ChatGPT

Computational Frameworks Bridging Sensation and Cognition

Modern cognitive science and AI are increasingly drawing on **biologically-grounded frameworks** to model how raw sensation gives rise to perception and higher cognition. These frameworks aim to formalize sensory processing and brain-like dynamics in code or math, enabling **programmable, testable models** of sensation-based consciousness. Below we explore several influential approaches – from predictive coding and active inference to embodied AI, dynamical systems, and spiking neural networks – focusing on how each treats sensation as the foundation of cognitive states. We also highlight core concepts, mathematical formalisms, and practical tools or models (in neuroscience and robotics) that demonstrate these ideas in action.

Predictive Coding and Predictive Processing

Conceptual schematic of a hierarchical predictive coding model with two levels. Each level's internal generative model (blue downward arrows) predicts the expected input at the level below, while any mismatch between prediction and actual sensory input is sent upward as a prediction error signal (red upward arrows). This illustrates how sensation enters the model as the difference *between expected and actual input.* The predictive coding framework posits that the brain is fundamentally a **prediction machine**, constantly generating a mental model of the world and using it to anticipate sensory inputs [1] [2]. Incoming sensations are not processed in a purely feed-forward way; instead, top-down predictions meet bottom-up signals, and only **mismatches** (prediction errors) propagate upward in the cortical hierarchy [3]. In other words, if the brain's higher-level model accurately predicts the sensory input, the sensory-driven activity is largely "explained away," and only unexpected elements of sensation drive further processing [3]. This flip on the conventional view makes sensation *foundational* but in a **surprise-driven** manner – sensation influences perception chiefly when it deviates from expectation.

Mathematically, predictive coding implementations often use **Bayesian inference** in hierarchical models [4]. The brain maintains probabilistic beliefs about hidden causes of sensory data, and it updates these beliefs by minimizing a measure of surprise or prediction error [4]. Each level of the hierarchy generates predictions about the level below, and specialized "error units" compute the difference between predicted and actual input [5]. Those error signals drive belief updates (often via gradient descent on prediction error or "free energy") to improve future predictions [6]. Notably, the same error signals can guide **learning** by adjusting synaptic weights so that both bottom-up receptive fields and top-down predictive connections tune to the statistical regularities of sensory input [7]. This dual use of prediction errors for inference and learning is a hallmark of predictive coding, linking it to deep learning approaches (e.g. hierarchical latent-variable models like Helmholtz machines or deep belief nets) but with an on-line, biologically-inspired twist [6].

In practice, predictive coding models have been applied to sensory cortex function and perception. A classic example is the **Rao and Ballard (1999)** model of the visual cortex, which showed that a simple 2-layer predictive coding network could reproduce known response properties of neurons in V1 by transmitting **residual errors** upward [8]. Since then, predictive processing ideas have been expanded to many domains – from visual and auditory perception to interoception and emotion [9] [10] – suggesting a unifying principle. Computationally, predictive coding algorithms have inspired machine learning architectures that **predict inputs or future states**, with the objective of self-supervised representation learning [11]. Overall, predictive coding provides a rigorous framework where **sensation enters as the signal to be predicted**, and perception emerges from minimizing the difference between expected and actual sensory input [2]. This puts sensation at the heart of cognition: the ultimate arbiter that either confirms our brain's model or forces it to update.

Active Inference and the Free Energy Principle

Active inference builds upon predictive coding by including **action** in the loop of prediction error minimization. In this framework, perception *and* behavior are two sides of the same coin – both aimed at minimizing "surprise" (formally, variational free energy) with respect to a generative model of the world [12]. Rather than issuing motor commands, the brain is hypothesized to send **descending proprioceptive predictions**: the motor system tries to make sensory proprioceptive input match the predicted values by executing movements [12]. In other words, action is *fulfilling* a sensory prediction. This concept of **active inference** treats the organism as a single inference machine that doesn't just passively perceive its environment, but actively samples it in order to minimize prediction errors across all modalities – visual, auditory, interoceptive, and proprioceptive [13]. Sensation remains central, as both perception and action aim to optimize the agent's future sensations to be in line with its expectations (which include survival-oriented "preferred" states).

