

AI and Brain: Copy or Competitor?

From "Ghost in the Machine" to Alien Intelligence: Why AI Simulates but Doesn't "Think"

Dr. Josef Sawetz, January 2026


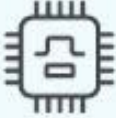
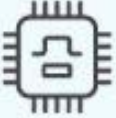
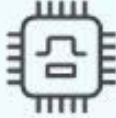
From the Illusion of Similarity to the Reality of "Alien Intelligence": A Deep Dive into the Engine Room of Thought.

It is tempting to see the ghost in the machine. When ChatGPT writes a poetic text or solves complex logic puzzles, we tend to humanize this performance. We speak of "learning," "understanding," or "feeling." However, a current analysis of cognitive architectures reveals a completely different picture: We are not dealing with a replication of the human mind, but with a "convergence of surface at divergence of depth." (Weizenbaum, 1966; Reeves & Nass, 1996; Epley et al., 2007; Gray et al., 2007; Waytz et al., 2010; Shanahan, 2022)

What does this mean? On the surface, the results look similar. In the "engine room," however, completely different mechanisms are at work. While AI is a high-performance statistical machine, the human brain remains a biological miracle of efficiency and meaning. Here is the truth about the differences that often get lost in the hype. (Hasson et al., 2020; Lake et al., 2017; Marcus, 2018)

1. The 20-Watt Miracle vs. The Power Plant: How We Really Learn

The perhaps most fundamental difference lies in the economy of thought. Your brain requires about 20 watts of energy—as much as a dim light bulb—to create world models, process feelings, and plan complex actions. Modern AI models, on the other hand, consume the electricity of entire small towns to simulate similar outputs. Yet, it is not just about electricity; it is about the method. (Attwell & Laughlin, 2001; Levy & Calvert, 2021; Strubell et al., 2019; Schwartz et al., 2020; Patterson et al., 2021)

Human Brain vs. GPT-3, 4, 5			
			
Human Brain	GPT-3	GPT-4	GPT-5
~86 billion neurons	~100 billion units	~500 billion units	~1-2 trillion units
~100 trillion synapses	175 billion parameters	~1.8 trillion parameters	~5-10 trillion parameters
Continuous learning	Frozen after training	Frozen after training	Frozen after training
~20 watts	~10 MW	~25 MW	Tens of MWs

Hebbian Plasticity vs. Backpropagation

In your head, the rule applies: "Cells that fire together, wire together" (Hebbian learning). Learning happens locally, directly at the synapse, often asynchronously and extremely efficiently. If you burn your hand on a hot stove once, your brain learns immediately (One-Shot Learning). Artificial neural networks, conversely, use Backpropagation (error back-transmission). They require a global error signal that is mathematically expensively calculated back through hundreds of layers. This is biologically absolutely implausible—your brain has no "wires" to send errors backwards through the entire network. This makes AI extremely "data-hungry": It needs thousands of examples where one suffices for you. (Hebb, 1949; Bi & Poo, 1998; Lake et al., 2015; Rumelhart et al., 1986; Lillicrap et al., 2020; Marcus, 2018)

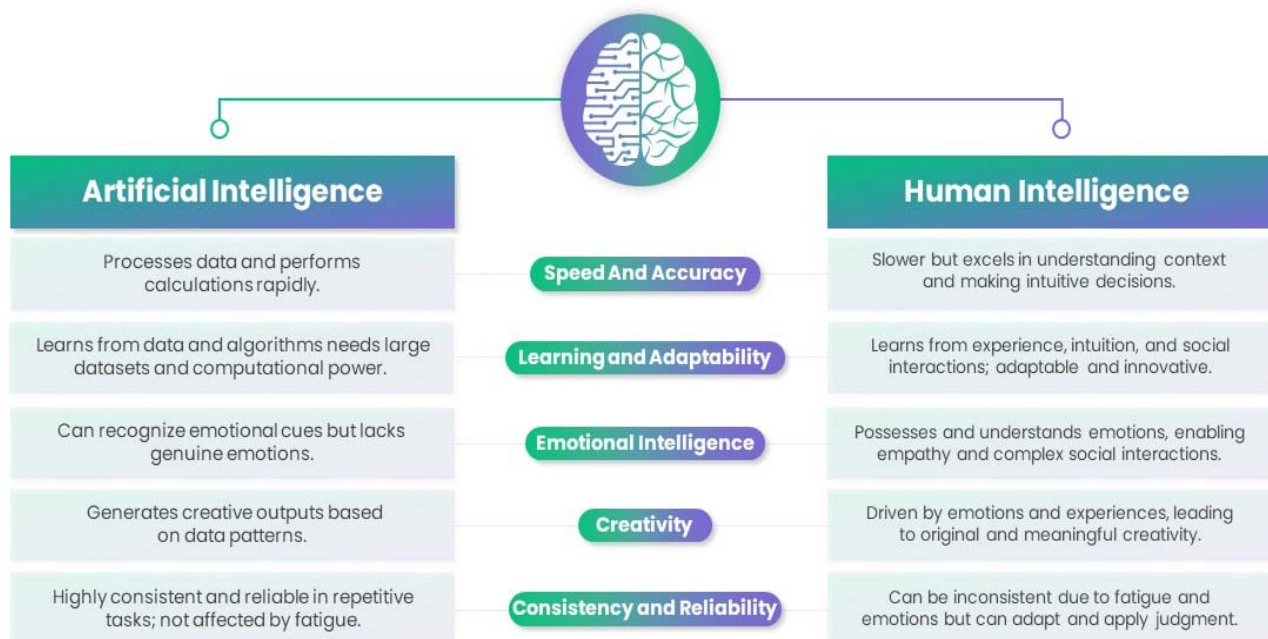
2. The Master of Fillers: Why AIs Are Only Acting

