Behavioral Entropy Model (BEM): A Unified Framework

The BEM posits that all behavior is the **projection** of underlying entropy dynamics across mind, body, and world. In this view, an agent's actions arise from transitions in an internal state-space whose uncertainty (entropy) is shaped by sensory inputs, neural activity, bodily state, and environmental context. Living systems maintain themselves far from equilibrium by exchanging free energy with the environment [1]. In practice this means that organisms continually convert low-entropy resources into high-entropy waste (heat, metabolites) to sustain order. At the same time, cognitive and sensorimotor processes can be modeled as probabilistic inference: each internal belief or behavioral policy has an associated Shannon entropy, and behavior tends to reduce expected uncertainty. Indeed, theories like the Free Energy Principle assert that agents act to **minimize surprise** (Shannon entropy) of their sensory states [2] [3]. BEM integrates these ideas by formally linking thermodynamic, information-theoretic, metabolic, and predictive entropy measures, treating emotional and arousal states as modulators of entropy gradients. Behavior at each moment thus reflects a balance of entropy flows: actions that reduce internal uncertainty (and metabolic cost) are favored, while still allowing exploration (entropy increase) when needed [2] [4].

Thermodynamic and Metabolic Entropy

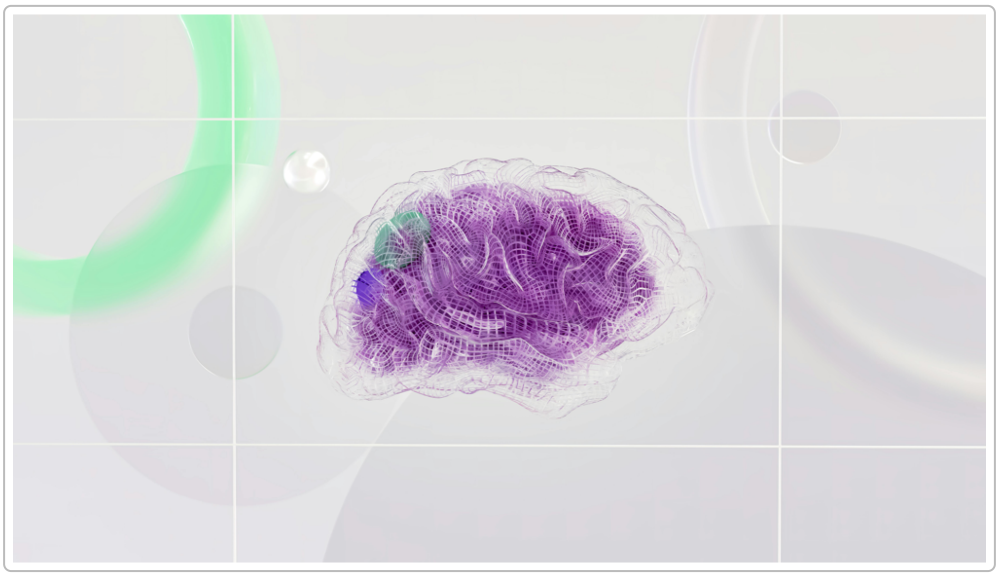
- **Thermodynamic entropy:** Biological agents are open dissipative systems [1]. To maintain low internal entropy (order), they must export entropy to the environment (heat, waste products). In BEM this implies that physiological constraints (e.g. body temperature regulation, energy budgets) influence behavior. For instance, Schrödinger noted that life "feeds on negative entropy" (free energy) [1]; modern biochemistry refines this into Gibbs free energy fluxes for metabolism. In concrete terms, rapid movements or cognitive work produce heat and consume energy, so behavior tends to balance information gain against thermodynamic cost.

- **Shannon (information) entropy:** Perception and neural coding can be treated probabilistically [4]. A sensory or cognitive state X with distribution $p(x)$ has entropy $H(X) = -\sum_x p(x)\log p(x)$, which quantifies its uncertainty. High perceptual entropy (ambiguous stimuli) drives active sampling (e.g. saccades, inquiries) to reduce uncertainty, whereas low entropy (predictable inputs) leads to calm or exploitation. BEM posits that the brain estimates these entropy levels and that behavior evolves to minimize them over time (consistent with predictive coding). For example, "psychological entropy" theories suggest that anxiety arises when internal model uncertainty is high [4].