Formally, active inference is often cast in terms of **Bayesian filtering and control**. The agent is assumed to have a **generative model** of sensory observations and hidden states, including a prior over preferred sensory states (encodings of goals) [14]. The *free energy* is a measure of the discrepancy between the agent's internal beliefs (posterior) and the observations and preferred outcomes; minimizing free energy leads the agent to adjust its beliefs (perception) and also select actions that are expected to lead to preferred sensory feedback [14] [15]. In practice, this means the agent performs **state estimation** (like an extended Kalman filter or particle filter) to interpret sensory inputs, and simultaneously performs **action selection** by evaluating which policy would minimize *expected* free energy (often decomposed into expected risk and ambiguity) [16]. Notably, this approach unifies classic components of decision-making: it generalizes Bayesian state estimation, planning under uncertainty, and even control as a single inference problem [17] [18]. The mathematics involves **variational inference** (updating beliefs to minimize surprise) and **expected free energy minimization** (choosing actions that balance achieving goals and gathering information) [19]. The result is a principled account of the perception–action cycle: *perception* updates the agent's model to better explain sensations, and *action* changes the world (and thus sensations) to better fit the agent's predictions [15].

Active inference has been demonstrated in neuroscience models and is now an exciting framework in robotics. By endowing robots with a *probabilistic model* of themselves and their environment, active inference allows them to handle perception, planning, and control in a unified way [20]. For example, researchers have used active inference to control robotic arms and humanoid robots, showing that the same principle of free-energy minimization can enable adaptive behaviors like online disturbance rejection and goal-directed exploration [21] [22]. One study highlighted that an active-inference-based humanoid could adapt its gait when its leg lengths changed, by treating the change as an increase in prediction error and adjusting accordingly [21]. The strong **neuroscience foundation** of active inference (deriving from Friston's Free Energy Principle) helps bridge engineering and life sciences, allowing **human-like adaptive control** strategies to be tested on machines [23]. Indeed, active inference controllers naturally fuse multi-sensory information (weighting each sensory prediction error by its estimated precision) and exhibit **goal-directed behavior with inherent curiosity** (since expected free energy includes an information gain term) [24] [25]. In summary, active inference formalizes an embodied agent that *continuously uses sensations* to update its beliefs and chooses actions to steer future sensations toward desired outcomes – effectively placing sensation at the core of both understanding the world and acting within it.

Embodied AI and Enactive Sensorimotor Cognition

An example of an embodied AI agent: SoftBank Robotics' Pepper *humanoid robot, which is equipped with cameras, tactile sensors, microphones, and wheeled locomotion. Embodied AI research gives such agents a physical presence in the world so that intelligence can emerge through direct sensorimotor interaction with real environments.* In contrast to disembodied algorithms that only manipulate abstract data, **embodied AI** emphasizes that cognition is deeply rooted in an agent's physical body and its **real-time interactions** with the environment [26] [27]. The key idea is that **intelligence arises from sensing and acting in the world**, as the agent's *own* actions influence its future sensations in a continual feedback loop. By giving AI systems **robotic bodies** (or virtual avatars in realistic simulations), we allow them to learn through the same process as humans and animals – *experiential learning* via exploration, sensorimotor feedback, and environmental embodiment [27]. This perspective takes inspiration from biology: our brains evolved in tight coupling with our bodies, constantly receiving sensory inputs and issuing motor outputs. Thus, an embodied AI agent can develop more human-like cognition by undergoing sensorimotor experiences, rather than solely ingesting static data [28] [29].