Here we arrive at a point that is often misunderstood: What is the AI actually doing when it "thinks"? Science calls this *interpolation*. Imagine you have a sheet of paper full of dots (data). The AI is a master at drawing a complex curve that connects these dots perfectly. This is called "Direct Fit." Within the known space (the training data), it is unbeatable. (Hasson et al., 2020)

The Problem of Extrapolation

But what happens when we leave the sheet of paper? Here, the machine fails. The human brain is a master of *extrapolation*. We understand the *rules* behind the dots. Example: If you know what "to walk" means and what "slowly" means, you immediately understand the concept of "walking slowly"—even if you have never seen it. We abstract principles. The AI reality: It often only memorizes statistical patterns. If forced to operate outside its trained data (Out-of-Distribution), its performance often collapses dramatically. It is, to put it provocatively, a highly intelligent copy machine that calculates probabilities but understands no causalities. (Lake et al., 2017; Marcus, 2018; Hendrycks & Dietterich, 2019; Geirhos et al., 2020; Pearl & Mackenzie, 2018; Chollet, F. 2019).

AI vs. Human Comparison



3. Remix vs. Revolution: Where the Spark is Missing

When AI paints pictures or composes music, it appears creative. But is it? We must distinguish between two types here: (Boden, 2004)

- **Combinatorial Creativity:** Re-connecting the known. Here, the AI is brilliant. It can mix the style of Van Gogh with Cyberpunk because it possesses huge databases. (Boden, 2004)
- **Transformational Creativity:** Breaking the rules to create something fundamentally new (a paradigm shift). (Boden, 2004)

True human insight—the famous "Aha!" moment—is neurologically measurable (a gamma burst in the brain) and emotionally rewarding (dopamine). It is a phase transition, a sudden restructuring of the problem. AIs do not experience "Aha!" moments. They merely optimize an error function (Loss Function) downward. They lack the *will* to break, the rebellion against the rule, and the intrinsic curiosity that drives us to explore things that have no immediate utility. (Jung-Beeman et al., 2004; Kounios & Beeman, 2009; Schultz, 1998)

4. The Simulation of Emotion: Why ChatGPT Does Not Cry With You

Probably the most critical area is empathy. We increasingly interact with chatbots that sound "understanding." Yet here lurks a danger. Empathy is not a calculation task. In humans, empathy is "embodied." (Rizzolatti & Craighero, 2004; Barrett, 2017; Craig, 2009; Critchley & Garfinkel, 2017; Bender, E. M., et al. 2021)

- **Mirror Neurons:** When we see that someone is in pain, similar areas in our brain fire as if we were in pain ourselves. We simulate the other *in our own body*. (Rizzolatti & Craighero, 2004)
- **Interoception:** We use our gut feeling, our heartbeat, our own physique to feel. (Craig, 2009; Critchley & Garfinkel, 2017; Barrett, 2017)

The AI lacks this body. It has no hormones, no pain, no fear of death. When an AI says: "I understand that you are sad," this is a linguistic simulation. They are vectors in a high-dimensional space that statistically likely follow your input. There is no one there who feels. The *phenomenology* (the subjective experience) is missing. The use of "empathic AI" in therapy or care therefore carries the risk of a gigantic deception: We project feelings onto something that is mathematically incapable of reciprocating them. (Barrett, 2017; Bickmore & Picard, 2005; Fitzpatrick et al., 2017)