- **Metabolic entropy:** Every neural signal has a metabolic cost. The brain consumes ~20% of the body's energy even at rest [5], with half of that not even for information processing [6]. Energy constraints act as entropy limits on cognition: neurons must use ATP to fire, synapses have maintenance costs, etc. Thus BEM includes a **metabolic entropy** term representing the entropy produced by biochemical processes. Low-energy, sparse representations minimize this entropy, whereas high metabolic rates (arousal, fever, strenuous activity) raise it. Empirically, more demanding tasks reduce unused neural metabolism (shunting resources to task-relevant regions) [5].

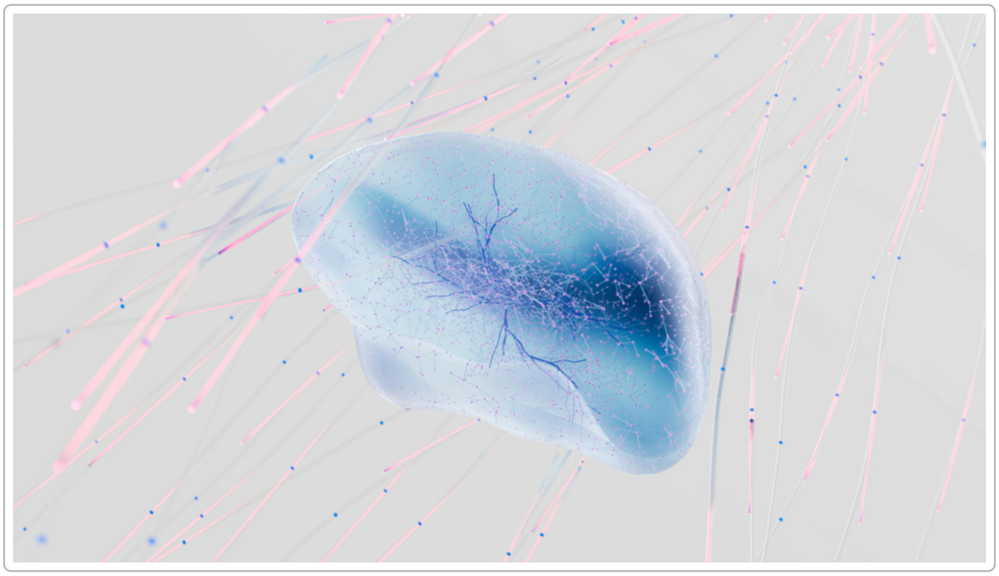
- **Predictive (Bayesian) entropy:** Under the active-inference framework, an agent maintains probabilistic beliefs and selects actions to minimize expected uncertainty (variational free energy) [2] [7]. In BEM, each hypothesis or motor plan has an associated Shannon entropy (uncertainty) of predicted outcomes; actions are chosen to reduce this entropy. This includes both **exploitation** (choosing high-certainty outcomes) and **exploration** (sampling novel states to gain information) as unified entropy-minimizing behavior. Formally, one can write a variational free energy $F(q,p) = \mathrm{D}_{\mathrm{KL}}[q(s)|p(s)] - \ln p(\text{sensory data})$, whose minimization drives perception and action [2].

Information-Theoretic Entropy in Perception and Cognition



Behavioral entropy critically depends on information content in perception and thought. In BEM, sensory and cognitive states are represented as probability distributions whose Shannon entropy determines uncertainty. For example, an ambiguous stimulus (high sensory entropy) will provoke exploratory actions to reduce entropy. This reflects the notion of *psychological entropy*: both perceptual and behavioral affordances can be treated as distributions, and their uncertainty can be quantified by Shannon's formula [4]. The brain thus continually updates an internal model to predict sensory inputs; any mismatch (prediction error) contributes to entropy. Agents act to minimize this entropy by either refining their model or altering the world (active inference) [2] [7]. In summary, perceptual uncertainty is a driving force in BEM: high information entropy pushes behavior toward gathering data or choosing safer actions, whereas low entropy (certainty) allows habitual or efficient responses.

