Controlled Hallucinations and Precision Weighting: Predictive Coding as a Computational Framework for Visual Consciousness

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Abstract. This article explores the mechanisms underlying visual consciousness using the predictive coding (PC) theory as a framework. PC theory posits that the brain is a hierarchical hypothesis-testing system that actively constructs visual perceptions, often referred to as "controlled hallucinations," by continuously comparing top-down predictions with bottom-up sensory inputs to generate and minimize prediction errors. Consciousness corresponds to a generative model state in which prediction errors are fully minimized. Existing neuroscience research provides extensive experimental support for this theory. For example, studies have demonstrated, through unconscious neural decoding, that predictive processing can occur even without visual information entering consciousness. Other studies have found that even in the absence of attention, the brain automatically generates early electrophysiological responses associated with expectation violations, suggesting the automatic nature of prediction error generation. Furthermore, the dissociation of neural oscillations of different frequencies in conveying prediction and prediction error signals provides mechanistic evidence for intercortical information exchange. These findings suggest that conscious content corresponds to a generative model state in which prediction errors are minimized. However, this theory still faces significant challenges, including unclear biological implementation mechanisms and the risk of conceptual circularity. Finally, future research needs to develop computational models that are closer to biological reality, combine TMS intervention on specific brain areas, and use Electroencephalography and Functional Magnetic Resonance Imaging recordings simultaneously to deepen the understanding of visual consciousness.

Keywords: Predictive coding, visual consciousness, precision weighting, prediction error.

1. Introduction

Visual perception is the primary means by which humans understand the world. How visual consciousness, the subjective experience of "seeing," arises from brain activity is a crucial question spanning philosophy, psychology, and neuroscience. This exploration not only holds profound theoretical significance but is also deeply relevant to human life and health. Common visual illusions in everyday life, such as the perceptual reversal of ambiguous figures, and even clinical pathological hallucinations, such as those seen in schizophrenia, all point directly to the constructed nature of the visual system. The world people perceive is not a precise copy of reality, but rather the brain's most likely interpretation [1]. From a macro and historical perspective, after Helmholtz proposed the concept of "unconscious inference" in 1990, the view that vision is a passive process gradually declined. Gestalt psychology further emphasized the active nature of perceptual organization [2]. With the rise of cognitive science and neuroscience, research has moved to a micro and empirical level, with researchers began searching for the neural correlates of consciousness (NCCs). The predictive coding (PC) theory integrates these views, arguing that the brain does not passively receive information but rather predicts external input. This view has developed into a highly influential computational framework that provides a unifying principle for explaining visual consciousness [3].

Although Bastos et al. discovered frequency-separated features of feedforward and feedback information flows, most studies have failed to elucidate the specific biological mechanisms by which prediction errors are transmitted across different neural network layers [4]. Computational research by Whittington and Bogacz further suggests that standard PC models differ significantly from the actual operation of biological neural networks, and that the global error propagation mechanisms they

rely on lack anatomical evidence in the brain [5]. Therefore, this article aims to systematically review and evaluate the role of predictive coding (PC) theory in explaining visual consciousness, the evidence, and the challenges it faces.

2. Core Concepts

PC is a theoretical model of brain function based on Bayesian inference. Its core concept is that the brain is essentially a hierarchical hypothesis-testing system. Perception is not a passive process of stimulus reception, but an active, unconscious hypothesis-testing activity [3]. In this framework, a generative model exists within the higher cortex of the brain. Based on past experience and current context, the higher cortex generates top-down predictions about the causes of current sensory input [6]. These are not vague "expectations" but rather specific and precise forecasts about the sensory signals themselves. Meanwhile, sensory organs continuously receive raw sensory data signals from the bottom up. At each brain level, a comparison process occurs, where sensory input from lower levels meets predictions from higher levels. The difference between the two is calculated as a prediction error—the deviation between the current input and the brain's expectations [7]. This prediction error signal does not represent the actual state of the external world, but rather the degree to which the internal model of the world is biased [8]. The brain's ultimate goal is to minimize these long-term prediction errors by continually adjusting its internal models [9].

