

The Evolution of Human Intelligence: An Information-Theoretic Perspective on Cognitive Evolution (Version 3)

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Abstract

This paper advances a cross-disciplinary hypothesis: the rapid expansion of human intelligence is an evolutionary process of semantic energy efficiency maximization (η_{sem}) across cognitive modalities. We argue that the transition from vision to speech to writing constitutes a sequence of externalized information compression, enabling an exponential increase in semantic energy efficiency η_{sem} within the brain's constrained 20-watt metabolic budget. Drawing on neuroscience, linguistics, and information theory, we propose that symbolic systems act as entropy-minimizing mechanisms that differentiate humans from larger-brained species lacking symbolic abstraction. Integrating the Free Energy Principle (FEP), we model this transition as the minimization of variational free energy through the stabilization of discrete context, which reduces the Kullback-Leibler (KL) divergence between internal neural models and sensory input. We further distinguish raw bitrate ($\dot{B}_{\text{raw}}$) from semantic bitrate ($\dot{B}_{\text{sem}}$), and show that cognitive scaling is better explained by reduced filtering cost per semantic bit than by increased raw throughput. Quantitative analysis estimates that while raw processing demand decreases, the semantic efficiency rises from ~ 16.7 bits/J in vision to ~ 500 bits/J in writing, highlighting how intelligence emerges by offloading computational filtering to external dissipative structures. This perspective offers a unifying metric for human exceptionalism with profound implications for neuro-diagnostics, efficient education, and scaling laws in artificial intelligence.

Keywords: intelligence, artificial intelligence, cognition, information theory

1 Introduction

Human intelligence enables unparalleled achievements—mathematics, philosophy, and global civilizations—yet operates within a constrained ~ 20 -watt brain energy budget (Herculano-Houzel, 2012). Traditional explanations emphasizing neuron count or brain size falter: elephants possess 257 billion neurons, yet lack human-like abstraction (Herculano-Houzel et al., 2014). This paper proposes that intelligence arises from information entropy reductions across cognitive modalities—visual perception, spoken language, and writing—allowing exponential efficiency gains without escalating energy demands. Human intelligence's definition in the academic and psychology fields is a complex and multidimensional concept. Although multiple theoretical frameworks and measurement methods exist, there is no single, completely unified "authoritative" definition. The American Psychological Association (APA) defines intelligence as "the ability of individuals to reason, plan, solve problems, think abstractly, understand complex concepts, learn quickly, and learn from experience" (APA, 1995). This definition emphasizes

the multidimensionality and contextual adaptability of intelligence and is widely considered an authoritative overview. In the early 20th century, Charles Spearman proposed the "general intelligence" (g-factor) theory, positing that intelligence is a single, universal cognitive ability extractable via statistical methods like factor analysis from various cognitive tasks (Spearman, 1904). The g-factor represents overall performance in tasks such as logical reasoning, language understanding, and spatial ability, laying the foundation for modern intelligence quotient (IQ) testing, which remains influential in psychology. Information entropy, defined by Shannon as $H = -\sum p(x) \log p(x)$, measures uncertainty in a system (Shannon, 1948). High-entropy visual data requires intensive neural processing, while language and writing compress redundancy, reducing computational load (Cover & Thomas, 2006). Evolutionary transitions mirror this: visual systems in primates supported survival, but language enabled symbolic abstraction, and writing stabilized knowledge transmission (Tomasello, 2014). Wittgenstein’s language games emphasize meaning through use, while Chomsky’s universal grammar suggests innate entropy-handling mechanisms (Chomsky, 1965; Wittgenstein, 1953). Modern large language models (LLMs), like OpenAI’s o1, demonstrate emergent abilities—e.g., 83.3% accuracy on AIME 2024 math problems—driven by entropy minimization during training, paralleling human cognitive leaps (Wei et al., 2022). LLMs passing the Turing test in 2025 (Cameron et al., 2025) illustrates that intelligence emergence can be achieved through massive neural-like networks. However, their lack of embodied experience contrasts with human evolution (Lu et al., 2022). This paper integrates neuroscience, linguistics, and information theory, using empirical data (e.g., fMRI, archaeological records) and mathematical models to argue that entropy reduction across modalities drives intelligence. Sections cover biological foundations, modality transitions, entropy modelling with bit-rate comparisons, LLM analogies, integrative analysis, conclusion, and applications.