Core principles of embodied AI include **perception–action coupling** and **learning through situated experience**. Perception is not seen as a separate module from action; instead, sensing and acting form an integrated loop, each immediately influencing the other [30]. For example, when an embodied agent's camera "sees" an obstacle, its control policy can rapidly adjust motor commands to move around it – perception directly and continuously guiding action, and action in turn changing the agent's sensory inputs [30]. This tight coupling means that cognition (decision-making, planning, etc.) is grounded at all times in the current sensorimotor context. Additionally, embodied agents **learn by doing**: like a toddler learning to walk or grasp, an AI robot improves through trial and error, using **feedback from its sensors** to refine its behavior [31]. This might involve reinforcement learning in a physical environment, where the agent's *reward signals* are tied to the outcomes of its actions in the real world [32]. Over time, such an agent can develop rich internal models of its environment – not abstracted from pixels alone, but from the **multimodal, active experience** of touching, moving, and seeing outcomes [33] [34].

To formalize these ideas, embodied AI often leverages **dynamical systems** and **situated cognitive architectures**. One classic approach is Rodney Brooks' *subsumption architecture*, which eschewed high-level world models in favor of layered sensorimotor routines – a robot reacts to sensor inputs through tightly-coupled behaviors, demonstrating that complex, adaptive conduct can emerge without explicit symbolic reasoning. More recent frameworks incorporate elements like computer vision, mapping, and planning, but they keep the agent's knowledge grounded in sensorimotor data. For instance, the **Habitat and iGibson simulators** provide photorealistic virtual environments where an AI with egocentric vision and continuous locomotion can learn tasks like navigating houses or manipulating objects. The **Human Brain Project's Neurorobotics Platform** goes a step further by connecting detailed brain simulations (e.g. spiking neural networks) to virtual robot bodies, enabling researchers to study how *brain-like control systems* perform in an embodied context (like controlling a humanoid to balance or reach). Across these approaches, sensation is fundamental: it is the **driving input** that an embodied agent must continually interpret to survive and achieve goals, and it is also the **feedback signal** that informs the agent of the consequences of its actions. As one proponent put it, to reach human-level cognition, AI systems should be built "with architectures that learn and improve in similar ways as the human brain, using its connections to the real world" – only by sensing and acting will AI truly **know** what its abstract computations mean [35].

Dynamical Systems Theory in Cognitive Modeling

Not all models of cognition rely on discrete algorithmic steps or static neural networks – **dynamical systems theory (DST)** offers an alternative paradigm for understanding mind and brain. In a dynamical framework, cognitive processes are viewed as **continuous time-evolving states** of a complex system, describable by differential equations rather than sequential logic. Formally, DST studies how abstract or physical systems change over time, analyzing their trajectories in a *state space* and the attractors (stable states or recurrent patterns) that govern long-term behavior [36]. Applied to the brain and behavior, the **dynamical hypothesis** holds that cognition *is* a dynamical system, and can be explained in terms of trajectories, attractor landscapes, and non-linear interactions, rather than as a series of computations over symbols [37]. This often means rejecting the idea of a central digital “program” for the mind – instead, cognition emerges from the self-organizing dynamics of neural populations, body, and environment in continuous interaction [38]. Sensation in this view is a perturbation or input to the ongoing dynamic system, which can shift the system’s state into different attractors corresponding to different perceptions or actions.

A concrete example of a dynamical approach is **Dynamic Field Theory (DFT)**, which provides a mathematical language for linking neural activity to cognition in an embodied context. DFT represents activation as continuous fields (spatial or feature spaces) where localized “peaks” of activity can form and dissipate over time. These activation peaks act as low-dimensional **representations** (e.g., a peak at a certain position on a “color” field might represent an attentional focus on that color). Crucially, the dynamics include feedback loops and lateral interactions that yield stable attractors – a peak can **stabilize as a memory or decision** until input changes cause it to destabilize [39] [40]. For instance, in a DFT model of decision-making, when sensory evidence (input to a field) accumulates and crosses a threshold, the field’s state “breaks” into a new attractor (a high peak at one end, representing a choice). This models how a categorical decision or percept can suddenly emerge from gradual changes in sensation. Because these fields are defined over perceptual or motor dimensions (color, spatial location, etc.), they naturally interface with sensation and action: a **perceptual field** takes continuous sensory input and settles into an attractor pattern that can guide behavior (say, a peak at a target location guiding eye movement), while a **motor field** might generate smooth trajectories toward an attractor state that represents a goal posture.

