Pure awareness, entropy, and the foundation of perception

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Abstract

Minimal Phenomenal Experiences (MPEs) represent states of consciousness reduced to their most fundamental elements, posing a unique challenge and opportunity for modeling consciousness. This paper introduces a novel computational framework based on Bayesian and active inference to model MPEs. We propose that MPEs arise when precision weighting shifts predominantly to the lower levels of a hierarchical inferential system, leading to a perceptual state characterized by increased entropy and reduced complexity. Crucially, awareness of this simplified state is maintained through *epistemic depth*: The reflexive sharing of the organism's reality model with itself. Therefore, although the contents of consciousness are exceptionally quiet, a reflexive knowing of the empty field of experience remains. We then propose an in silico simulation to test the relationship between precision distribution and entropy, outlining how this model could generate synthetic EEG data to empirically validate the theoretical framework. By advancing our understanding of pure awareness through this computational approach, we provide a foundation for future research into the mechanisms underlying various altered states of consciousness, contributing to a more comprehensive understanding of the full spectrum of conscious experience.

Keywords: Minimal Phenomenal Experience, Bayesian Inference, Active Inference, Free Energy Principle, Entropy, Consciousness.

1 Introduction

Minimal Phenomenal Experiences (MPE) represent states of consciousness in their most minimal form, where the usual rich tapestry of sensory, cognitive, and affective content is stripped away, leaving behind a bare awareness. Metzinger (2024) describes MPE as a form of pure awareness or pure consciousness, experienced during deep states of meditation or dreamless sleep. This state is characterized by the absence of complex mental content, such as thoughts, sensory perceptions, time, and self-referential awareness. Instead, it is a state where consciousness is experienced as an awareness of awareness itself with very little content. As such, MPE could be considered the simplest form of conscious experience, one that lacks the typical features of experience, such as spatial self-location, temporality, and the experience of being a subject. Indeed, Metzinger further suggests that this state of pure awareness can exist without a first-person perspective, challenging the idea that consciousness is inherently subjective (see, cf. Block, 1995; Chalmers, 1995; Nagel, 1974; Searle, 1992; Varela, Thompson, & Rosch, 1991). In MPE, consciousness is minimally conceptual, presenting a form of self-knowing that is distinct from typical experiences of self-awareness (Metzinger, 2024).

Recently, Laukkonen and Chandaria (2024) proposed a hierarchical active inference model of consciousness, in which awareness emerges as a result of recursive inferential processes at different levels of abstraction. They suggest that MPEs can be understood as states where the precision weighting shifts predominantly to the lower levels of a hierarchical system, leading to a perceptual state characterized by low abstraction but high awareness. This paper builds on their model by exploring how these states, defined by a unique phenomenology of 'awareness of awareness,' arise when the inferential hierarchy is dominated by an empty reality model—a state of high epistemic depth with minimal abstraction. Each of these new terms will be introduced in detail later.

While this paper will focus on the computational mechanisms underlying the reduction of abstraction, it is worth to consider how this process fits into a more complex unfolding of processes that jointly allow for the emergence of MPEs. Initially, (1) precision weighting is shifted predominantly to the lower levels of the hierarchical system, leading to a reduction in the abstraction hierarchy (Laukkonen & Slagter, 2021). Next, (2) precision is withdrawn (i.e., relaxed or deconstructed) from all contents of consciousness, including the low-levels from the previous step. Importantly, this process of withdrawing precision seems to be easier if the system has previously reduced it's abstraction, thus the importance of step one. The withdrawn precision then (3) creates the conditions to recognizing the awareness that was always present. Laukkonen and Chandaria (2024) introduce the concept of epistemic depth to describe this process of awareness being aware of itself. Epistemic depth describes the degree to which the process of perceiving is itself a precept that is perceived. Thus, there is a loop where the perception (i.e., reality model) shares itself with itself (i.e., knows itself). The more minimal the remaining perceptual content, the more evident this self-reflexive perception (cf. Sandved-Smith et al., 2021). We propose that this state of low hierarchical depth and high epistemic depth—i.e., an empty perception (reality model) reflecting itself—is the mechanism underlying MPEs. This argument has interesting consequences, such as (5) that it is now possible to have a high epistemic depth even with a rich tapestry of contents, once you've discovered this awareness. It is like noticing the background hum of a refrigerator that was always there. During MPE, we reduce the world to that background hum of awareness. The aim of this paper is to suggest a computational model that sheds further light on the initial step which is the reduction of the abstraction hierarchy.

The central hypothesis put forth in this paper is that MPEs are preceded by a significant shift in precision weighting towards the lowest levels of the inferential hierarchy. Furthermore, we hypothesize that this shift implies a less constrained perceptual state, causing an increase in the entropy rate of the system. This increase in entropy, combined with high epistemic depth, characterizes the phenomenology of minimality in the pure awareness states of MPEs. Below, we will first introduce the theoretical framework that grounds our model, followed by a detailed exploration of how hierarchical active inference and precision weighting contribute to the generation of MPEs. This will be supplemented by empirical evidence and an outline of a computational simulations aimed at validating our hypotheses.

2 Theoretical Framework

Perception can be construed as a Bayesian process, where the brain continuously integrates prior knowledge with incoming sensory data to make sense of the world (Knill & Pouget, 2004). In this framework, perception is not a direct or passive reception of sensory information but rather an active inferential process (K. Friston, 2010). The Bayesian perception model addresses the challenge of inferring the most probable external causes of the sensory data we receive (Hohwy, 2013; Kersten, Mamassian, & Yuille, 2004).

Bayes' Theorem is further formalized in the Free Energy Principle, which extends the Bayesian framework to explain how biological systems, including the brain, maintain a stable state by minimizing surprise or uncertainty about their environment (K. Friston, 2010). The Free Energy Principle posits that organisms strive to minimize the difference between their predicted sensory inputs (based on internal models of the world) and the actual sensory data they receive. This difference, known as "free energy," is a measure of surprise or prediction error. By minimizing free energy, the brain effectively updates its internal models to better align with the incoming sensory data, thereby reducing uncertainty (Clark, 2013; K. Friston, Kilner, & Harrison, 2006; K. Friston & Stephan, 2007).

Minimizing free energy is not just about passively updating beliefs based on sensory data—it's also about actively gathering data to reduce uncertainty (K. Friston, Adams, Perrinet, & Breakspear, 2012). To account for this active process, the Free Energy Principle has been extended with the Active Inference framework, which describes the mechanisms of seeking out information that minimizes prediction errors (K. Friston & Frith, 2015a). The brain not only adjusts its internal models in response to sensory input but also takes actions to actively shape its sensory inputs in ways that align with its predictions. This allows organisms to not only passively perceive the world but also actively interact with it in a way that reduces uncertainty and maintains homeostasis (Pezzulo, Rigoli, & Friston, 2015).

Notably the inferential process described above happens at multiple levels of abstraction within the brain (Clark, 2016; K. J. Friston & Kiebel, 2009). Each level of this hierarchy is responsible for generating increasingly abstract representations of the sensory data. In this process, layers with higher abstractions constrain layers with lower abstractions via top-down predictions (i.e., expectations) while less abstracted layers pass information to the more abstract layers to provide new evidence that allows for the updating and refinement of the sensory predictions (K. Friston & Frith, 2015b; Hesp, Smith, Parr, Allen, & Friston, 2021; Parr & Friston, 2017).

