognitive tasks—now technically feasible with intracranial EEG and EM field modelling—could test this prediction directly.

8. Critical Data Gaps and Proposed Experiments

8.1. Comparative Intracranial EM Field Recordings and Geometric Eigenmode Analysis

The single most important experiment for SEFH is comparative high-density intracranial recording of EM field dynamics in corvids during cognitive tasks, combined with geometric eigenmode analysis of their pallial tissue (following Pang et al., 2023). SEFH predicts that corvid associative pallium should show dynamic cross-frequency coupling between geometric eigenmodes rivalling primates, despite completely different neural architecture—and that the number of excited eigenmodes during cognitively demanding tasks should scale with wattage density × log(harmonic capacity). Similar recordings in elephants (predicting a large but weakly energised eigenmode repertoire) and, if technically feasible, honeybees (where local field potential recordings in mushroom bodies during learning tasks could test whether a limited eigenmode repertoire supports the domain-specific excellence predicted by the model) would be equally informative.

8.2. Cortical-Specific Neuron Counts for Cetaceans

Only one cetacean species (northern minke whale) has been examined with the isotropic fractionator. Bottlenose dolphin and orca cortex counts are urgently needed.

8.3. Species-Fair Cognitive Batteries

Olfactory integration tasks for dogs and rodents, infrasound coordination tasks for elephants, and echolocation complexity tasks for cetaceans that distinguish cortical from subcortical processing would transform the interpretability of cross-taxon neural–cognitive correlations.

8.4. Invertebrate Neural Energetics

The per-neuron energy budget of insect neurons remains poorly characterised. Determining whether Herculano-Houzel's (2011) mammalian constant applies to insect neurons would validate or invalidate cross-kingdom wattage density comparisons.

8.5. Myelination Architecture Mapping

High-resolution DTI of corvid vs. galliform brains would test whether corvids' nuclear pallium creates effective field channelling through mechanisms other than laminar cortical organisation. Comparative DTI between elephant and primate cortex would quantify the architectural differences SEFH invokes.

9. Discussion

The comparative data examined here provide a mixed but, on balance, encouraging picture for the SEFH framework. The strongest support comes from three sources: the corvid/parrot density–

cognition relationship, the honeybee's extraordinary cognitive efficiency per neuron, and the elephant's underperformance relative to its total neuron count once cerebellar neurons are excluded.

The inclusion of invertebrate data marks an important extension of SEFH analysis. The honeybee case simultaneously provides the strongest evidence that density matters (bees dramatically outperform their neuron count) and the clearest evidence that density alone is insufficient (bees do not exceed vertebrate cognition despite far greater density). This dual role forces the model to articulate what we call the *harmonic capacity constraint:* the geometry and volume of field-permeable tissue determines how many geometric eigenmodes can coexist in the resonant medium, imposing a hard ceiling on the richness of harmonic dynamics regardless of how intensely each cubic millimetre of tissue generates EM fields. Drawing on Pang et al.'s (2023) demonstration that geometric eigenmodes—not connectome topology—fundamentally constrain brain dynamics, and Atasoy et al.'s (2016, 2018) identification of harmonic brain modes as the building blocks of spatiotemporal dynamics, we propose a two-variable model: wattage density × log(harmonic capacity). While contemporary computational neuroscience has advanced well beyond McCulloch–Pitts logic gates to incorporate continuous dynamics and oscillatory processing, the SEFH's two variables derive from a fundamentally different ontological commitment—that the EM field, not neural spiking, constitutes the primary computational and experiential medium.

The rodent and songbird data add a complementary refinement. Mouse cortex, at 15,000–20,000 neurons/mg, is denser than human cortex, yet mice show far less cognitive flexibility. The bee case extends this pattern to its extreme: ~960,000 neurons/mg but still far less cognitively flexible than humans. Both cases confirm the harmonic capacity constraint, but bees add the important observation that density *does* enhance cognition within a given harmonic range—bees dramatically outperform ants and most other insects with comparable or even greater total neuron counts but lower density.

The cetacean case remains SEFH's most significant challenge. Unlike other apparent "challenges" that may reflect anthropocentric measurement bias (dogs, elephants), cetacean social cognition—including cooperative hunting with role differentiation, cultural transmission, and vocal learning—represents cognitive performance that is difficult to dismiss as poorly measured. The current two-variable model underestimates cetacean cognitive capacity, and we consider this an honest limitation rather than a problem to be explained away. Future refinements may need to incorporate additional variables (e.g., cortical specialisations for acoustic processing) or revise the assumption that wattage density fully captures the relevant field physics in all neural architectures.

It is important to note what this analysis does not establish. We have not demonstrated that EM fields play a causal role in cognition; the correlations reported here are consistent with SEFH but also with simpler accounts based on neuron count and connectivity alone. The distinctive contribution of the EM field framework lies in its emphasis on field *density* (explaining the corvid and bee cases), *harmonic capacity* (explaining why mice and bees, despite high density, do not exceed larger-brained species), and dynamic *harmonic range* (explaining the within-human CFC–IQ relationship). Whether these variables genuinely reflect EM field dynamics, or merely correlate with other neural features that happen to covary with field properties, can only be resolved by the direct EM field measurements and geometric eigenmode analyses proposed in Section 8.

10. Conclusions

We have systematically tested predictions of the Strong Electromagnetic Field Hypothesis against existing comparative neuroscience data spanning thirteen taxa across vertebrates and invertebrates. After excluding cerebellar neurons and calculating integrative tissue EM field production densities, we find that SEFH predictions are strongly confirmed in the corvid/parrot density–cognition relationship, the honeybee's remarkable cognitive efficiency, the elephant's underperformance when cortical neurons are isolated, and the within-human CFC–IQ dynamic range data. The model faces moderate challenges from cetaceans and is insufficiently tested in taxa whose cognition may be substantially olfactory (dogs, rodents) or infrasonic (elephants).

The honeybee data prove especially illuminating. They simultaneously confirm that neural density is a powerful predictor of cognitive efficiency per neuron and demonstrate that the geometry and volume of the field-permeable tissue—its harmonic capacity—imposes a hard constraint on cognitive complexity. Drawing on Pang et al.'s (2023) demonstration that geometric eigenmodes fundamentally constrain brain dynamics and Atasoy et al.'s (2016, 2018) identification of harmonic brain modes as the building blocks of cognition and consciousness, we propose a two-variable predictive model: cognitive capacity ∝ wattage density × log(harmonic capacity). This formulation is fully native to field-based physics and derives its variables from EM field dynamics rather than spike-based computation. The critical experiments—comparative intracranial EM field recordings during cognitive tasks combined with geometric eigenmode analysis across taxa, including invertebrates—are technically feasible with current methods and would provide decisive evidence for or against the framework. We urge the comparative neuroscience community to pursue these measurements.

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