Mathematically, such models often use **nonlinear differential equations** inspired by neural dynamics (e.g. Amari’s neural field equation or Wilson-Cowan equations). They capture phenomena like multistability (multiple possible stable perceptions for the same input), limit cycles (oscillatory routines like walking), and chaos (extreme sensitivity to initial conditions in some cognitive processes). One well-known application is **dynamical neural networks for motor control**. For example, *dynamical movement primitives* represent motor behaviors as point attractors or limit cycles in a low-dimensional system [41]. A walking robot can be controlled by a set of coupled oscillators that naturally produce rhythmic gait; sensory feedback (like a slip detected by a foot sensor) can shift the oscillator phases, effectively *entraining* the pattern to new conditions and achieving **stable locomotion under perceptual guidance** [42]. Another example is **Randall Beer’s agent models**, where a simulated organism (like a minimalist artificial insect) is controlled by a continuous-time recurrent neural network; the agent’s successful behavior (e.g. chasing a food source) corresponds to the system settling into an attractor that couples the agent’s sensorimotor loop with the environment. Such models show that what we call “cognitive functions” – decision, memory, perception – can be understood as *emergent properties of dynamical interactions*, rather than explicit computations. Sensation influences these dynamics continuously: a slight change in a sensory input can nudge the system’s trajectory toward a different basin of attraction, thus altering the agent’s behavior or cognitive state in a graded but law-governed way.

It's worth noting that the DST approach often complements embodied AI. Both emphasize the **perception-action cycle** as a closed loop and often downplay the need for internal symbolic representations. Indeed, DST provides tools like **phase space analysis** to understand sensorimotor coupling: for example, plotting an agent's joint sensor and actuator state can reveal attractor orbits that correspond to stable behaviors (like tracking a moving object with gaze). The framework has also been applied to developmental psychology (e.g., Thelen's dynamic systems model of infant motor development) and neuroscience (e.g., Kelso's coordination dynamics for explaining rhythmic interlimb coordination). In all cases, sensation is integral – it continuously modulates the system's state. A dynamical model of **working memory**, for instance, might be a neural network with recurrent excitation that can hold a memory as a sustained active pattern (attractor) in the absence of input. When a new sensory stimulus arrives, it perturbs the field; if the input is strong or persistent enough, it can **bifurcate** the system to a new attractor (replacing the memory with a new one). Thus, DST formalizes cognition as *a dance between stability and change*, where sensory inputs trigger state transitions and the inherent dynamics ensure continuity and coherence.

Spiking Neural Networks and Neuromorphic Models

The **spiking neural network (SNN)** approach aims to capture the *biological realism* of real neurons, down to the timings of individual spikes. In the hierarchy of neural network models, SNNs are often called the "third generation," adding temporal dynamics and event-based communication to the neuron model. **Biologically, neurons communicate via electrical impulses (spikes)**, and SNN models reflect this by having neurons integrate inputs over time and fire discrete spikes when their membrane potential crosses a threshold [43]. This seemingly small change introduces a rich repertoire of coding possibilities (such as spike rate, spike timing, synchrony, and oscillations) that analog neuron models lack. From a computational neuroscience perspective, SNNs are a bridge to the brain: they can simulate phenomena like refractory periods, spike-frequency adaptation, and precise spike-time dependent plasticity (STDP), which are crucial for understanding sensation and cognition in vivo. Sensation can be encoded in SNNs as patterns of spikes – for example, a retinal neuron might spike in response to a light flash, or an auditory neuron might fire bursts locked to sound frequency. **Perception then emerges from the collective dynamics of spikes** coursing through networks that resemble biological circuits (e.g., layered visual cortex). Crucially, SNNs treat **time as an explicit dimension** in computation, much as the brain does; this enables them to naturally model temporal aspects of perception (like motion sensing, rhythmic patterns, and working memory via persistent firing).