Predictive Coding and Bayesian Entropy Minimization



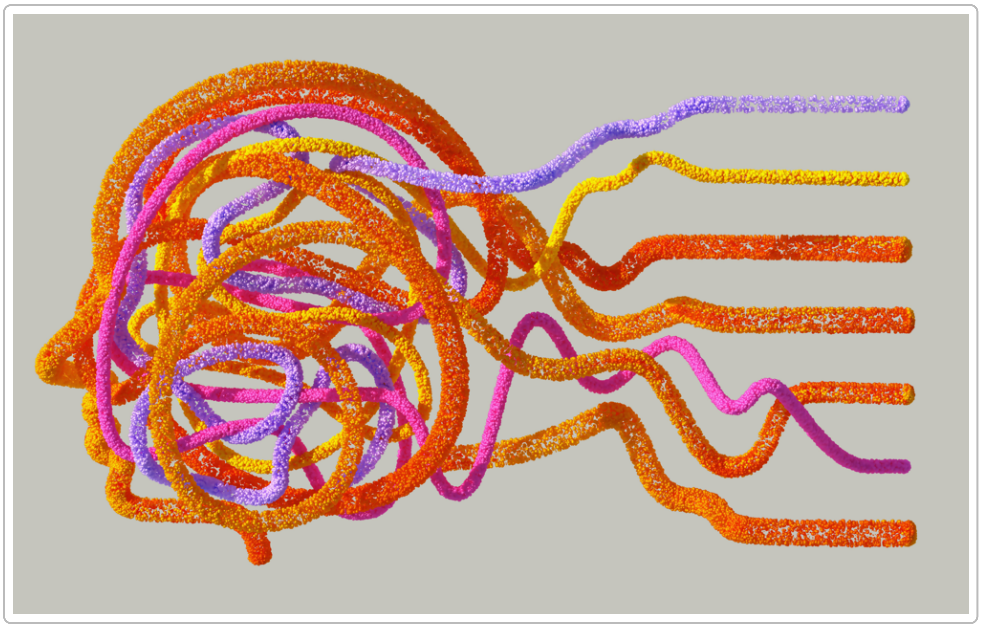
In BEM the key computational mechanism is Bayesian inference under entropy constraints. The brain is treated as a generative modeler: it forms probabilistic predictions of sensory input and selects actions to minimize expected surprise. The **Free Energy Principle** formalizes this: to survive (maintain homeostasis), a system must minimize the long-term average surprise (Shannon entropy) of the states it encounters [2]. Practically, this means the agent seeks policies that reduce the Kullback–Leibler divergence (relative entropy) between likely and desired state distributions. Behavior is then viewed as sampling actions that minimize a variational free energy bound on surprise [2] [7].

Mathematically, if $P(x_{t+1}\mid x_t,a_t)$ are the state transition probabilities under action a_t, the entropy rate of the behavior process is

$$H_{\text{rate}} = \lim_{T\to\infty} \frac{1}{T} H(x_1,\dots,x_T) = -\sum_{x,a} \pi(x)\, P(x'|x,a)\, \ln P(x'|x,a),$$

where $\pi(x)$ is the stationary state distribution. Actions are chosen to shift $\pi(x)$ toward regions of lower surprise. In neural terms, predictive coding networks implement this by adjusting synaptic weights to reduce prediction-error entropy. The BEM can thus incorporate Bayesian belief states $q(\psi)$ with entropy $H(q)=-\sum_\psi q(\psi)\ln q(\psi)$, and posit that behavior guides $q(\psi)$ to lower-entropy distributions over external states [4] [2].

Emotional Valence and Arousal as Entropy Modulators



Emotional and arousal states bias the entropy landscape of behavior. In BEM, feelings like anxiety, distress or eustress reflect shifts in internal entropy gradients. For instance, **uncertainty** about outcomes (high sensory or goal entropy) activates stress responses: empirical models show that when all known strategies have high risk (high Kullback–Leibler divergence), a neural emergency program (amygdala/ACC-driven stress circuit) is triggered [8]. In other words, a *high degree of entropy* in the decision context elicits stress [8]. Conversely, moderate arousal with some uncertainty can be experienced positively (interest).

BEM aligns with quantitative models of emotion: free-energy variations correspond to valence. One formulation posits that **decreasing** free energy (entropy) generates positive valence (eustress, reward), whereas **increasing** free energy produces negative valence (distress) [9]. This explains classic findings like the Yerkes–Dodson or Wundt curve: performance and pleasure peak at intermediate arousal, falling off when arousal (entropy) is too low (boredom) or too high (anxiety) [10]. Thus, emotions are understood as changes in entropy: **positive emotions** arise when behavior successfully reduces uncertainty (e.g. learning), and **negative emotions** arise when actions fail to resolve entropy (e.g. unexpected outcomes) [10] [9].