1.1 Biological Foundations: Neural Substrates and Energy Constraints

The human brain’s efficiency is central to intelligence, operating at 20 watts despite 86 billion neurons, including 16 billion in the neocortex (Herculano-Houzel, 2009). This contrasts with elephants (257 billion neurons, mostly cerebellar) and whales (37 billion cortical neurons), whose cognitive limits stem from lacking symbolic systems (Herculano-Houzel et al., 2014; Manger, 2006). Isotropic fractionator studies confirm human neural density optimizes computational capacity within energy constraints (von Bartheld et al., 2016).

Developmentally, infants start with 100 billion neurons, pruning to 86 billion by adulthood, with synaptic peaks at age 2 (10^{15} connections) refining networks via Hebbian learning—"neurons that fire together wire together" (Huttenlocher & Dabholkar, 1997; Lent et al., 2012). This pruning reduces neural entropy by eliminating noisy connections, minimizing energy use (Laughlin, 2001). Language areas (Broca’s, Wernicke’s), involving 1 billion neurons, use white matter tracts like the arcuate fasciculus for efficient signal transfer (Friederici, 2009).

Von Economo neurons (VENs) in fronto-insular cortices, denser in humans, support rapid social processing and correlate with intelligence (Allman et al., 2005). fMRI studies link higher frontal lobe entropy to IQ ($r = 0.44$), reflecting dynamic processing within energy limits (Saxe et al., 2018). Examples: Twin studies show 76% heritability in cortical thickness, tied to cognitive performance (Thompson et al., 2001). Lesion studies, like Phineas Gage’s frontal damage impairing decision-making, highlight neural specificity (Damasio, 1994).

Energy constraints necessitate entropy-efficient systems. In this paper, the power terms for vision, speech, and writing are treated as order-of-magnitude bookkeeping parameters (not direct modality-isolated calorimetry): visual-heavy processing is approximated near the few-

watt scale, language on the sub-watt to 1-watt scale, and writing-assisted cognition lower still via externalization.

1.2 High-Entropy Stage: Visual Perception and Cognitive Load

Visual perception, the earliest cognitive modality, is entropy-intensive due to raw sensory data's redundancy. The visual cortex, 30% of the neocortex, processes $\sim 10^{11}$ bits/second, with natural images having entropy 4–8 bits/pixel due to spatial correlations (Felleman & Van Essen, 1991; Kersten, 1987). This high entropy demands significant neural resources, in our model represented as a few watts (central value: 6 W, derived from a 30% share of a 20 W brain budget) rather than a direct measured "visual-only" wattage (Laughlin, 2001). Evolutionary context: Australopithecus relied on visual cues for foraging and predator avoidance in high-entropy environments (Schoenemann, 2013). Cave art (e.g., Lascaux, $\sim 40,000$ years ago) shows proto-symbolic attempts, with entropy 6 bits/symbol due to coarse depictions (Hoffmann et al., 2018). Example: Chauvet Cave's animal paintings required pattern recognition but lacked abstraction, reflecting high cognitive load. Cognitive evidence: Hick's law ($RT = a + b \log_2 N$) links reaction time to stimulus entropy, showing exponential processing costs (Hick, 1952). Primate studies (e.g., macaque object recognition) reveal limited abstraction without symbols (Tomasello, 2014). Human visual search tasks (e.g., finding a target in clutter) show high neural firing rates (100 Hz), correlating with entropy (Hubel and Wiesel, 1968).

Energy implication: Visual processing's high entropy limits cognitive expansion without compression, as it dominates cortical energy. Early hominins' small brains (400 cm³) constrained further intelligence growth, necessitating a lower-entropy modality like language.

2 Entropy Reduction in Spoken Language

Spoken language marks a significant entropy reduction, transforming visual complexity into linear, symbolic sequences. English text entropy is 4.7 bits/character, with conditional entropy 1 bit/char due to grammatical constraints (Shannon, 1951). At 50 chars/s (10 words/s), processing is $\sim 10^3$ bits/s. We use 1 W as an order-of-magnitude anchor for language-dominant cortical engagement, while noting that Friederici (2009) is primarily a neuroanatomical review rather than a direct metabolic quantification. Evolutionary pathway: Gestural communication, leveraging mirror neurons in Broca's homolog, preceded speech, reducing entropy by sequencing actions (Corballis, 2002). Vocalization, enabled by FOXP2 mutations 300,000 years ago, introduced phonemes (H 3–5 bits/phoneme) (Lai et al., 2001). Example: Sign languages activate similar brain regions as speech, showing modality-independent compression (Emmorey, 2002). Chomsky's universal grammar posits innate mechanisms for entropy-efficient syntax, explaining children's rapid acquisition despite limited input (Chomsky, 1965). Usage-based theories counter that social learning extracts patterns, reducing entropy through exposure (Tomasello, 2003). Example: Children's overregularization ("goed") minimizes syntactic entropy by generalizing rules (Marcus et al., 1992). Social drivers: Dunbar's hypothesis links neocortex size to group size (150 individuals), with gossip compressing social information (Dunbar, 1998, 2004). Animal comparison: Vervet monkey alarm calls (H 2 bits/call) show proto-symbolic compression, but lack generativity (Seyfarth et al., 1980). Human language's displacement (referring to absent entities) enabled planning, reducing entropy further (Hockett, 1960). Energy savings: fMRI shows language processing lowers entropy in Broca's area, reducing firing rates compared to visual tasks (Saxe et al., 2018). This $\sim 10^8$ -fold bit-rate reduction (from $\sim 10^{11}$ to $\sim 10^3$