Mathematically, spiking networks are described by differential or difference equations capturing each neuron's membrane potential. A simple and common model is the **leaky integrate-and-fire neuron**, where input currents (including spikes from other neurons) gradually charge the neuron's membrane; when it reaches a threshold, a spike is emitted and the potential resets. More detailed models like Hodgkin-Huxley or Izhikevich neurons include multiple variables (voltage, gating channels, etc.) to replicate fine physiological properties. In all cases, the network's state is **high-dimensional and time-dependent**: instead of a static activation vector, we have a stream of spikes. Simulation of SNNs often requires event-driven algorithms (since nothing changes between spikes) or fine time-step integration. From the perspective of linking to cognition, one powerful formalism is the **Neural Engineering Framework (NEF)**, which provides methods to harness spiking neurons for high-level computations [44] [45]. The NEF treats populations of spiking neurons as representing vectors and performing functions on those vectors. Using NEF, researchers built *Spaun*, the world's largest functional brain model at the time, with 2.5 million spiking neurons performing cognitive tasks [46]. In Spaun, **sensation, perception, and action are all implemented in spikes**: it receives images of handwritten digits as input (encoded into spikes by a simulated retina), processes them through layers of spiking neurons analogous to visual and prefrontal cortex, and finally controls a simulated arm (via motor cortex spikes) to write out an answer [47] [48]. Remarkably, Spaun can do multiple tasks (like copying drawings, doing simple arithmetic, and sequence prediction) and even reproduces some human-like errors and reaction time patterns [49] [50]. This demonstrates that spiking networks can go beyond low-level sensory processing to support **integrated perception–cognition–action** loops. Sensation is the driving input for Spaun's spiking neural networks – e.g., the image of a digit causes a cascade of spikes that lead to recognition of that digit – and any subsequent cognitive operation (like solving "1 2 3 … ?") must be achieved through the dynamics of those spikes interacting across the model's modules [47].

One of the exciting practical aspects of SNNs is the rise of **neuromorphic hardware**. These are physical computing devices inspired by the brain's architecture, often implementing networks of spiking "neurons" in silicon with analog or mixed-signal circuits. Neuromorphic chips like **Intel's Loihi** and IBM's TrueNorth run SNNs natively, using massively parallel, event-driven computation that can be far more energy-efficient than conventional CPUs/GPUs for certain tasks [51] [52]. Because they operate via spikes, these chips can interface directly with **event-based sensors**, such as neuromorphic vision sensors (which output spikes for pixel intensity changes) or dynamic audio sensors, to create a hardware **sensory-processing loop**. For example, Loihi has been used in robotics for things like object recognition with a silicon retina or controlling a robotic arm via a spiking controller. Researchers have demonstrated neuromorphic systems for **robotic touch** (e.g., artificial skin feeding spikes into a neural network) and even olfactory sensing (Loihi was trained to recognize odors from chemosensor inputs using spiking patterns) [53]. In essence, neuromorphic hardware enables *embodied SNNs*: a robot can have a brain-like chip that directly processes its sensor signals and issues motor commands in real time, with incredibly low power consumption (approaching the efficiency of biological brains). This is a compelling testbed for sensation-based consciousness models, as it forces our theories to operate under physical constraints similar to the brain's. Indeed, a recent review argues that the trade-off between computational power and biological plausibility may be best resolved by neuromorphic systems, which provide an **"accountable empirical testbench"** for probing both synthetic and natural cognition in an embodied setting [54] [55]. In summary, spiking neural networks bring us closer to the biological level of detail for sensation and cognition, and when implemented on neuromorphic platforms or large-scale simulations, they allow us to *test* how conscious-like behaviors could emerge from spatio-temporal spike patterns grounded in sensory input.