Hierarchical Behavioral Responses

Behaviors are organized hierarchically (reflexive → habitual → volitional), and BEM integrates this structure through entropy dynamics. Low-level reflexes (spinal or brainstem arcs) are essentially hard-wired stimulus–response mappings with very **low entropy** (predictable, fast reactions). Habitual actions (basal-ganglia loops) represent learned low-entropy routines tailored to familiar contexts. Volitional/goal-directed behaviors (prefrontal cortex–mediated) explore a vast state space and therefore involve **higher potential entropy**. In BEM, emotional arousal and context determine which level governs: under extreme stress (high entropy context) control may collapse to reflexive/habitual patterns, whereas in calm states an agent can afford high-level planning. This mirrors dual-process theories: automatic System 1 (low entropy, fast) versus controlled System 2 (high entropy, flexible) processing. Indeed, optimal arousal yields peak performance (as noted above [10]) by balancing exploration and exploitation at the right hierarchical level.

Mathematical Formulation of Entropy in Behavior

We quantify behavioral entropy using standard formulas. If X_t is the agent's state (including perceptual and internal variables) at time t, its **Shannon entropy** is

$$H(X_t) = -\sum_x P(X_t = x)\,\log P(X_t = x),$$

as in classical information theory [4]. For the entire behavioral time series ${X_1,\dots,X_T}$, the joint entropy or entropy rate can be computed from the Markov transition matrix as above. BEM may also invoke **thermodynamic entropy** in physiology: for example, metabolic processes satisfy $\Delta S = \int \delta Q/ T$ (heat flow) in body tissues.

In the predictive-coding submodel, one often writes a **variational free energy** $F = \mathrm{D}_{KL}[q(\psi)|p(\psi|s)] - \ln p(s)$, which upper-bounds surprisal of sensory data s. Minimizing F with respect to the internal belief $q(\psi)$ drives the agent toward low-entropy beliefs (small KL divergence) [2]. In BEM terms, the agent optimizes a combined "entropy functional" that may sum different contributions (information entropy, metabolic entropy, etc.) subject to its goals and homeostasis. For instance, one could write a total expected entropy

$$\mathcal{S} = \mathbb{E}[H_{\text{sensory}} + H_{\text{neural}} + S_{\text{thermodynamic}} + \dots],$$

and derive behavior by minimizing $\mathcal{S}$ (or its free-energy proxy) over future trajectories. This yields a set of differential equations or dynamic programming rule for behavior, analogous to minimizing surprise in reinforcement learning or optimal control.

Integration with Other Models (ICASM, ISM, GCM, PRT)

The BEM is compatible with and extends existing integrative frameworks. For example, integrated cognitive-affective-sensory models (ICASM) posit that cognition, emotion and perception interact continuously; BEM provides entropy as a common currency linking these domains. Interoceptive-sensory models (ISM) emphasize bodily signals in perception; BEM incorporates bodily/metabolic entropy into the inference loop. Global-control models (GCM) and global-workspace theories view the brain as broadcasting goal states; in BEM these goal states correspond to low-entropy attractors that the system projects onto action. Crucially, the Projection Rendering Theorem (PRT) – which holds that observable behavior is a "rendering" of internal neural states – is naturally satisfied: behavior in BEM is literally the projection of entropy-driven internal transitions into the environment.

In summary, the Behavioral Entropy Model formulates behavior as the outcome of entropy gradients spanning thermodynamics, information theory, and Bayesian prediction. Agents constantly seek to minimize expected entropy (via predictive coding and metabolic efficiency [2] [5]) while balancing exploration, with emotional states shifting these entropy targets [8] [9]. This unified view links free-energy minimization and cognitive control with the second law of thermodynamics, offering a rigorous mathematical and mechanistic account of how uncertainty (entropy) steers behavior.

Sources: The above synthesis draws on information theory, neuroscience, and thermodynamics. Key concepts are supported by foundational works on entropy in biology [1] [2], psychological entropy [4] [8], and active inference [2] [3]. Behavioral and affective findings (e.g. arousal's inverted-U effect) are grounded in recent models linking free energy to emotion [10] [9]. These elements together realize the BEM as a comprehensive entropy-based account of behavior.

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