Laukkonen and Chandaria (2024) extend this multi-layered hierarchical arrangement of inferential processes by introducing the concept of *epistemic depth*, which accounts for the awareness of the inferential process itself. They propose that the content of consciousness is not limited to perceiving external inputs but could for some individuals under some conditions also involve a recursive awareness of the internal model that is generating these perceptions. This 'awareness of awareness,' is what gives rise to a self-reflexive experience of perceiving. In their model, this recursive process can be thought of as a looping mechanism, similar to how we hear our own voice when we speak. The brain generates a reality model (analogous to the voice), which is then monitored and refined based on incoming sensory data (analogous to hearing our own speech). This recursive loop allows for the continuous updating and recursive sharing of the reality model, ensuring that it remains coherent but also aligned with sensory inputs.

Both the hierarchical depth and the epistemic depth can range on a spectrum from high to low. Inspired by Laukkonen and Chandaria (2024) we argue that MPE is characterized as a perceptual mode where **(1) the hierarchical depth is low**—i.e., perception becomes stripped of most of it's usual content—while **(2) epistemic depth is high** —i.e., the reality model is recursively perceiving itself. The combination of both these conditions gives rise to a state of pure awareness, where the mostly empty reality model 'knows' itself through recursive reality-monitoring.

The process leading to MPE involves not just focusing on low-level sensory data but progressively deconstructing more abstract layers of perception. By reducing the precision allocated to these layers, the mind systematically exposes less fabricated experiences until only awareness of awareness remains. This "deconstruction" of experience reveals pure consciousness, not through heightened attention to low-level sensory phenomena, but by pacifying them, allowing for deeper introspection. As abstraction decreases, subtler layers of perception become visible, enabling profound insights into the constructed nature of experience. In advanced contemplative states, this process can lead to experiences such as cessations or the recognition of pure awareness, wherein foundational elements of cognition and perception dissolve, and the true nature of awareness is fully realized. MPE is thus a progressive unraveling of perceptual content, revealing deeper, liberative aspects of consciousness.

In the process of active inference, precision weighting plays a crucial role in determining how different pieces of sensory data are used to update our internal models of the world (K. Friston, Daunizeau, & Kiebel, 2009). Precision refers to the confidence or reliability assigned to specific sensory inputs or predictions, effectively weighting the importance of different sources of information. When certain data is deemed more reliable or relevant, it receives higher precision, meaning the model will give it greater influence in shaping our perceptions and actions (Feldman & Friston, 2010). This precision weighting is driven by the needs of the model to reduce uncertainty and maintain coherence in its predictions. For example, in a noisy environment, the brain might down-weight less reliable auditory inputs and give more precision to visual data, thereby prioritizing the information that is most relevant for making accurate inferences about the world (H. Brown, Adams, Parees, Edwards, & Friston, 2013).

In the hierarchical model of active inference, moving precision upwards in the abstraction hierarchy corresponds to increasing the power of complex and global narratives. At higher levels of the hierarchy, the brain deals with increasingly abstract representations of sensory input. Depending on where precision is allocated, perception will be more dominated by less or more abstract phenomena (K. J. Friston & Kiebel, 2009). When precision is allocated to the highest level of this epistemically deep model there are global priors that summarize the totality of the inferential space, likely priors such as "I am", the most global priors a conscious agent engenders. Conversely, as we move precision downwards in this hierarchy, we shift the focus of the inferential process towards raw sensory data. This results in less abstract and less conceptual experiences. By prioritizing the moment-to-moment unfolding of sensory data without imposing abstract concepts or abstractions, we approach a state where experience is direct and immediate, unfiltered by higher cognitive processes (Laukkonen & Slagter, 2021).

We propose that MPE arises through a process where we initially shift precision almost entirely to the lowest level of the inferential hierarchy of abstraction, followed by a process of pacifying this low level processing, leading to an increase in epistemic depth which is the ability of the system to turn back in its own modeling process. Taken together, these steps allow for a state where there is low content (pacified sensory processing) together with deep epistemic grip (the ability to turn back towards the processing itself), the two conditions for MPE to arise. In this state, perception is under the smallest influence from higher-order abstractions. As a result, the experience is stripped of conceptual content and thought, focusing instead on the pure, unmediated flow of sensory information as it occurs. This downward shift of precision in the abstraction hierarchy could explain the characteristic simplicity and immediacy of MPE, making it a state of consciousness where the mind is fully immersed in the present moment without any overlay of temporally deep conceptual inferences (see, cf. Laukkonen & Chandaria, 2024).

3 The MPE Model

In this section, we introduce the basic mathematical formalism underlying Bayes' Theorem, the Free Energy Principle, and Active Inference. We then build on this formalism to account for the abstraction of phenomena across multiple layers of inference using Bayesian binding (Laukkonen & Chandaria, 2024). In a final section, we will then discuss the importance that Bayesian binding has on the emergence of MPEs.

We begin with the foundational idea of Bayesian inference, where an agent attempts to infer the hidden cause of sensory data (v) based on the sensory data (u) to which the agent has access. The optimal probabilistic solution for this inference can be expressed using Bayes' Theorem:

$$P(v \mid u) = \frac{P(u \mid v)\, P(v)}{\sum_{v_i} P(u \mid v_i)\, P(v_i)}$$

Here, $P(v \mid u)$ represents the posterior probability of the hidden cause v given the sensory data u, $P(u \mid v)$ is the likelihood of observing u given v, $P(v)$ is the prior probability of v, and the denominator represents the normalizing constant, which sums over all possible causes v_i.

However, in many real-world scenarios, the exact solution to this problem is intractable due to the computational complexity of the normalizing constant (Bishop, 2006; Dayan & Abbott, 2001). To address this, the Free Energy Principle, proposed by Karl Friston (K. Friston, 2010; K. Friston & Stephan, 2007), serves as a statistical approximation. The Free Energy Principle introduces a variational approach where the objective is to minimize a quantity called "free energy," which serves as an upper bound on the intractable negative log evidence (also known as "surprise"). This principle forms the basis for understanding how biological systems, including the brain, maintain a stable state by minimizing surprise or uncertainty about their environment (Clark, 2016; K. Friston et al., 2009).

By minimizing a quantity F called the free energy, we minimize the difference between the agent's internal model of the world, represented by an approximate posterior distribution $Q(v \mid u)$, and the true distribution of the causes, represented by the sensory evidence $P(u \mid v)$. This difference can be expressed using the Kullback-Leibler (KL) divergence, which measures the divergence between two probability distributions:

$$D_{KL}\left[Q(v \mid u) \parallel P(v \mid u)\right] = \mathbb{E}_Q\left[\ln \frac{Q(v \mid u)}{P(v \mid u)}\right]$$

Using this, the free energy F can be formulated as follows (Chandaria, 2023):

$$F = \mathbb{E}_Q\left[-\ln P(u \mid v)\right] + D_{KL}\left[Q(v \mid u) \parallel P(v)\right]$$

In this equation: F represents the free energy, $\mathbb{E}_Q\left[-\ln P(u \mid v)\right]$ is the expected negative log-likelihood, or "surprise," under the approximate posterior $Q(v \mid u)$, and $D_{KL}\left[Q(v \mid u) \parallel P(v)\right]$ is the KL divergence between the approximate posterior $Q(v \mid u)$ and the prior $P(v)$, representing the complexity cost or the divergence between the agent's beliefs and prior expectations.

The goal of the Free Energy Principle is to minimize F, which effectively minimizes both the prediction error (surprise) and the complexity of the model. By minimizing free energy, the agent's internal model becomes more accurate and efficient in predicting sensory data, thereby improving its ability to infer the hidden causes v that generate u. This framework is fundamental to understanding the emergence of MPEs as states characterized by low abstraction and high epistemic depth.