Other Frameworks and Models for Sensation-Based Consciousness

Beyond the major paradigms above, there are other noteworthy frameworks that connect sensation, perception, and consciousness in computational models:

- **Adaptive Resonance Theory (ART):** ART, developed by Stephen Grossberg, is a cognitive neural network theory focused on how the brain **learns to recognize patterns** in a stable yet flexible way. It centers on the interaction between **top-down expectations and bottom-up sensory signals** [56]. In ART models, when a sensory input is presented, it is first compared against a *learned prototype* (a memory template) for a category. If the input matches closely enough (within a "vigilance" threshold), the system resonates – the sensory features and memory template reinforce each other, which is hypothesized to correspond to conscious recognition of the object or pattern [56]. If the mismatch is too large (input differs significantly from any known prototype), the system triggers a **reset**: essentially, it treats the input as novel, activates a new category neuron, and learns this new pattern without forcing it into an unsuitable existing category [57]. This mechanism allows continuous learning of new sensations **without catastrophically erasing old memories**, addressing the stability–plasticity dilemma [58]. ART has mathematical formulations (often involving coupled differential equations for the dynamics of matching and resetting) and has been applied to problems like auditory scene analysis and visual object learning. Notably, it treats *attention* as an emergent property of the matching process (the resonant state corresponds to focused attention on that sensory input). In terms of sensation-based consciousness, ART proposes that an input that successfully triggers resonance with a top-down expectation is what enters awareness as a recognized perception [56]. This is an explicit nod to the idea that **conscious perception requires a good match between what is sensed and what is predicted/remembered**, echoing themes from predictive coding but with an emphasis on **stable category learning** and conscious attention.

- **Global Workspace Theory (GWT):** Originally a psychological theory by Bernard Baars, GWT has inspired computational models of consciousness where multiple specialized processors (brain modules) compete or cooperate for access to a **global workspace** – a kind of communication bus that, when a piece of information enters it, broadcasts that information to all other processes (making it globally available, as consciousness does for different cognitive faculties). In neural terms, **Global Neuronal Workspace (GNW)** models (proposed by Stanislas Dehaene and colleagues) suggest that a stimulus becomes consciously perceived if it triggers **widespread, self-sustaining activation across the brain**, particularly through strong feedback connections forming an ignition event [59]. In practice, computational models have implemented this with ** spiking neural networks **or deep networks having a bottleneck that imitates the workspace. For example, a recent 2024 study designed an** embodied agent **(a virtual avatar in a 3D environment) whose internal architecture was based on GWT [60]. The agent received realistic sensory inputs (vision and audition) and had to navigate and perform tasks, and the GWT-inspired design allowed different sensory streams and memory to integrate in a global workspace layer. The results showed that this GWT agent could solve tasks more flexibly, and analyses of its internal activations showed interpretable "attentional patterns" – essentially the agent was selectively amplifying certain sensory representations in its workspace, analogous to how conscious attention might work [60]. Such models are still in early stages, but they offer a bridge between a high-level theory of consciousness and concrete algorithms. Sensation in GWT is critical: a sensory input must** compete for entry into the global workspace**, and only if it gains enough strength (due to intensity, novelty, or top-down bias) will it ignite the global broadcasting state that corresponds to conscious perception.

- **Sensorimotor Enactivism:** Philosophical frameworks like the **sensorimotor theory of consciousness** (O'Regan and Noë) argue that what we experience (qualia of perception) are not internal reconstructions of the world, but rather our *mastery of sensorimotor contingencies* – the laws governing how our sensations change as we act. While this idea is philosophical, it has inspired models in robotics and AI. For instance, an enactive model might not explicitly represent "red" as an internal object, but the agent "knows" red by the way it can interact (e.g. it knows moving its eye changes the pixel inputs in a characteristic way for a red object versus a green one). Computationally, this leads to approaches where an agent learns **sensorimotor predictive models** (what sensory outcome to expect for a given action) and uses discrepancies to drive learning – essentially blending predictive coding with embodiment. These models treat *sensation as fundamental* in that the agent's entire knowledge is encoded in terms of possible sensorimotor patterns. One example is work on **projective simulation and predictive processing for sensorimotor loops**, where the perception of a stable object arises when an agent's predictions about how its movements will affect its sensory input are confirmed over and over, creating an experienced "presence" of that object. Though hard to quantify, some researchers have built neural network models that simulate this principle and have noted that certain sensorimotor loops can create self-sustaining activity correlating with attention and conscious-like states [60].