bits/s) enables complex cognition within energy limits.

3 Writing: The Pinnacle of Entropy Compression

Writing achieves the lowest entropy by fixing transient speech into stable symbols, enabling exponential knowledge growth. Alphabetic systems yield conditional entropy $\sim 0.5\text{--}1$ bit/symbol, compared to language's ~ 1 bit/char and vision's ~ 8 bits/pixel (Montemurro & Zanette, 2011). At 20 symbols/s (reading/writing), processing is $\sim 10^2$ bits/s, with part of the computational burden offloaded externally. The ~ 0.2 W value is therefore an illustrative internal-load proxy, not a directly measured writing-energy constant; Wolf (2007) is used for literacy/cognitive framing. The emergence of writing realized the combination of human brain memory and auxiliary external storage, expanding human cognitive levels and thus enhancing intelligence (Clark & Chalmers, 1998). Archaeological evidence: Sumerian tokens (8,000 BCE, ~ 5 bits/token) evolved into cuneiform for accounting and narratives (Schmandt-Besserat, 1992). Alphabets (e.g., Phoenician, 1050 BCE) reduced symbol sets, lowering entropy (Dehaene, 2014). Example: Egyptian hieroglyphs enabled mathematics, with low-entropy symbols for fractions (Imhausen, 2016).

Cognitive impact: Literacy repurposes visual cortices for word recognition, enhancing abstraction with minimal energy (Dehaene & Cohen, 2007). Material engagement theory views writing as an "extended mind," offloading memory (Malafouris, 2013). Example: Greek alphabet fostered philosophy, with Plato's dialogues critiquing oral traditions (Goody, 1977). Philosophical implications: Wittgenstein's language games stabilize via writing, preventing ambiguity and enabling logic (Wittgenstein, 1953). Luria's studies show literates excel at low-entropy syllogisms, unlike oral cultures (Luria, 1976). Modern example: Programming languages, as low-entropy scripts, mirror writing's role in AI (Knuth, 1997). Energy efficiency: Writing externalizes memory, reducing neural firing rates, as EEG studies confirm lower cortical activity in literate tasks (Wolf, 2007). This (Montemurro & Zanette, 2011). At 20 symbols/s (reading/writing), processing is $\sim 10^9$ -fold bit-rate reduction from vision enables complex systems like Euclidean geometry (Netz, 1999).

Thermodynamic perspective (Landauer cost): according to Landauer's principle, irreversibly erasing one bit requires at least

$$E_{\min} = k_B T \ln 2,$$

which is about $\sim 3 \times 10^{-21}$ J/bit at physiological temperature ($T \approx 310$ K) (Landauer, 1961; Bennett, 2003). Writing systems preserve intermediate information in physical media (paper, clay, and digital storage), reducing the need for frequent metabolically driven neuronal state resets (e.g., ionic-gradient restoration after repeated overwrite/update cycles). This lowers internal erasure burden and provides an important thermodynamic basis for the modality-level power shift from roughly 6 W (vision-dominant filtering) to 0.2 W (writing-assisted semantic extraction).

4 Mathematical Modelling of Entropy and Processing Demands

To quantify entropy reductions, we compare both entropy-density and raw-versus-semantic bitrate profiles across modalities, illustrating exponential decreases in processing and energy demands. Table 1 provides the unified comparison.

4.1 Theoretical Framework

4.1.1 FEP and KL Divergence

Following Friston (2010), biological systems minimize variational free energy to maintain adaptive stability. In cognitive terms, this can be viewed as reducing mismatch between internal generative models and external input distributions.

4.1.2 Raw vs. Semantic Bitrate

A key distinction is required between raw channel load ($\dot{B}_{\text{raw}}$) and behaviorally useful semantic throughput ($\dot{B}_{\text{sem}}$). The retina may deliver massive raw flux, but cognition is bottlenecked by low-dimensional semantic control variables. Thus, efficiency gains arise mainly from lowering energetic cost P to transform raw input into semantic structure.