Active Inference extends this framework by incorporating action into the inferential process. The agent not only updates its internal models to minimize free energy but also selects actions that will minimize future free energy, thereby reducing uncertainty and optimizing perception and behavior (K. Friston, Daunizeau, Kilner, & Kiebel, 2010; K. Friston & Frith, 2015b). This dynamic interaction between perception and action allows the system to actively shape its sensory inputs in a way that aligns with its predictions (Allen & Friston, 2018; Pezzulo et al., 2015).

This process occurs within a hierarchical generative model, where multiple layers of abstraction interact to produce a coherent representation of the world. Each layer in the hierarchy is responsible for inferring causes at different levels of abstraction, from raw sensory data to complex conceptual representations (K. Friston, 2008; Hohwy, 2013). The generative model can be visualized as a nested hierarchy, where lower levels encode simple, immediate features of the environment, while higher levels encode more abstract, temporally extended structures.

3.1 Precision-Weighted Posterior Formula

A crucial component of this hierarchical model is precision weighting, which determines the relative influence of different sources of information—such as sensory data and prior beliefs—on the posterior distribution (Feldman & Friston, 2010; K. Friston, 2009). Precision, defined as the inverse of variance, represents the confidence or reliability of the data or predictions. Higher precision indicates greater certainty, while lower precision reflects greater uncertainty (Clark, 2016; Mathys, Daunizeau, Friston, & Stephan, 2011). By dynamically adjusting precision, the brain can prioritize certain inputs over others, effectively shaping the inferential process.

In the context of Bayesian inference, precision is used to weigh the relative contributions of the prior ($P(v)$) and the likelihood ($P(u \mid v)$) in forming the posterior distribution ($P(v \mid u)$). This precision-weighted approach allows the model to dynamically adjust the influence of the data and the prior based on their relative reliabilities.

In a hierarchical generative model, each layer performs Bayesian inference to update its posterior beliefs. In general, there is no closed form solution to the Bayesian inference problem, however, if all the probability distributions are assumed to be Gaussian there is a closed form solution to the posterior which is also Gaussian (i.e. the Laplace approximation) (Bishop, 2006; MacKay, 2003). In what follows we shall assume a uni-dimensional Gaussian approximation which allows us to have a closed form solution to the Bayesian inference problem. See figure 1 for a more detailed mathematical definition of this Laplace approximation.

Using the Laplace approximation, we can derive the posterior mean $\mu_{\text{posterior}}$ from a combination of the prior mean (μ_{prior}) and the data mean (μ_{data}), weighted by their respective precisions. The posterior precision (π_{post}) is the sum of the precisions of the prior (π_{prior}) and the data (π_{data}):

$$\pi_{\text{post}} = \pi_{\text{data}} + \pi_{\text{prior}}.$$

The posterior mean is then given by:

$$\mu_{\text{posterior}} = \left(\frac{\pi_{\text{data}}}{\pi_{\text{post}}}\right)\mu_{\text{data}} + \left(\frac{\pi_{\text{prior}}}{\pi_{\text{post}}}\right)\mu_{\text{prior}}.$$

This formula shows that the posterior mean is a weighted combination of the data and prior means, where the weights are determined by the relative precision of the data and the prior. This is crucial for understanding how the brain, or any Bayesian agent, balances new information with existing beliefs.

3.2 Bayesian Binding and Inference Across Layers

Laukkonen and Chandaria (2024) have introduced the term *Bayesian binding* to describe how Bayesian principles govern the integration of information across multiple sources and inferential levels of a hierarchical model into a unified posterior distribution. In a hierarchical generative model, each layer updates its posterior belief based on its own data and the posterior of the layer below. In this process, binding refers to the merging of multiple sources of information into a single posterior. This process

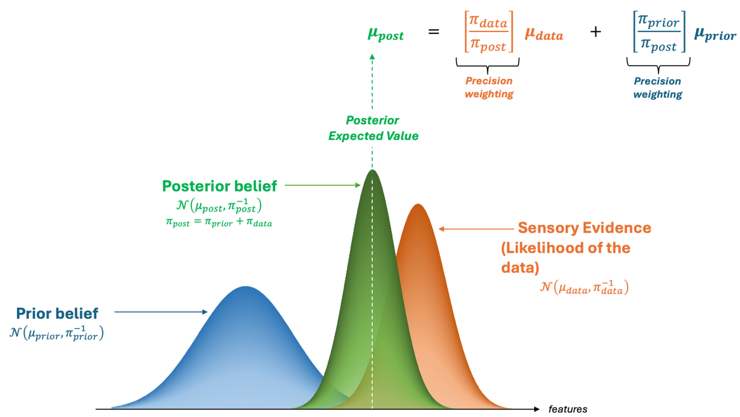

Figure 1: The diagram illustrates Bayesian updating using precision-weighted posterior estimation for univariate Gaussian distributions. In this context, the posterior mean μ_{post} is computed as a precision-weighted combination of the data mean μ_{data} and the prior mean μ_{prior}, given by $\mu_{\text{post}} = \left(\frac{\pi_{\text{data}}}{\pi_{\text{post}}}\right) \mu_{\text{data}} + \left(\frac{\pi_{\text{prior}}}{\pi_{\text{post}}}\right) \mu_{\text{prior}}$, where the posterior precision π_{post} is the sum of the data precision π_{data} and the prior precision π_{prior}, expressed as $\pi_{\text{post}} = \pi_{\text{prior}} + \pi_{\text{data}}$. In Bayesian inference, the precision-weighted approach allows the posterior to shift towards the distribution with higher precision (lower variance), reflecting greater reliability in the estimation. The Laplace approximation simplifies this process by approximating the true posterior with a Gaussian distribution $\mathcal{N}\left(\mu_{\text{post}}, \pi_{\text{post}}^{-1}\right)$, making it computationally feasible while maintaining the influence of precision in updating the posterior belief.

continues up the hierarchy, effectively binding together the information across all levels to form a coherent representation of self and world.

At each level l, the posterior mean is updated based on the precision-weighted combination of the incoming data and the prior:

$$\mu_{\text{posterior},l} = \left(\frac{\pi_{\text{data},l}}{\pi_{\text{post},l}}\right) \mu_{\text{data},l} + \left(\frac{\pi_{\text{prior},l}}{\pi_{\text{post},l}}\right) \mu_{\text{prior},l},$$

where:

- $\pi_{\text{data},l}$ is the precision of the data at level l,
- $\pi_{\text{prior},l}$ is the precision of the prior at level l,
- $\pi_{\text{post},l} = \pi_{\text{data},l} + \pi_{\text{prior},l}$ is the posterior precision at level l.

This precision-weighted binding across levels enables the system to dynamically adjust the influence of sensory data and prior beliefs, allowing for flexible inference across varying levels of abstraction.

3.3 Nesting of Bayesian Updates in Hierarchical Models

One of the key features of Bayesian inference in hierarchical models is the recursive nesting of Bayesian updates across layers. The posterior distribution computed at one layer becomes the prior for the next layer up in the hierarchy. This nesting process allows for the integration of information across different levels of abstraction, from raw sensory data at lower levels to more abstract concepts and representations at higher levels. In this abstraction hierarchy, lower layers provide immediate, less abstract sensory data, while higher layers involve complex, temporally extended inferences (K. Friston, 2008; K. J. Friston, Harrison, & Penny, 2003).