- **Integrated Information Theory (IIT):** While IIT is more a theoretical measure of consciousness than a process model, it deserves mention as a **mathematical framework linking causality, information, and conscious experience**. IIT postulates that the degree of consciousness a system has corresponds to how much *integrated information* (denoted Φ) it possesses – loosely, how much the whole system's state carries information above and beyond the information of its parts. In practice, computing Φ involves analyzing the cause–effect structure of a network (which can be neurons or logic gates or any nodes) to see how discriminative and irreducible the network's responses to inputs are. A system that has complex feedback and feedforward interactions (like cortical networks) might have a high Φ, whereas a feedforward or highly modular system has Φ near zero. Some researchers have applied IIT to neural data and small simulated networks to test its predictions. In the context of sensation-based cognition, one could use IIT to **quantify** how integrated a sensory processing network is – for instance, comparing a network that includes recurrent connections (mimicking thalamo-cortical loops) to one that doesn't, and seeing which yields higher Φ (and presumably closer to supporting conscious perception). While IIT doesn't yet provide a blueprint for building conscious machines, it offers tools like the *PyPhi* software for calculating integrated information in simulated networks. This allows testing, for example, whether adding certain feedback pathways (which bind sensory features together) increases integration, aligning with theories that those pathways are critical for conscious scenes. Thus, IIT provides a **bridge between a mathematical property of sensation-processing networks and the presence or level of consciousness**, complementing frameworks like GWT and predictive coding.

Each of these additional frameworks brings a unique perspective, but all share a common theme: **sensation is not an afterthought, but the bedrock of cognition and consciousness**. Whether it's matching sensations to memory templates in ART, broadcasting salient sensory content in a global workspace, enacting perception through sensorimotor loops, or measuring the holistic informational structure of sensory circuits in IIT – the treatment of sensation in these models is central. They formalize in different ways the intuitive idea that *what we feel and perceive guides and constitutes what we know and are*. As research progresses, these frameworks often inform each other and can be combined (for example, active inference models have been used to derive measures akin to integrated information, and embodied predictive coding models are being tested on robots). The ultimate goal is a **unified, biologically-grounded theory of sentient cognition**: one that can be implemented in a machine, make testable predictions about brains, and explain how the flow of sensory signals through neural dynamics can give rise to the rich tapestry of perception, action, and awareness.

Sources:

- Sprevak, M. (2024). *Predictive coding: Introduction*. *Compass* – (overview of predictive coding as a model of cognition).
- Rao, R. & Ballard, D. (1999). *Predictive coding in the visual cortex: a computational account*. NeuroReport 10(7).
- Friston, K. (2010). *The free-energy principle: a unified brain theory?* Nature Reviews Neuroscience, 11(2), 127–138.
- Sajid, N., et al. (2022). "How Active Inference Could Help Revolutionise Robotics." *Entropy*, **24**(6): 694 [61] [17].
- Lanillos, P., et al. (2021). *Active Inference in Robotics and Artificial Agents: Survey and Challenges*. arXiv:2112.01871.
- Prescott, T. & al. (2023). "Embodied AI: Bridging the Gap to Human-Like Cognition." *Science Robotics* 8(78): eadg6014 – summary in HBP News [26] [27].
- Lamarr Institute Blog (2023). *Embodied AI Explained: Principles, Applications, and Future Perspectives* [62] [30].