This ultimately results in visual perception not being a faithful reproduction of the retinal image, but rather a controlled hallucination constructed by the brain based on its most likely predictions [3]. When predictions closely match the input, prediction error is minimized, and perception tends to be stable. However, when significant errors occur, such as in the case of unexpected or ambiguous stimuli, error signals are transmitted upward, forcing higher-level brain networks to update their predictions, thereby triggering changes in perceptual content. This ongoing cycle of prediction, comparison, and update forms the computational foundation of all visual consciousness [9].

Visual consciousness refers to an individual's subjective experience and qualia of visual stimuli [10]. It transcends the physiological process of seeing—the encoding and transmission of visual information across the retina, lateral geniculate nucleus (LGN), and primary visual cortex (V1)—to the psychological state of awareness. This is the behavioral basis for individuals to report, reflect on, and act upon visual content [11]. Furthermore, stable visual consciousness corresponds to a generative model whose prediction error has been minimized [12]. When this model can interpret incoming sensory signals with high confidence, its predictions enter consciousness. Therefore, consciousness is not a specific signal but rather a state of reasoning in which the model and evidence are highly consistent. This also explains why, even in dream states where sensory input is absent or highly ambiguous, individuals can still experience strong conscious experiences due to the dominance of top-down predictions [13].

Furthermore, precision weighting describes the confidence and strategy of an individual's reasoning. It serves as a critical bridge between PC and cognitive functions such as attention [14]. In Bayesian statistics, precision is the inverse of variance and represents the reliability of a signal or estimate. High precision implies low noise and high confidence [15]. At the neural level, both prediction signals and prediction error signals are assigned precision weights. But the brain does not treat all predictions and all sensory errors equally. Instead, the brain estimates the reliability of different signal sources in the current context and weights them accordingly [16]. In this framework attention which can be refers to the optimal allocation of prediction error precision. For example, when individuals focusing on a stimulus, the brain prioritizes processing the error signal from that stimulus [17]. In Nobre & van Ede study, participants engaged in visual stimulation activated relevant neural modulation, thereby enhancing accuracy in a visual task which is slant discrimination task [18]. When individuals direct their attention into a spatial location or feature, this neural computationally upregulates the precision of the prediction error signal from that channel [19]. This means that these attended error signals are given a higher weight in the error minimization process. And resulting in

the brain assigning them greater importance and prioritizing them for updating prediction. Conversely, ignoring irrelevant stimuli is equivalent to downregulating the precision of their error signals, preventing them from interfering with current internal models, such as regulation of daily habits [17]. Furthermore, precision weighting plays a decisive role in perceptual competition. During binocular rivalry, the brain will temporarily increases the precision of the input signal from one eye, than allowing the prediction error of that eye to dominate the perceptual state, thereby suppressing the input signal from the other eye and leading to awareness of only one image [19]. Therefore, the precision weighting mechanism not only can determines what an individual will see, but also determines which information enters the individual's conscious field of vision [20].

3. Literature review

3.1. Electroencephalography (EEG) Evidence of Illusions in Predictive Coding

In Baker study, researchers employed a continuous flicker suppression paradigm [21]. This paradigm can present a dynamic Mondrian noise pattern to the dominant eye and a low-contrast static Gabor spot to the non-dominant eye. This approach successfully created an experimental condition in which the stimulus was physically present but completely invisible. Seventeen sighted participants performed a passive viewing task during this process and were required to immediately report any stimulus trace that broke suppression, to ensuring that subsequent EEG data analysis came from trials in which the stimulus was completely invisible. By using multivariate pattern analysis, researchers find a common neural decoding method, the study first trained a linear support vector machine decoder to distinguish EEG patterns between left and right eye stimuli under the visible stimulus conditions. The trained decoder was then applied to trials in which the stimulus was invisible. Results showed that the decoder achieved 54% accuracy in the invisible condition, which significantly exceeding chance (50%). This finding suggests that despite participants' complete lack of awareness of the Gabor spot, their brain activity retained reliable "eye-source" information. Time course analysis further revealed that successful decoding occurred between 100 and 200 milliseconds after stimulus onset, corresponding to the early visual cortical processing stage. Compared to the visible condition, this finding suggests that conscious engagement can be enhance and prolong the strength and duration of neural representations. This finding echoes research on attentional mechanisms. Hoffmann & Falkenstein research also suggested that attention may influence information processing by modulating the gain of prediction error signals in precision weighting [22]. In Baker study suggested that the enhanced representation under conscious engagement may reflect a precision weighting mechanism, where conscious engagement increases the reliability weight of the relevant neural signals [21]. Further research by Sohn et al. showed that this pre-stimulus predictive activity might originate in higher-level cognitive brain regions such as the prefrontal cortex and anterior cingulate gyrus, which are believed to be responsible for generating and maintaining internal predictive models [23]. Furthermore, the strength of this predictive signal was significantly correlated with an individual's perceptual stability, which can be displayed that individuals with stronger predictive ability had lower frequencies of perceptual flips, a crucial role for PC in maintaining perceptual stability. Furthermore, Alexander & Brown study found that this predictive activity is modulated by attentional states, when participants focused their attention, the strength of the predictive signal increased significantly, suggesting that attention may influence perceptual processes by regulating the accuracy of the predictive signal [24]. These findings collectively demonstrate that conscious perception is largely determined by pre-existing predictive states within the brain, and that sensory input serves more to verify or fine-tune these pre-generated hypotheses than to completely reconstruct perception. This also supports the PC's view that the brain performs predictions and error calculations at an unconscious level.