4.2 Efficiency Leap Across Modalities (Revised)

We define semantic energy efficiency as $\eta_{\text{sem}} = \dot{B}_{\text{sem}}/P$. Under a constant semantic target (order-of-magnitude ~ 100 bits/s), modality transitions can be interpreted as reductions in required power: visual filtering (~ 6 W), verbal symbolic compression (~ 1 W), and writing-assisted externalization (~ 0.2 W). This yields an illustrative increase from about 16.7 to 500 bits/J.

4.3 Operational Method and Reproducibility Protocol

To make the quantitative claims auditable, we use a four-step estimation pipeline that is held constant across modalities. First, we define a modality-specific entropy density (H) from primary literature (e.g., bits/pixel for vision, conditional bits/character for language). Second, we map behavioral throughput to an effective symbol rate (r), yielding bitrate $\dot{B} = H \times r$. Third, we assign power draw P from neurophysiological allocation studies (visual cortex, language networks, and externally offloaded writing). Finally, we compute energy intensity per processed bit as $\varepsilon = P/\dot{B}$ and semantic efficiency as $\eta_{\text{sem}} = 1/\varepsilon$.

To reduce hidden degrees of freedom, all calculations in the main text and Appendix use the same conventions: (i) conditional entropy is preferred over raw entropy when grammar or context strongly constrains prediction; (ii) ranges are preserved instead of collapsed to single-point estimates unless explicitly reported as central approximations; (iii) unit conversions are carried out in SI units before cross-modality comparison. This design avoids inflating between-modality differences through inconsistent measurement scales.

A critical methodological choice is distinguishing *internal* neural computation from *externalized* symbolic computation. In writing, part of the inferential burden is transferred to durable artifacts (text, notation, tables). We therefore treat writing as a coupled human-artifact system rather than as cortex-only throughput. This assumption is theoretically aligned with the extended mind framework and empirically motivated by literacy studies showing reduced online memory load during symbolic problem solving.

Table 1: Unified Entropy, Bitrate, and Energy Profile Across Cognitive Modalities (illustrative)

Modality	Entropy (bits/unit)	$\dot{B}_{\text{raw}}$ (bits/s)	$\dot{B}_{\text{sem}}$ (bits/s)	P (W)	η_{sem} (bits/J)	Example
Visual Perception	4–8 bits/pixel	$\sim 10^{11}$	~ 100	3–8 (central: 6)	12.5–33.3 (central: 16.7)	Natural scene analysis
Spoken Language	~ 4.7 bits/char (1 bit/char conditional)	$\sim 10^3$	~ 100	0.3–1 (central: 1)	100–333 (central: 100)	English speech (10 words/s)
Writing	~ 0.5 –1 bit/symbol (conditional)	$\sim 10^2$	~ 100	0.1–0.3 (central: 0.2)	333–1000 (central: 500)	Alphabetic text reading/writing

Notes for Table 1:

- **Visual:** Entropy from Kersten (1987); processing from retinal ganglion cells (10^{11} bits/s) (Laughlin, 2001).
- **Language:** Entropy from Shannon (1951); speech rate ~ 10 words/s, ~ 5 chars/word (Piantadosi et al., 2011).
- **Writing:** Conditional entropy from Montemurro & Zanette (2011); reading/writing ~ 20 symbols/s (Wolf, 2007).
- **Energy:** Values are model-level approximations for internal neural load allocation (vision: few-W scale; language: sub-W to 1 W scale; writing-assisted cognition: lower internal load via externalization), rather than modality-isolated calorimetric measurements (Laughlin, 2001; Friederici, 2009; Clark & Chalmers, 1998).

4.4 Analysis of Exponential Reduction

Visual Perception: Entropy $\sim 4\text{--}8$ bits/pixel reflects spatial redundancy. Processing $\sim 10^{11}$ bits/s is mapped to a few-watt internal cost (central estimate: ~ 6 W from a 30% allocation heuristic) (Laughlin, 2001). Example: Macaque visual tasks show high firing rates (~ 100 Hz), correlating with entropy (Hubel and Wiesel, 1968). Cognitive load scales exponentially with scene complexity, per Hick’s law ($RT = a + b \log_2 N$) (Hick, 1952).