To illustrate this, consider the following nested structure of Bayesian updates:

$$\mu_{\text{posterior},l} = \left(\frac{\pi_{\text{data},l}}{\pi_{\text{post},l}}\right) \mu_{\text{data},l} + \left(\frac{\pi_{\text{prior},l}}{\pi_{\text{post},l}}\right) \mu_{\text{posterior},l-1},$$

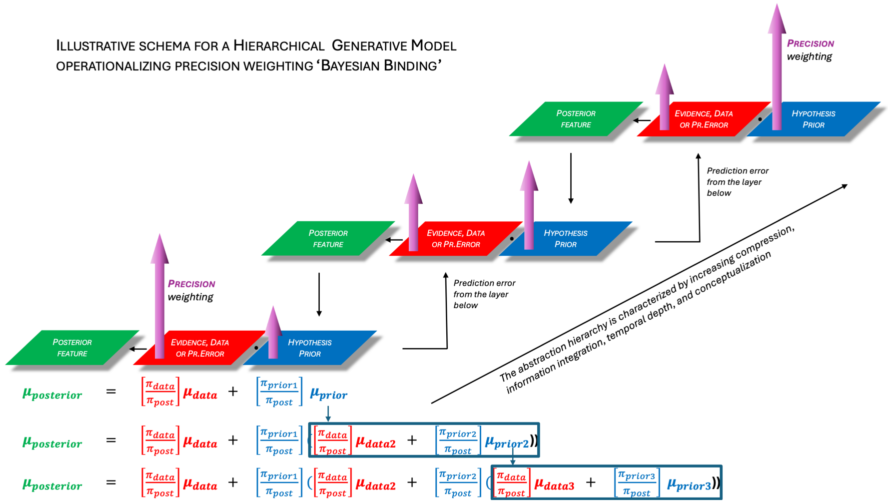

Figure 2: This figure illustrates the concept of precision-weighted 'Bayesian Binding' within a hierarchical generative model, showing how information is integrated across three layers of inference. At each level, the posterior belief ($\mu_{\text{posterior}}$) is updated based on a precision-weighted combination of the incoming data (μ_{data}) and the prior hypothesis (μ_{prior}), according to the formula $\mu_{\text{posterior}} = \left(\frac{\pi_{\text{data}}}{\pi_{\text{post}}}\right) \mu_{\text{data}} + \left(\frac{\pi_{\text{prior}}}{\pi_{\text{post}}}\right) \mu_{\text{prior}}$, where $\pi_{\text{post}} = \pi_{\text{data}} + \pi_{\text{prior}}$. The precision terms ($\pi_{\text{data}}$ and π_{prior}) determine the influence of new sensory evidence or prediction error versus prior beliefs. In this hierarchical structure, the prior (μ_{prior}) at one layer can be derived from the posterior of the layer above, recursively integrating information up the hierarchy. This process, depicted here up to three layers, allows for increasingly abstract and temporally extended inferences but can be expanded to represent more layers, supporting complex cognitive structures. The mathematical formalism shown in the lower section of the figure emphasizes the nesting structure of these updates, as precision-weighted Bayesian inference propagates across the model's layers, with each posterior serving as the prior for the next level. This is a simplistic example assuming a univariate Gaussian probability distribution, but is helpful in illustrating the telescoping and abstraction structure of hierarchical generative models in general.

where $\mu_{\text{posterior},l-1}$ is the posterior mean from the previous layer $l-1$, which now serves as the prior for the current layer l. This shows that the posterior at level l is a weighted combination of the new data at level l and the posterior from the previous layer $l-1$, modulated by their respective precisions.

This nesting can be expanded further:

$$\mu_{\text{posterior},l} = \left(\frac{\pi_{\text{data},l}}{\pi_{\text{post},l}}\right) \mu_{\text{data},l} + \left(\frac{\pi_{\text{prior},l}}{\pi_{\text{post},l}}\right) \left(\left(\frac{\pi_{\text{data},l-1}}{\pi_{\text{post},l-1}}\right) \mu_{\text{data},l-1} + \left(\frac{\pi_{\text{prior},l-1}}{\pi_{\text{post},l-1}}\right) \mu_{\text{posterior},l-2} \right).$$

This formula explicitly shows how the posterior mean at each layer is a function of not only its own data but also the nested structure of posteriors from all preceding layers, each weighted by their respective precision. Just to reiterate, this formula is purely illustrative to show the telescoping nature of hierarchical inference. The formula is intended to serve as an intuition pump, but is clearly not a solution to the free energy minimization problem in general. See figure 2 for a visual representation of this Bayesian binding mechanism.

The precision weighting at each layer determines the extent to which the posterior at that layer is influenced by new data or a priors (which are themselves posteriors from lower layers). This hierarchical structure allows for a flexible and context-sensitive integration of information. If the precision of the data ($\pi_{\text{data},l}$) at a particular layer is high, the posterior at that layer will be more heavily influenced by the new data at that layer, potentially overriding the influence of lower layers. If on the other hand the precision of the prior ($\pi_{\text{prior},l}$) is high, the posterior will rely more on the accumulated knowledge (posteriors) from lower layers, reflecting a reliance on deeper, more stable information.

This mechanism allows the model to dynamically allocate influence based on the reliability of the data and priors at each level. Higher precision at a particular layer means that layer's information will dominate the inference process, potentially filtering or overriding less precise information from other layers.

A shift of precision predominantly towards the lowest level of the inferential hierarchy leads to a a state dominated by minimally abstracted sensory experiences with minimal influence from higher-order conceptual models. This is a perceptual state of simplicity and immediacy where the mind is fully immersed in the present moment without the overlay of complex narratives about abstract concepts. It is this simple perceptual state that allows the mind to explore and discover the ground of perception through a process of self understanding (self modeling). This results in a reality model that is devoid of the usual content but remains recursively aware of itself (Laukkonen & Chandaria, 2024). The looping nature of the empty reality model perpetually knows its own absence of content, resulting in the phenomenology of luminous emptiness, or MPE.

3.4 Attention as a Mechanism for Modulating Precision

Attention serves as a crucial mechanism for dynamically modulating precision across different layers of the hierarchical generative model. By allocating attention to specific levels of the hierarchy, the brain can sample more accurate data and thereby increase the precision (π) of predictions or sensory data at those levels, thereby enhancing their influence on the overall inference process. When attention is directed toward a particular sensory input or cognitive representation, the precision of the corresponding data at that layer increases, leading to a greater weighting of this information in the Bayesian update. Conversely, when attention is withdrawn, the precision decreases, reducing the influence of that data on the posterior distribution. This attentional modulation allows for flexible and context-sensitive processing, enabling the brain to focus on relevant information while filtering out less pertinent details. In this way, attention can dynamically shift the balance between lower-level sensory evidence and higher-level priors, effectively controlling which layers dominate the inference process at any given moment. This dynamic adjustment is crucial for optimizing perception, decision-making, and behavior in complex and ever-changing environments (Feldman & Friston, 2010; Hohwy, 2012; Parr & Friston, 2019).

3.5 Hierarchically Nested Levels of Inference and Associated Phenomenology

In this paper, we treat perception as a hierarchical inference process, where each level of the hierarchy is associated with progressively more abstract representations of sensory data. Taylor, Hobbs, Burroni, and Siegelmann (2015) describe abstraction as "*a process of creating general concepts or representations by emphasizing common features from specific instances, where unified concepts are derived from literal, real, concrete, or tangible concepts, observations, or first principles, often with the goal of compressing the information content of a concept or an observable event, and retaining only information which is relevant for an individualized goal or action.*" This view suggests that higher levels of abstraction involve a greater degree of information compression, where detailed sensory information is transformed into more concise and generalized representations.