- Sandamirskaya, Y. (2014). “Dynamic Neural Fields as a Step Towards Cognitive Neuromorphic Architectures.” *Front. Neurosci.* 7:276 [39] [40].
- Ijspeert, A. et al. (2013). “Dynamical Movement Primitives: Learning Attractor Models for Motor Behaviors.” *Neural Computation* **25**(2): 328–373 [41].
- Eliasmith, C. et al. (2012). “A Large-Scale Model of the Functioning Brain” (Spaun). *Science* **338**(6111): 1202–1205 – and *Nature* News summary by Ed Yong [49] [47].
- Do Pham, M. et al. (2023). “From Brain Models to Robotic Embodied Cognition: Biological Plausibility in Neuromorphic Systems.” *Brain Sciences* **13**(9): 1316 [63] [55].
- Wikipedia: **Adaptive Resonance Theory** [56]; **Global Workspace Theory**; **Predictive Coding** [64] [12].
- Dossa, R.F.J. et al. (2024). “Design of a global workspace agent embodied in a multimodal environment.” *Front. Comput. Neurosci.* **18**: 1352685 [60].
- O’Regan, J.K. & Noë, A. (2001). “A sensorimotor account of vision and visual consciousness.” *Behav. Brain Sci.* **24**(5): 939–973.
- Tononi, G. et al. (2016). “Integrated Information Theory: from consciousness to its physical substrate.” *Nature Reviews Neuroscience* **17**(7): 450–461.

---

1 2 3 4 5 6 7 8 9 10 11 12 13 64 Predictive coding - Wikipedia
https://en.wikipedia.org/wiki/Predictive_coding

14 15 16 17 18 19 20 21 22 23 24 25 61 How Active Inference Could Help Revolutionise Robotics - PMC
https://pmc.ncbi.nlm.nih.gov/articles/PMC8946999/

26 27 28 29 35 Embodied AI: Bridging the Gap to Human-Like Cognition
https://www.humanbrainproject.eu/en/follow-hbp/news/2023/08/09/embodied-ai-bridging-gap-human-cognition/

30 31 32 33 34 62 Embodied AI Explained: Principles, Applications, and Future Perspectives
https://lamarr-institute.org/blog/embodied-ai-explained/

36 37 38 (PDF) Dynamical Systems Theory in Cognitive Science and Neuroscience
https://www.researchgate.net/publication/341992159_Dynamical_Systems_Theory_in_Cognitive_Science_and_Neuroscience

39 40 sandamirskaya.eu
http://sandamirskaya.eu/resources/71560_Sandamirskaya_ProvisionalPDF.pdf

41 42 ini.rub.de
https://www.ini.rub.de/upload/file/1561648783_9c241bd977a20865a548/IjspeertEtAl2013.pdf

43 44 45 46 51 52 54 55 63 From Brain Models to Robotic Embodied Cognition: How Does Biological Plausibility Inform Neuromorphic Systems?
https://www.mdpi.com/2076-3425/13/9/1316

47 48 49 50 Simulated brain scores top test marks | Nature
https://www.nature.com/articles/nature.2012.11914?error=cookies_not_supported&code=d5defe5d-2e09-4418-92c3-18ae7c194a2e

53 Intel Advances Neuromorphic with Loihi 2, New Lava Software Framework and New Partners :: Intel Corporation (INTC)
https://www.intc.com/news-events/press-releases/detail/1502/intel-advances-neuromorphic-with-loihi-2-new-lava-software

56 57 58 Adaptive resonance theory - Wikipedia
https://en.wikipedia.org/wiki/Adaptive_resonance_theory

59 Adversarial testing of global neuronal workspace and integrated ...
https://www.nature.com/articles/s41586-025-08888-1

60 Frontiers | Design and evaluation of a global workspace agent embodied in a realistic multimodal environment
https://www.frontiersin.org/journals/computational-neuroscience/articles/10.3389/fncom.2024.1352685/full