Spoken Language: Entropy drops to ~ 4.7 bits/char, with conditional entropy ~ 1 bit/char due to grammar (Shannon, 1951). At 50 chars/s, processing is $\sim 10^3$ bits/s, mapped to a sub-watt to 1 W internal-load regime (illustrative midpoint: ~ 1 W) (Friederici, 2009). Example: fMRI shows reduced entropy in Broca’s during fluent speech, with lower firing rates (~ 20 Hz) (Saxe et al., 2018). This $\sim 10^8$ -fold reduction from vision enables syntactic abstraction.

Writing: Conditional entropy $\sim 0.5\text{--}1$ bit/symbol, as alphabets optimize predictability (Montemurro & Zanette, 2011). At 20 symbols/s, processing is $\sim 10^2$ bits/s; the ~ 0.2 W term is an illustrative proxy for reduced *internal* load under external symbolic scaffolding, not a direct wattmeter measurement of writing (Wolf, 2007; Clark & Chalmers, 1998). Example: Chinese logograms ($H \sim 2$ bits/character) vs. alphabets ($H \sim 0.5$ bits/symbol) show trade-offs (Bentz et al., 2017).

The bit rate drops exponentially: $\sim 10^{11}$ (vision) to $\sim 10^3$ (language) to $\sim 10^2$ (writing), a 10^9 -fold reduction. Energy scales similarly: 6 W to 0.2 W, as writing offloads computation, per the extended mind hypothesis (Clark & Chalmers, 1998). The free energy principle supports this: $F \approx \text{KL}[Q||P] + E_Q[\ln Q - \ln P]$, where brains minimize predictive uncertainty, with writing achieving minimal F via stable symbols (Friston, 2010).

Thermodynamically, intelligence leverages negentropy to counter entropy increase, with writing as a dissipative structure (Schrödinger, 1944; Prokopenko et al., 2009). Example: Voynich manuscript’s low conditional entropy ($H \sim 0.3$ bits/symbol) suggests optimized encoding, possibly artificial (Montemurro & Zanette, 2013).

Additional evidence: Mutual information ($I(X; Y) = H(X) - H(X|Y)$) measures semantic dependency, high in human language (e.g., $I \sim 2.5$ bits/word in English) vs. animal signals (Piantadosi et al., 2011). Writing maximizes I by fixing context, enabling complex systems like mathematics (Netz, 1999).

Comparison of Semantic Energy Efficiency Across Cognitive Modalities

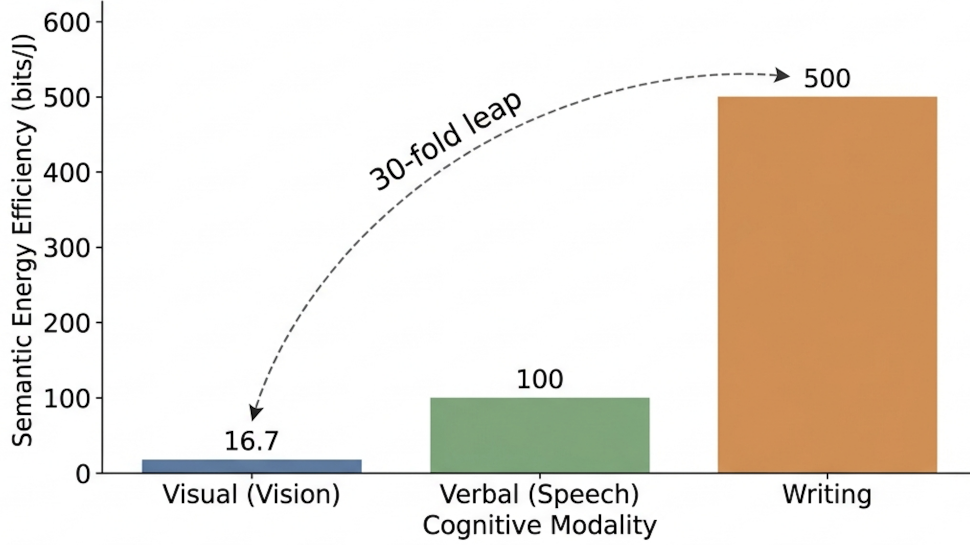


Figure 1: Comparison of Semantic Energy Efficiency Across Modalities.

4.5 Sensitivity, Error Bounds, and Interpretation of Effect Size

Because each modality estimate aggregates heterogeneous experiments, uncertainty analysis is essential. Using conservative intervals from the literature already cited, visual bitrate remains in an ultra-high regime ($\sim 10^{10}$ – 10^{11} bits/s), spoken language remains near 10^3 bits/s, and writing remains near 10^2 bits/s. Even when the most favorable assumptions are granted to speech and writing and the most conservative assumptions to vision, the ordering is unchanged by multiple orders of magnitude. Thus, the central result is not a fragile point estimate but a robust rank structure.