As such, we can associate each level of the hierarchically nested inference process to increasingly abstract and global representations of perceptual data. Although the exact number of layers, their correspondence to specific brain structures, and the definitive association between layers and phenomenology remain topics of ongoing research, we propose a preliminary illustrative distribution of these layers and the phenomenological experiences they may correspond to. We should reiterate that the following is purely a constructed example inspired by machine learning on 17,000 fMRI experiments to infer a cortical hierarchical structure of the brain (Taylor et al., 2015) together with various phenomenological descriptions (Metzinger, 2024). See figure 3 for a visual overview of these stages.

- **Level 1: Sensations** — At the most basic level, the system infers the mere presence of perceptual data. This layer represents a state of perceptual potentiality, where raw sensations are not yet formed into any distinct perceptual objects. Phenomenologically, this state may correspond to the least fabricated and least inferred state of experience.

- **Level 2: Perception of Sensations** — Moving one level up, the system begins to focus on the perception of individual sensations, particularly those that change and are most informative. This layer is characterized by the perception of a constant flux of experience and a constant quick stochastic movement of attention between different data, driven by their perceived relevance and importance. Phenomenologically, this level may be described as a vibration or energy. Here, the system detects dynamic, sensory inputs without yet assigning them any conceptual meaning.

- **Level 3: Initial Conceptualization** — At this level, the system begins to infer the smallest building blocks of perceptual experience, such as lines in vision, touch sensations in proprioception, individual tones in auditory processing, or specific smells in olfaction. Phenomenologically, this layer may correspond to experiences that are partially conceptual but devoid of complex meaning. Sensations are recognized as distinct percepts, but they remain isolated and not yet integrated into larger (e.g., multimodal) concepts.

- **Levels 3.1 to 3.X: Progressive Conceptual abstraction** — Within this intermediate range, multiple sub-layers of which each infers increasingly complex concepts may exist. Each of these layers is characterized by more conceptual abstraction associated to richer and more complex phenomenological experiences. Each sub-layer contributes to a more refined and abstract conceptual understanding of sensory inputs.

- **Level 4: Inference of Patterns of Meaning** — At this level, the system infers patterns of meaning from the conceptualized objects. This includes the inference of causal structures or intentions behind the perceptions, linking objects and events into coherent narratives or cause-effect relationships (e.g., the ball bounces from the tennis racket). Phenomenologically, this is where the experience of meaningful patterns, intentionality, and causality emerges.

- **Levels 4.1 to 4.X: Further Abstraction of Meaning** — Just as in Level 3, there may be additional sub-layers that represent inferences of more and more complex and abstract cognitive structures including linguistic categories. These layers are responsible for high-level conceptual and contextual understanding, where abstract ideas, beliefs, and expectations are formed.

- **Level 5: Inference of a Unified Self** — At the highest level of this hierarchy, the system synthesizes the multitude of experiences into the concept of a narrative, temporally extended, sense of self. This level represents the integration of all lower-level inferences into a coherent sense of unification.

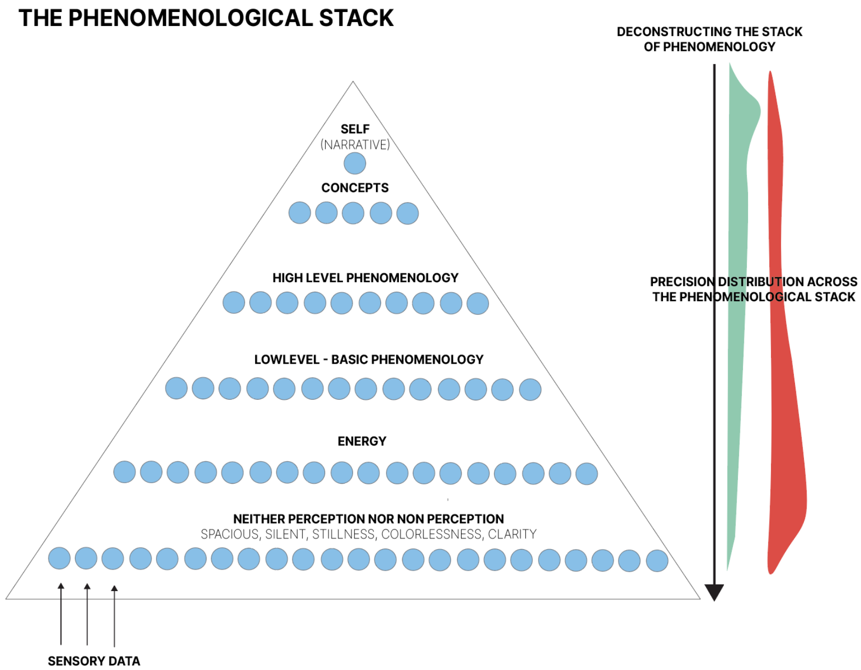

Figure 3: This figure presents an illustrative hierarchy of nested perceptual inferences, where each layer corresponds to distinct features of the phenomenal experience, ranging from basic sensory data to the narrative sense of self. The dominance of a particular phenomenology in conscious experience is determined by the precision distribution across these layers, as represented by the red and green distributions on the right. A higher precision in a specific layer means that the brain assigns greater confidence to the inferences made at that level, thus bringing its associated phenomenology to the foreground of experience. This illustration serves as a conceptual framework for understanding how different levels of abstraction and precision weighting shape the overall structure of conscious experience. (cf. Taylor et al., 2015)

3.6 Sociocultural Bias Toward Higher Levels of Abstraction

Through socialization, individuals are often conditioned to prioritize attention on the more abstract layers of this hierarchy, particularly the inference of patterns of meaning and the unified sense of a narrative self (Foucault, 1982; Vygotsky, 1978). Socioculturally, it is advantageous to develop and maintain strong inferences at these higher levels, as they facilitate complex social interactions, narrative construction, and identity formation . This bias manifests as a tendency to allocate more precision (and thus attention) to these abstract levels, ensuring that the inferences of meaning and self are realized with the greatest accuracy and lowest free energy.

However, this prioritization comes at a cost. By focusing heavily on the higher layers of abstraction, precision (and attention) is often drawn away from the lower, more fundamental layers of experience, such as the raw, pre-conceptual sensations and the dynamic flux of sensory data. As a result, the free energy associated with these lower levels may be less efficiently minimized, leading to a potential disconnect between abstract inferences and the concrete sensory experiences upon which they are built.

This sociocultural bias toward higher-level abstractions may also contribute to certain psychological phenomena, such as the feeling of being disconnected from the present moment or the inability to fully engage with the raw, unmediated flow of experience (K. W. Brown & Ryan, 2003; Metzinger, 2003). By understanding this hierarchical structure and the influence of sociocultural factors on precision weighting, we can begin to explore how attention can be more evenly distributed across the hierarchy (i.e., using techniques such as meditation), potentially leading to a more balanced and integrated experience of reality (Lutz, Dunne, & Davidson, 2007; Tang, Hölzel, & Posner, 2015).

3.7 MPE and the Hierarchy of Inference

Each layer of the phenomenological stack is associated with distinct phenomenologies. For our case of better understanding MPEs, level 1—the layer of least abstraction and fabrication—is of most interest. At this foundational level, the system infers only the mere presence of perceptual data without assigning any specific meaning, structure, or categorization. This layer represents a state of perceptual potentiality, where raw sensations have not yet been formed into distinct perceptual objects or integrated into a coherent sense of the world. As such, perceptual states that are dominated by this layers have no conceptual content but are mere experiences of the potentiality of perceiving. The inherent inferential drive of the cognitive system is temporarily paused, allowing to perceive this pre-conceptual state. It is this state of reduced hierarchical depth that allows the cognitive system to model (and thus perceive) the very process of modelling (or perception), which is a state of high epistemic depth. It is this combination of low hierarchical depth and high epistemic depth that brings forth an experience of MPE.