Furthermore, in van Rhijn et al. research team employed frequency labeling combined with a binocular rivalry paradigm to further explore the neural mechanisms of perceptual switching [25]. The experimental design presented participants with grating stimuli of different orientations, gratings

of varying orientations, which were systematically altered to produce a biased stimulus. This design ensured that the bias could only be detected when the visual system maintained binocular information separation. The study also compared two attentional conditions, in the "attentional rivalry" condition, participants were required to actively attend to the stimuli and report their perceptual experience. The experiment found a significant Visual Mismatch Negativity (vMMN) component in both the 130-160 millisecond and 196-226 millisecond time windows, primarily located in the occipital-parietal regions. This component remained consistent across both attentional and conditions. The vMMN is widely considered a prediction error signal generated in the sensory cortex, reflecting the brain's detection of discrepancies between expected and actual input [26]. This result suggests that the generation of the vMMN is independent of conscious attention and reflects an automatic pre-attentive processing process. Since this bias detection is only possible when the visual system maintains binocular information separation, the vMMN originates relatively early in the visual hierarchy, before binocular information integration. This finding also same with the findings of May, who both demonstrated that the vMMN arises from a violation of an internal predictive model rather than simple sensory adaptation [27]. In-depth source localization analysis revealed that the vMMN likely originates from multiple nodes within the visual cortical hierarchy, including areas V2/V3 and higher-order temporal cortex, reflecting the propagation of prediction errors throughout the cortical hierarchy. When participants actively controlled perceptual switching through cognitive strategies, the amplitude of the vMMN was significantly reduced, suggesting that top-down cognitive control can influence perceptual decisions by modulating prediction error signals [28]. Furthermore, Male study found that the response characteristics of the vMMN were influenced by stimulus probability and contextual expectations, with the vMMN amplitude significantly increasing in response to low-probability stimuli, further supporting its nature as a Bayesian prediction error signal [29]. These findings collectively indicate that prediction error signals play a key role in driving the updating of conscious content. When there is an insurmountable discrepancy between persistent perceptual predictions and actual sensory inputs, the resulting prediction error signal is transmitted upward, ultimately forcing higher-level neural networks to correct existing predictions and generate new predictions, thereby updating conscious content. This also suggests that PC mechanisms begin to play a role in the earliest stages of visual processing, supporting the view that prediction error calculation is a fundamental automatic process of the brain.