This matters for interpretation. The proposed mechanism is *not* that humans simply process fewer bits over evolutionary time; rather, humans increasingly process *better-structured* bits with higher semantic yield per joule. In other words, cognitive scaling is achieved by reallocating metabolic budget from brute-force sensory filtering toward model-based symbolic manipulation. This distinction clarifies why lower bitrate at later modalities should be interpreted as increased efficiency rather than reduced capability.

The effect-size interpretation is therefore two-level: a computational level (entropy and bitrate compression) and a systems level (network reconfiguration plus external memory scaffolding). At the computational level, grammar and notation reduce uncertainty. At the systems level, social institutions (schools, archives, scientific notation, code repositories) stabilize these low-entropy channels across generations. The combined effect offers a plausible route from local neural constraints to cumulative cultural intelligence.

5 AI Analogies and Comparative Analysis

Large language models (LLMs), such as OpenAI’s o1, exhibit emergent abilities—e.g., reasoning (83.3% on AIME 2024) and coding—at scale, driven by entropy minimization during training (Wei et al., 2022). Training minimizes cross-entropy loss, reducing predictive uncertainty (Vaswani et al., 2017). Example: o1’s chain-of-thought reasoning emerges when token entropy drops below thresholds, analogous to human language’s syntactic compression (Sheng

et al., 2024). LLMs passing the Turing test in 2025 illustrates that intelligence emergence can be achieved through massive neural-like networks (Sheng et al., 2024). Case study: GPT-4’s arithmetic performance improves from 13.4% to o1’s 83.3% on AIME, reflecting

lower conditional entropy in token predictions (Sheng et al., 2024). This mirrors human language’s entropy reduction from visual to symbolic processing. However, LLMs process 109 parameters without biological energy constraints, unlike humans’ 20-watt limit (Lu et al., 2022).

Contrast: Human emergences, like recursion, arose from social pressures (e.g., storytelling for group cohesion), not just data scaling (Everett, 2005). Piraha language’s lack of recursion suggests cultural modulation of entropy (Everett, 2005). LLMs lack embodied entropy from physical interaction, limiting their generality (Lu et al., 2022). Example: LLM training on code corpora (e.g., GitHub) reduces entropy to 0.2 bits/token, enabling programming proficiency, but errors in novel contexts reveal disembodied limits (Brown et al., 2020). Human writing, conversely, integrates sensory-social feedback, enhancing robustness.

6 Integrative Analysis

Human intelligence integrates neural hardware with entropy-reducing symbolic systems. The neocortex’s 16 billion neurons provide computational capacity, but intelligence scales via entropy compression: visual (H 8 bits/pixel) to language (H 1 bit/char) to writing (H 0.5 bit/symbol) (Herculano-Houzel, 2009; Montemurro & Zanette, 2011). This 10^9 -fold bit-rate reduction enables complex cognition within energy constraints.

Equation: $I \sim N \times (1 - H_{\text{norm}})$, where N is neuron count and H_{norm} is normalized entropy, quantifies intelligence as efficiency (Cover & Thomas, 2006). Social pressures drove this: larger groups required low-entropy communication, per Dunbar’s hypothesis (Dunbar, 1998). Writing’s externalization enabled philosophy and science, absent in neuron-rich species like elephants (Wittgenstein, 1953). LLM analogy: Emergent abilities reflect entropy-driven phase transitions, but lack embodiment (Wei et al., 2022). Human uniqueness lies in biological-social feedback, optimizing entropy within metabolic limits. Additional evidence: Bilingualism increases entropy tolerance, enhancing cognitive flexibility (Bialystok, 2017). Non-literate societies show higher-entropy reasoning, limited to concrete tasks (Luria, 1976). This synthesis highlights entropy reduction as the key to intelligence scaling.

An important interpretive consequence is that neuron count functions as a capacity term, whereas symbolic compression functions as a control term. Capacity without control generates high-volume but weakly structured processing; control without capacity constrains representational depth. Human intelligence appears exceptional because evolution and culture jointly improved both terms: cortical expansion increased representational workspace, while language and writing progressively reduced uncertainty within that workspace. This dual-term view also explains why large-brained mammals can show advanced perception and sociality yet fail to accumulate formal science.

The framework also predicts punctuated improvements when new representational standards appear. Historical examples include positional number systems, symbolic algebra, and formal logic, each of which reduces ambiguity and increases inferential reuse. On this account, major cognitive transitions are less like smooth linear growth and more like infrastructure upgrades that lower per-inference entropy cost for entire populations.