In addition to the low hierarchical depth that we have discussed and modelled at length in the previous section, MPEs furthermore require high epistemic depth that provides a rich and reflexive quality to the experience, even as the abstraction level remains minimal (Laukkonen & Chandaria, 2024). This means that the system is not only minimally engaged in conceptual processing but is also highly aware of the simplicity and transparency of its own reality model. Specifically, Laukkonen and Chandaria (2024) propose that in MPEs, the reality model becomes so minimal that the recursive process of self-monitoring, or reflexivity, becomes the dominant input, leading to an experience of "awareness of awareness" itself.

In this state, consciousness is reduced to its most basic elements—where awareness itself becomes a state of pure, contentless being. This aligns with the view that MPEs are a unique forms of consciousness, devoid of any self-referential or narrative content, time, or spatial self-location (Metzinger, 2024). Instead, MPEs are a luminous and non-dual awareness, where the usual 'grabbiness' or representational content of sensory experiences is minimized. This allows for a direct, unmediated experience of the 'suchness' or 'is-ness' of reality.

Laukkonen and Chandaria 2024 further elaborate that this recursive reflexivity in MPEs can be thought of as a "beautiful loop," where the system is perpetually engaged in a high-precision knowing of its own simple state. This high epistemic depth, combined with low abstraction, results in a unique phenomenological character that is both transparent and highly aware. In other words, while the system is minimally engaged with external sensory data or conceptual thought, it is simultaneously maximally aware of the simplicity of its own state.

In such a state, any phenomenal content that does arise is fleeting, unstructured, and lacks the depth and stability associated with higher layers of inference. There is no "binding" of sensory features into coherent objects, no inference of causality, and no integration into narrative structures. Instead, what is experienced is the raw "suchness" or "is-ness" of sensory data, where the mind remains fully open to the present moment, unencumbered by concepts, categories, or judgments. This state is closely aligned with descriptions of advanced meditative states—such as certain forms of Jhana, Zen, or Vipassana meditation—where practitioners report a dissolution of the self and a direct, non-conceptual experience of being (Goldstein, 2013; Kapleau, 1989; Shankman, 2008; Suzuki, 1970; Thera, 1972; Wallace, 1999).

3.8 Entropy and the Hierarchy of Inference

Contemplative practices and psychedelic states have previously been associated alterations in the entropy rate—a measure of randomness or disorder—of Nero-physiological measures (Carhart-Harris et al., 2014; Kumar, Sharma, Ramakrishnan, & Adarsh, 2021; Vivot, Pallavicini, Zamberlan, Vigo, & Tagliazucchi, 2020). Robin Carhart-Harris (2018; 2014) even proposed the Entropic Brain Hypothesis, stating that the level of entropy in brain activity can explain different states of consciousness, with low entropy linked to more structured, goal-directed states and high entropy linked to altered, flexible, and more chaotic states. The Entropic Brain Hypothesis furthermore emphasizes the importance of maintaining a balance between order and disorder in brain activity, suggesting that increased entropy through altered states (e.g., via psychedelics) could have therapeutic benefits for mental health conditions associated with excessively rigid thought patterns (Carhart-Harris, 2018; Carhart-Harris & Friston, 2019; Carhart-Harris et al., 2014). Inspired by this work, we wish to use a theoretical neuro-biological approach to investigate the relationship between MPEs and entropy rates.

As we move up the hierarchy, from raw sensory data at lower levels to more abstract concepts at higher levels, the process of abstraction acts to compress information. This compression reduces the complexity of the representation, effectively reducing the amount of information that needs to be processed (Chater & Vitányi, 2003). This idea aligns with the concept of Kolmogorov Complexity, which measures the complexity of a data stream based on the length of the shortest computer program that can reproduce it on a universal Turing machine. Data that is highly compressible—meaning it can be represented by a shorter program—has lower entropy. Conversely, data that is less compressible, requiring a longer program for its reproduction, has higher entropy. (Cover & Thomas, 2006)

In the context of the hierarchical generative model, Level 1 (which is central to cultivating MPEs) is the layer with the least abstraction and thus the least compression of information. At this level, the system processes raw, unfiltered sensory data, which is characterized by high variability and temporal volatility. Because this level represents data that has not yet undergone significant compression or transformation into higher-order representations, it corresponds to higher Kolmogorov Complexity. The data at this level is closer to its original form, which means that it requires a longer descriptive program and thus exhibits higher entropy.

Kolmogorov Complexity, as an information-theoretic measure, is closely related to entropy, particularly in terms of Shannon entropy under specific conditions (Cover & Thomas, 2006). Higher levels in the hierarchy, which involve more abstraction and compression, are associated with a lower Kolmogorov complexity because the information is summarized and compressed. This results in a shorter description length and, therefore, lower entropy. Conversely, lower levels with less compression—like Level 1—require a longer description length due to the raw, unaggregated nature of the sensory data. This is what gives rise to higher entropy.

Another way to understand the relation between these levels of inference and entropy is the varying temporal scales across these layers. Entropy is dependent on the predictability or unpredictability of how data streams unfold over time. At lower levels of abstraction, where temporal scales are faster and there is reduced temporal depth, there is greater temporal variation. This rapid fluctuation leads to a higher rate of entropy. In contrast, at higher levels of the hierarchy, where representations are more abstract and temporally extended, changes occur more slowly, leading to lower entropy rates. As noted by Karl Friston and others, temporal depth in the abstraction hierarchy is a crucial factor in determining the rate of change and, consequently, the entropy of the system (K. Friston, 2008; Murray et al., 2014).

This change in entropy across different levels of abstraction can be empirically measured. We propose that entropy rates—note that we are not strongly attached to a specific measure of entropy—could serve as empirical markers for the level of abstraction in the inferential hierarchy. While our argument here is based on theoretical assumptions, it would be valuable to simulate a hierarchical generative model and test how different layers of abstraction generate data with different entropy rates. Such simulations could use real-world data, such as time-series data from visual or auditory modalities to infer some underlying meaning. It would be important to find a hierarchical generative model that allows to extract the predictions made at each hierarchical level to then apply an entropy measure to each such layer. Based on our theoretical model above, we would suggest that the entropy rate would become smaller, the higher up this inferential hierarchy we go.

In conclusion, Level 1 in the hierarchy of inference is characterized by minimal abstraction and maximal raw sensory input, leading to high entropy due to low information compression. Perceptual states that are dominated by inferences on this lowest level are minimally conceptual and where information is rich, unfiltered, and dynamically fluctuating. This low hierarchical depth allows to increase epistemic depth, the ability of the system to model it's own modeling, which gives rise to the phenomenology of MPEs as described by Metzinger (2024). Understanding this relationship between entropy, abstraction, and phenomenology provides a theoretical foundation for future research into the neural and cognitive correlates of minimal states of consciousness.

3.9 Navigating the Depths of the Abstraction Hierarchy

While this paper focuses on the abstraction hierarchy as a model for MPEs, we acknowledge that MPEs may arise from various mechanisms and models. Our model is one contribution among many, and we do not claim it should reduce all other approaches. Lowering abstraction levels is likely necessary for MPEs, but not sufficient. Above, we have already introduced the importance of epistemic depth as another central mechanisms that is necessary for the rising of MPEs (Laukkonen & Chandaria, 2024).