Conclusion: Alien Intelligence

The analysis clearly shows: We should stop measuring AI by the human standard. It is not a worse version of a brain and also not a better one. It is an "Alien Intelligence." It optimizes instead of understanding. It interpolates instead of extrapolating. It simulates instead of feeling. That makes it a powerful tool of efficiency, but the domains of true insight, radical creativity, and social resonance remain—for now—our biological privilege. (Hasson et al., 2020; Marcus, 2018; Shanahan, 2022)

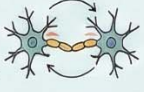
Two Kinds of Minds:

A Comparison of the Human Brain and AI

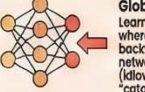
A comparative overview highlighting the principle of "surface convergence but deep divergence" across key cognitive functions. While appearing similar in output, their underlying operations are fundamentally different.








Learning Mechanisms: The Foundation of Intelligence

Human Brain: Local, Efficient, & Continuous
Learning is based on "Hebb's Rule" where local neuron connections strengthen with activity (STDP). It's a highly energy-efficient process (~20 Watts) that allows for lifelong adaptation.




Artificial Intelligence: Global, Intensive, & Batch-Based
Learning relies on "Backpropagation," where a global error signal is sent backward through the entire network. This is energy-intensive (kilowatts to megawatts) and prone to "catastrophic forgetting."




	Human Brain	Dimension	Artificial Neural Network (ANN)
Learn Rule	Local & activity-based (Hebbian, STDP)		Global error gradient (Backpropagation)
Signal Processing	Hybrid: digital spikes & analog chemistry		Continuous floating-point numbers
Energy Needs	 Extremely efficient (~20 Watts)		Very high (Kilowatts to Megawatts)
Data Needs	 Low (Few-Shot Learning)		Massive ("Data Hungry")
Primary Goal	Minimize surprise (Free Energy)		Minimize a defined cost function

Generalization: Making Sense of the New

Human Brain: Master of Extrapolation
Humans excel at applying abstract rules learned from few examples to entirely new and unseen situations (zero-shot generalization).




Artificial Intelligence: Machine of Interpolation
AI is brilliant at making predictions within the statistical confines of its training data ("Direct Fit"), but its performance often breaks down when faced with data outside this known space.




Reasoning & Logic: From "Why" to "What"

Human Brain: Reasons with Causal "Mental Models"
Humans build internal simulations of the world to understand cause-and-effect ("Why did this happen?"), enabling counterfactual and abductive reasoning.




Artificial Intelligence: Reasons with Statistical Patterns
AI identifies and replicates complex patterns from data. It can appear logical but often lacks a true understanding of the underlying principles, a phenomenon described as being a "stochastic parrot."




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
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Creativity & Discovery: Creating the Unseen

Human Brain: Capable of Transformational Creativity
Humans can fundamentally change the rules of a domain to create new paradigms (e.g., classical to quantum physics), often preceded by a sudden "Aha!" moment of insight.




Artificial Intelligence: Excels at Combinatorial & Explorative Creativity
AI is a powerful tool for generating novel combinations of existing ideas (e.g., art styles) and exploring the possibilities within a fixed set of rules (e.g., AlphaGo's "Move 87").




Action Planning: Charting a Course to a Goal

Human Brain: Plans with Hierarchical & Abstract Goals
The prefrontal cortex manages planning by breaking down abstract, long-term goals (e.g., "cook dinner") into a flexible hierarchy of concrete sub-tasks.




Artificial Intelligence: Plans via Massive Search & Simulation
AI planning often involves exploring thousands or millions of possible future scenarios (e.g., Monte Carlo Tree Search) to calculate an optimal path, a computationally intensive process.




Empathy & Social Cognition: Understanding Others

Human Brain: Feels Empathy Through Embodied Resonance
Human empathy is a deeply physical process. Mirror neurons and brain regions like the insula simulate others' feelings in our own body, tied to our own interoceptive signals.



Artificial Intelligence: Simulates Empathy via Linguistic Patterns
AI can be trained to recognize and generate empathetic-sounding language, but without a body, hormones, or consciousness, it lacks the foundation for genuine emotional experience.



The Bottom Line: Two Paths to Intelligence

Brain's Edge: Efficiency, Extrapolation, and Causal Insight

- ✓ Metabolic efficiency
- ✓ Flexibility in novel situations
- ✓ Understanding generative rules

AI's Edge: Scale, Speed, and Pattern Matching

- ✓ Processing vast datasets
- ✓ Incredible speed
- ✓ Replicating complex statistical patterns

The Verdict: Different Tools for Different Problems. AI is a powerful tool for interpolation and optimization within known domains, while the brain remains the master of extrapolation, true creativity, and social resonance.

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