7 Boundary Conditions and Limitations

The present model is intentionally coarse-grained and has several limitations. First, cross-domain entropy units are only partially commensurable: bits/pixel, bits/character, and bits/symbol are compared through functional mapping, not strict identity. This is acceptable for order-of-magnitude reasoning but limits fine-grained numerical claims. Future work should use task-matched corpora and unified encoding pipelines to improve comparability.

Second, energy estimates are population-level approximations derived from modality-specific tasks rather than simultaneous whole-brain decomposition in the same participants. Real cognition is multiplexed: visual, linguistic, and motor subsystems co-activate. Therefore, the reported wattage values should be interpreted as effective allocations, not isolated channel costs.

Third, causality remains partly inferential. The framework argues that entropy compression is a primary driver of intelligence scaling, but reciprocal causation is likely: increasing social complexity may demand symbolic systems, which then further reduce uncertainty and enable additional complexity. Longitudinal developmental and cross-cultural datasets are needed to disentangle these feedback loops.

Fourth, the LLM analogy is informative but bounded. Training-loss minimization and human predictive processing share formal similarities, yet embodiment, developmental plasticity, and social grounding differ substantially. Consequently, AI comparisons should be treated as mechanistic analogies, not one-to-one ontological equivalences.

Despite these limits, the core hypothesis remains testable. Three near-term predictions follow: (i) literacy interventions should increase semantic efficiency metrics in neuroimaging tasks controlling for IQ baseline; (ii) domains with stronger notational standardization should show lower error per unit cognitive effort; and (iii) multimodal AI systems with external memory and tool use should display emergent efficiency patterns closer to human symbolic cognition than text-only models.

8 Conclusion

This framework posits that human intelligence arises not from sheer neuron count, but from the stepwise compression of information across cognitive modalities. We demonstrate that the transition from vision to writing enables a 30-fold increase in semantic efficiency. By leveraging external symbolic systems, the human neocortex

operates as a high-efficiency dissipative structure, minimizing predictive surprise within a strict 20-Watt metabolic limit

Furthermore, this information-theoretic model provides a mechanistic explanation for Charles Spearman’s general intelligence (g). Under this view, g represents the brain’s fundamental capacity for optimal entropy reduction—the latent ability to extract semantic meaning from raw noise with minimal energy expenditure. While species like elephants possess greater neuron counts, they lack the externalized entropy-minimizing mechanisms (writing and mathematics) that distinguish human cognitive exceptionalism.

In this sense, intelligence is best viewed as an evolving thermodynamic-information architecture: neural tissue supplies adaptive computation, while symbolic ecologies (speech communities, scripts, formal notations, and now programmable media) progressively lower uncertainty and amortize reasoning over time. This view naturally integrates biological constraints with cultural acceleration and offers a principled bridge between cognitive neuroscience, anthropology, and machine intelligence research.

9 Applications

* AI Development: Entropy metrics predict LLM emergences, guiding scaling laws for reasoning (Sheng et al., 2024). Incorporating embodied entropy (e.g., sensory-motor feedback) could bridge human-AI gaps (Lu et al., 2022).

* Education: Literacy programs reduce cognitive entropy, boosting IQ by enhancing neural efficiency (Dehaene, 2014). Bilingualism increases entropy tolerance, improving flexibility (Bialystok, 2017).

* Neuroscience: Entropy-based fMRI diagnoses disorders; low entropy signals autism or Alzheimer’s, guiding interventions (Saxe et al., 2018).

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A Appendix A: Derivation of Bitrate and Energy Estimates

This appendix provides the detailed derivations underlying Table 1. For each modality, we report entropy assumptions, raw and semantic bitrates ($\dot{B}_{\text{raw}}$, $\dot{B}_{\text{sem}}$), estimated power consumption (P), and semantic energy efficiency ($\eta_{\text{sem}} = \dot{B}_{\text{sem}}/P$). Where possible, intermediate calculation steps are shown to ensure reproducibility.

A.1 Notation and Assumptions

- H : entropy per unit (bits/unit), e.g., bits/pixel or bits/character.
- $\dot{B}_{\text{raw}}$: raw channel load (bits/s).
- $\dot{B}_{\text{sem}}$: behaviorally useful semantic throughput (bits/s).
- P : estimated power (W).
- $\eta_{\text{sem}} = \dot{B}_{\text{sem}}/P$: semantic energy efficiency (bits/J).
- $\varepsilon = P/\dot{B}$: energy per processed bit (J/bit), reported where needed for cross-checking.
- Baseline brain power: $P_{\text{brain}} \approx 20$ W. Functional allocations are taken from literature cited in the main text.