Reducing conceptual depth leads to a state of minimal conceptual thickness and high entropy, enabling the perception of raw sensory data and even the modeling process itself. This deconstruction toward the core of experience (MPE) reveals a space where information simply rises and falls. Achieving this is not straightforward; it requires methodical effort to transcend the layers of abstraction we are typically anchored to. The reason we tend to ignore early processing stages is because the predictive brain is optimizing its energy expenditure by working primarily with predictions on the middle and upper levels where predictions are about things in the world that are relevant for life maintenance. Producing and being moved by predictions on the middle and upper levels results in good enough adaptivity, rendering further metabolic investment on the perception of lower level predictions pointless

The process involves investigating each abstraction layer until the practitioner is able to notice the sensory data that is driving the inferneces at a given layer. Once this is achieved, the practitioner can now observe that data to notice once again that this data is itself an inference of even more low level data. Moving down the hierarchy means to investigate each layer with such precision that one can notice and observe this inferential process. This is a recursive process for each layer, one at a time, until one reaches the earliest stages of conscious processing. Although the data becomes more uncertain as abstraction decreases, it also becomes more universal and fundamental.

This transformation involves systematically modeling and transcending each layer, ultimately reaching the earliest processing stages of consciousness that we have access to (Metzinger suggests that this may be tonic-wakefulness). In this state, we are both ultra-uncertain as a system, due to high entropy, and ultra-certain as an agent, as our awareness moves toward more fundamental consciousness structures. Fundamental here means deep in the generative hierarchy and therefore the slowest ot change and the most universal (Hohwy, 2013). The high certainty is that we now observe an object that is relatively "unchanging", the unpredictability of the lowest inferential mechanisms in the cognitive hierarchy is now becoming highly predictable. It is this union of high and low certainty that captures the inherent quality of MPEs. Thus, the value of MPEs is not in simply residing in deconstructed states but in recognizing the universal potentiality of experience and thereby providing a "refuge" of relative stability and tranquility. This potentiality, inherent to all phenomena, transcends most abstract or conceptual experience, offering a profound understanding of some of the basic constructing features that produce conscious experience, and so deep insight in the nature of our own (predictively created) reality.

4 In Silico Simulation of Precision Distribution and Entropy

Building on the theoretical framework of hierarchical inference and entropy discussed earlier, we propose an in silico simulation to explore how shifts in precision across different levels of the hierarchical model influence entropy rates in perceptual processing. This simulation tests the hypothesis that increasing precision at lower, sensory-driven levels results in higher entropy rates, indicative of less abstract and more dynamically variable perceptual states, akin to MPEs.

4.1 Model Setup

The simulation leverages a hierarchical generative model of perception within the active inference framework, where each level l of the hierarchy represents a different degree of abstraction and information compression. Lower levels correspond to raw, unprocessed sensory data, while higher levels encode progressively more abstract representations. Each level performs Bayesian inference to update its beliefs based on bottom-up sensory data and top-down predictions.

To simulate how precision allocation affects entropy, we model the interaction between levels as a dynamic system where precision (π) is adjusted across time and levels. Specifically, we use the same precision-weighted posterior formula introduced in the Bayesian telescoping section:

$$\mu_{\text{posterior},l} = \left(\frac{\pi_{\text{data},l}}{\pi_{\text{post},l}}\right)\mu_{\text{data},l} + \left(\frac{\pi_{\text{prior},l}}{\pi_{\text{post},l}}\right)\mu_{\text{posterior},l-1},$$

where:

- $\pi_{\text{post},l} = \pi_{\text{data},l} + \pi_{\text{prior},l}$ is the posterior precision at level l,

- $\mu_{\text{posterior},l-1}$ is the posterior mean from the previous layer $l-1$, which now serves as the prior for the current layer l.

By varying the precision values ($\pi_{\text{data},l}$ and $\pi_{\text{prior},l}$) across levels, the simulation can model different scenarios where precision shifts predominantly toward lower or higher levels, reflecting different cognitive and perceptual states.

4.2 Simulating Entropy and Synthetic EEG Data

To empirically validate the model, synthetic EEG data can be simulated using the hierarchical generative model under different precision distributions. The dynamics at each level of the hierarchy are modeled using the same Bayesian update rules described above, which represent the evolution of hidden states over time, influenced by both sensory inputs and higher-level predictions. The underlying assumption is that the same mechanism approximates the working of the brain. Therefore, deriving time series of the posterior distributions serves as a proxy for EEG time series.

The simulated EEG signal $y(t)$ is constructed as a combination of these hidden states across levels:

$$y(t) = \sum_{l=1}^{L} h_l(\mu_{\text{posterior},l}(t)) + \epsilon(t),$$

where $h_l(\mu_{\text{posterior},l}(t))$ represents the contribution of each level's posterior mean to the EEG signal and $\epsilon(t)$ accounts for noise. By applying entropy measures, such as Shannon entropy or Kolmogorov complexity, to these synthetic EEG signals, we can assess how shifts in precision affect the entropy rates of the system.

4.3 Expected Outcomes and Hypothesis Testing

The key hypothesis is that increasing precision at lower levels (e.g., those associated with raw sensory data) will lead to higher entropy rates in the simulated EEG data. This outcome would reflect a perceptual state dominated by rapid, less predictable fluctuations, consistent with the characteristics of MPEs where experience is minimally structured and conceptually unbound.

As precision is shifted toward lower levels, the entropy of the system is expected to increase due to greater variability and less stable representations. Conversely, precision shifts toward higher levels should result in lower entropy rates, indicative of more stable and abstract representations.

4.4 Linking Simulation Outcomes to Minimal Phenomenal Experiences (MPE)

The proposed simulation offers a computational basis for understanding the relation of entropy and pure awareness, states where the precision of inferential processes is weighted heavily towards lower, less abstract layers of the hierarchy. As argued earlier, the dominance of lower-level inferences in the hierarchy of perception, characterized by a lack of stable, higher-order cognitive structures and a focus on the immediate, unprocessed flow of sensory information, together with high epistemic depth, is what gives rise to experiences of MPE.

By generating synthetic EEG data that mirrors these theoretical predictions, the simulation provides a valuable tool to empirically test our theoretical model and empirical hypothesis. If (A) the simulations indeed show that precision shifts towards less fabricated inferential hierarchies correlate with an increase in the entropy rate and (B) we furthermore find that subjects experiencing MPEs also show higher entropy rates as measured by EEG, then taken together, this would provide good evidence that entropy is indeed a good and reliable marker to measure MPEs.

5 Preliminary Empirical Evidence

The theoretical framework and simulations discussed above provide testable hypotheses regarding the relationship between precision distribution in the inferential hierarchy and entropy rates as measured by EEG. Specifically, if the model's predictions are accurate, we would expect EEG measures of subjects experiencing MPEs to demonstrate higher rates of entropy compared to non-MPE states. In addition to preliminary findings of our own empirical work, there is a convincing amount of literature published on the relationship between meditation and entropy that supports our hypothesis.

A recent review by Atad, Mediano, Rosas, and Berkovich-Ohana (2023) concluded that overall, meditation tends to lead to increased measures of complexity during meditative states when compared to waking rest or mind-wandering, and decreased baseline complexity as a trait following regular meditation practice. It is, of course, not the case that all meditative states are equivalent to MPEs. However, we believe that it is a fair assumption to make that meditative states in general tend to be more similar to MPEs than waking rest or mind-wandering. While this review has found a general trend that meditative states yield higher rates of complexity (i.e., entropy), it is important to note that not all 13 studies that are included in this review confirm this trend. Amongst these 13 studies, only four found an increase in complexity in all applied measures (Do et al., 2023; Kakumanu et al., 2018; Kumar et al., 2021; Lu & Rodriguez-Larios, 2022). Another four studies found both increased and decreased measures of complexity depending on the type of meditaiotn, the measure of entropy, or the frequency band that the measure is applied to (D'Andrea et al., 2024; Irrmischer et al., 2018; Vyšata et al., 2014; Walter & Hinterberger, 2022). And another four studies found a decrease of entropy measures (Aftanas & Golocheikine, 2002; Davis, Kozma, & Schübeler, 2023; Sik et al., 2017; Young, Arterberry, & Martin, 2021).