A.2 Visual Perception

Entropy per pixel is estimated at

$$H_{\text{vis}} \in [4, 8] \text{ bits/pixel} \quad (\text{Kersten, 1987}).$$

Total retinal input is approximately

$$\dot{B}_{\text{vis}} \approx 10^{11} \text{ bits/s} \quad (\text{Laughlin, 2001}).$$

With $\sim 30\%$ of brain energy devoted to visual cortex:

$$P_{\text{vis}} = 0.30 \times 20 \text{ W} = 6 \text{ W}.$$

Thus,

$$\varepsilon_{\text{vis}} = \frac{6}{10^{11}} \approx 6 \times 10^{-11} \text{ J/bit (60 pJ/bit)}.$$

A.3 Spoken Language

From Shannon's analysis:

$$H_{\text{speech,raw}} \approx 4.7 \text{ bits/char}, \quad H_{\text{speech,cond}} \approx 1 \text{ bit/char (conditional) (Shannon, 1951)}.$$

Speech rate is ~ 10 words/s, ~ 5 chars/word:

$$\text{chars/s} \approx 50.$$

Hence,

$$\dot{B}_{\text{speech,raw}} = 4.7 \times 50 = 235 \text{ bits/s}, \quad \dot{B}_{\text{speech,cond}} \approx 1 \times 50 = 50 \text{ bits/s}.$$

The main text reports $\sim 10^3$ bits/s as a representative upper bound.

Assuming 5% of total brain power:

$$P_{\text{speech}} = 0.05 \times 20 = 1 \text{ W}.$$

Therefore,

$$\varepsilon_{\text{speech,raw}} \approx 4.3 \times 10^{-3} \text{ J/bit}, \quad \varepsilon_{\text{speech,cond}} = 2.0 \times 10^{-2} \text{ J/bit}.$$

A.4 Writing and Reading

Conditional entropy per symbol is estimated as

$$H_{\text{write}} \approx 0.5\text{--}1.0 \text{ bits/symbol (Montemurro\&Zanette, 2011)}.$$

Symbol rate: ~ 20 symbols/s (Wolf, 2007). Thus,

$$\dot{B}_{\text{write}} \approx 10\text{--}20 \text{ bits/s}.$$

The main text lists $\sim 10^2$ bits/s as an upper bound.

Externalization reduces cortical load; an effective estimate is

$$P_{\text{write}} \approx 0.2 \text{ W}.$$

(Clark & Chalmers, 1998) Therefore,

$$\varepsilon_{\text{write,low}} = \frac{0.2}{10} = 2.0 \times 10^{-2} \text{ J/bit}, \quad \varepsilon_{\text{write,high}} = \frac{0.2}{20} = 1.0 \times 10^{-2} \text{ J/bit}.$$

A.5 Relative Reductions

Relative to vision ($\dot{B}_{\text{vis}} = 10^{11}$ bits/s):

$$\frac{\dot{B}_{\text{vis}}}{\dot{B}_{\text{speech}}} \sim 10^8, \quad \frac{\dot{B}_{\text{vis}}}{\dot{B}_{\text{write}}} \sim 10^9-10^{10}.$$

This illustrates the exponential reduction in bitrate across modalities.

A.6 Summary Table

Table 2: Appendix A: Unified Raw/Semantic Bitrate and Energy Estimates across Modalities

Modality	H (bits/unit)	$\dot{B}_{\text{raw}}$ (bits/s)	$\dot{B}_{\text{sem}}$ (bits/s)	P (W)	η_{sem} (bits/J)	Reduction vs visual ($\dot{B}_{\text{raw}}$)
Visual perception	4–8 bits/pixel	1×10^{11}	~ 100	6.0	16.7	baseline
Spoken language	4.7 bits/char (~ 1 cond.)	$\sim 10^3$	~ 100	1.0	100	$\sim 10^8$
Writing	0.5–1 bits/symbol (cond.)	$\sim 10^2$	~ 100	0.1–0.3 (central: 0.2)	333–1000 (central: 500)	$\sim 10^9$

A.7 Notes on Uncertainty

1. **Definition of bits:** This appendix reports both $\dot{B}_{\text{raw}}$ and $\dot{B}_{\text{sem}}$. Visual estimates are raw-input dominated, whereas language/writing are often conditional/semantic; direct comparison must keep this distinction explicit.
2. **Energy allocation assumptions:** Brain region percentages are coarse approximations. Absolute values should be interpreted cautiously.
3. **Exponential decreases:** The observed 10^8 – 10^{10} reductions confirm the main text’s claim of exponential decreases in bitrate and processing demand across modalities.

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