However, among the diverging results, Atad et al. (2023) conducted further classification to better understand the underlying trends. Overall, their review found a clear trend of increased entropy—a measure of neural complexity—during meditative states, especially among experienced meditators. This supports the idea that meditation, particularly with prolonged practice, leads to a more dynamic and rich neural environment compared to waking rest or mind-wandering. In long-term meditators, the relaxation of cognitive control and the reduction of higher-order cognitive processes during meditation allows for more bottom-up sensory information to flow, leading to higher unpredictability and greater neural variability.

At the same time, reductions in entropy were found in studies with novice meditators or during certain types of meditation that prioritize cognitive control or focused attention, rather than open awareness. For instance, focused attention meditations, particularly in less experienced practitioners, can lead to lower entropy due to increased control over thoughts and attentional focus, which creates more structured and predictable neural activity. Mediators with little experience may still be developing their practice and therefore show more cognitive effort or "trying". Additionally, some of the studies that found reduced entropy, such as those by Aftanas and Golocheikine (2002) and Sik et al. (2017), focused on specific meditation styles, like Sahaja Yoga, which involves highly structued and stable states and thereby may reduce the richness of sensory input and neural variability, which contrasts with more open and less directive practices like mindfulness or open monitoring.

The review also highlights that preprocessing methods, meditation styles, and measurement techniques (e.g., EEG band frequencies or entropy measures used) could influence outcomes. Complexity measures like fractal dimension and long-range temporal correlations capture different aspects of neural dynamics, explaining why some studies observed mixed or opposite trends depending on the measures applied.

Ultimately, while there are context-dependent reductions in entropy, these results do not detract from the broader trend of increased neural complexity during meditation, especially in experienced practitioners. Rather, they underscore the diversity in meditation experiences, showing that the neural effects of meditation vary based on meditation style, experience level, and methodology, with more advanced practices consistently leading to increased entropy and neural dynamism.

We, the authors, also have some ongoing empirical work with advanced meditators, and preliminary analysis suggests that the depth of meditation states positively correlates with entropy rates. These preliminary empirical findings lend support to the mathematical model and the resulting simulations outlined above. The observed increase in entropy rates during deep meditation states suggests that MPEs are indeed characterized by higher entropy, consistent with the idea that these states involve a shift in precision weighting towards lower levels of the inferential hierarchy. These findings provide a promising foundation for further research, suggesting that advanced meditative practices can serve as a valuable model for studying MPEs and the underlying neural mechanisms that give rise to these minimal states of consciousness. However, more empirical work is required to validate the hypothesis that MPE is characterized by high rates of entropy across a wider range of MPE states.

6 Discussion and Implications

6.1 Theoretical Implications

In this article we propose a computational model that links precision-weighting across hierarchical inferential levels to the phenomenology of pure awareness. We offer a novel explanation for how these minimal states of consciousness might arise. Specifically, the model suggests that MPEs result after the hierarchical depth of perception is reduced through a process of shifting precision to the levels lower in the inference hierarchy. This reduction of the hierarchical depth in combination with an increase in epistemic depth is central to the phenomenology of MPEs.

Previously, MPE has been presented as a form of meta-cognitive awareness—a layer of consciousness more abstract and removed from ordinary experience (Lutz, Jha, Dunne, & Saron, 2015; Sandved-Smith et al., 2021; Sandved-Smith & Metzinger, 2024). In that case, MPEs were associated with the higher end of the inferential hierarchy, where abstract and reflective processes dominate. However, our model challenges this view by positioning MPEs at the low end of the inferential hierarchy, closer to raw sense perception and further away from meta-cognitive layers. This re-conceptualization of MPE as grounded in the immediate, pre-conceptual processing of sensory data offers a fresh perspective on the generation of these minimal states of consciousness, emphasizing their simplicity and immediacy rather than abstraction and reflection. Importantly, our notion of high epistemic depth is not an abstract metacognitive model, rather, epistemic depth is an awareness of perception that is present in all levels of the inferential hierarchy, but may only be noticed once the inferential hierarchy is stripped to its minimal form by reducing hierarchical depth.

Furthermore, the integration of active inference principles with hierarchical Bayesian models provides a unified framework for understanding the dynamic interplay between precision, attention, and consciousness. This framework not only accounts for the emergence of MPEs but also offers a potential mechanistic explanation for other altered states of consciousness, including those induced by meditation, psychedelics, or certain psychiatric conditions. By shifting the focus to lower-level inferential processes, our model opens new avenues for exploring how consciousness can be modulated across different contexts and practices, shedding light on the fundamental mechanisms that underlie both ordinary and altered states of consciousness.

6.2 Future Directions

Future research could explore the application of this model to other forms of MPEs, such as those experienced during NREM sleep, deep relaxation, or even certain drug-induced states. Additionally, further refinement of the model could involve incorporating more sophisticated neurophysiological correlates, such as connectivity patterns in specific brain networks or the role of neurotransmitter systems in modulating precision. Another promising direction would be to investigate the temporal dynamics of precision-shifting in real-time using neuroimaging techniques, such as fMRI or MEG, combined with advanced computational modeling. This could help to empirically validate the model and provide deeper insights into the mechanisms underlying MPEs and other altered states of consciousness.

7 Conclusion

This paper has introduced a computational model that explores the relationship between precision weighting in a hierarchical inferential framework and the phenomenology of MPEs. By integrating principles of active inference and Bayesian models, we proposed that MPEs are characterized by a significant reallocation of precision towards the lower levels of the inferential hierarchy (i.e., low hierarchical depth) together with an increase in epistemic depth. In combination, the low hierarchical depth and high epistemic depth manifest as a form of pure awareness or 'awareness of awareness,' devoid of the usual conceptual and self-referential content. The proposed model aligns well with empirical findings in advanced meditative practices where practitioners often report experiences consistent with MPEs. Preliminary empirical evidence from our research team, empirical work by others in the field, and our theoretical work support that these states are associated with increased entropy rates, supporting the hypothesis that MPEs involve less constrained, more dynamically variable brain states.

8 Ethical Statement

This study considers ethical issues related to both human participants and the use of sophisticated computational models. Some of this work relies on empirical work with advanced meditators and their wellbeing was considered by ensuring that participation in all studies was voluntary and, as far as we can tell based on the research publications of other research groups, no mediator was asked to engage in practices beyond their existing expertise and comfort.

The computational models used in this study are sophisticated simulations designed to explore theoretical aspects of perception and consciousness. They do not generate or replicate conscious experiences and are strictly limited to mathematical representations of specific cognitive processes. Consequently, we belief that the current models cannot experience suffering or well-being, thus mitigating the risk of any ethical concerns related to sentient AI. However, while we believe that the current models are not yet complex enough to give rise to sentience, we do acknowledge the possibility that even more complex models may be able to do so (see, cf. Laukkonen & Chandaria, 2024)

More generally, we acknowledge the broader ethical implications of using computational models to simulate aspects of consciousness. While this research aims to enhance our understanding of minimal phenomenal experiences and has no direct application to creating sentient AI, it is crucial to remain vigilant about how such findings might be interpreted or applied in the future. To prevent potential misuse, we commit to transparent and responsible dissemination of our results, ensuring that they are contextualized within their theoretical framework and limitations.

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