Bastos et al. used a linear multielectrode array to simultaneously record local field potentials (LFPs) and multiunit activity (MUA) from three visual areas, V1, V2, and V4, in awake macaques performing a visuospatial attention task [4]. The experimental design included both attention and inattention conditions. In the attention condition, the macaques were instructed to attend to and respond to a moving grating stimulus at a specific location, while in the inattention condition, they ignored the contralateral stimulus. The researchers used spectral Granger causality analysis to quantify information flow between brain regions, revealing the directionality of predictive interactions between layers. A directionality index was used to distinguish the net strength of feedforward and feedback information flows. The results demonstrated for the first time the existence of bidirectional information flow and its frequency-separable properties at the macrocortical level. Specifically, the findings showed that feedback information flow from higher-level areas (V4) to lower-level areas (V2/V1) was primarily carried by low-frequency alpha (8-13Hz) and beta (13-30Hz) oscillations, while feedforward information flow from lower-level areas to higher-level areas was primarily carried by high-frequency gamma (40-80Hz) oscillations. This frequency-segregated communication pattern is significantly enhanced under attention. Attention not only increases the intensity of feedforward gamma-band activity, indicating increased sensory input gain, but also enhances feedback beta-band synchronization, reflecting strengthened top-down control. These findings provide direct physiological evidence for PC theory, demonstrating that the brain implements parallel transmission of predictions and prediction errors through frequency-specific oscillatory channels. Attention optimizes the process of minimizing prediction errors by adjusting the gains of different frequency channels, perfectly corroborating the computational principle of precision

weighting in PC. This finding is further supported by van Pelt et al., who used Granger causality analysis to demonstrate that gamma-band activity is indeed guided by alpha/beta-band activity, providing causal evidence for inter-level predictive interactions [30]. Further analysis revealed that the strength of this cross-frequency coupling was significantly correlated with individual perceptual performance: individuals with stronger coupling performed better on perceptual tasks, suggesting that the efficiency of PC mechanisms directly influences perceptual function. Furthermore, Vinck et al. found that neuromodulators such as acetylcholine may influence PC by regulating the balance of oscillations at different frequencies, providing a new perspective for understanding how neuromodulator systems influence perception [31]. These findings collectively demonstrate that the brain implements the core computational process of PC through frequency-specific neural oscillation mechanisms, and that oscillations of different frequencies form the physiological basis for information exchange between cortical layers, providing empirical evidence for understanding the generation and updating of visual consciousness.

3.2. Critiques of Predictive Coding

While the PC framework demonstrates considerable explanatory power in explaining visual consciousness, it also faces some opposing viewpoints. These present methodological and interpretative challenges to the core assumptions of PC theory. For example, Whittington and Bogacz conducted a comparative analysis of PC-based neural networks and backpropagation (BP) through systematic computational simulations [5]. By setting the output layer noise parameter (Σ) to a fixed value rather than a dynamic estimate and updating weights according to the local Hebbian rule, the study showed that when $\Sigma_i^{(0)}$ is small, the weight update directions of the PC network and the BP network differ to some extent. However, as $\Sigma_i^{(0)}$ increases, the update directions of the two networks converge, and in the extreme case, they completely converge, indicating that the PC network is approximately equivalent to the BP algorithm. This also suggests that by simplifying the PC by ignoring dynamic precision, the core functionality can be retained while better approximating the implementation mechanism of the biological neural system. It also demonstrates that the standard PC mathematical framework is difficult to directly map to neural mechanisms, and that other theories are needed to make the theory compatible with the brain.

Seth suggested that PC's overreliance on the concept of "illusion" may constitute a potential logical trap, potentially jeopardizing the theory's explanatory power [32]. In a study by Suzuki et al., using augmented reality (AR) technology, participants' heartbeats were mapped in real time to the color changes of a virtual hand [33]. The results showed that the rubber hand illusion was stronger when the color changes of the virtual hand were synchronized with the participant's heartbeat, and weaker when they were asynchronous. This provides empirical support for the relationship between multisensory integration and prediction error regulation. Furthermore, in a study by Aspell et al., participants viewed a virtual full-body image surrounded by a halo that flickered either synchronously or asynchronously with their heartbeat [34]. The results showed that under the synchronous condition, participants were more likely to identified the virtual body as their own. These studies suggest that minimizing prediction error in multisensory integration can induce hallucinatory experiences of body perception, experimentally simulating the mechanism of "controlled hallucinations." Although PC assumes that normal and abnormal perception share the same predictive mechanism, hallucinations in schizophrenia may arise from misestimation of prediction error precision or abnormal solidification of higher-order priors, rather than simple prediction errors [32]. Therefore, if it is not clearly defined which parameters of the prediction process are dysregulated and lead to pathological hallucinations, PC may overgeneralize across different perceptual phenomena and become logically self-defeating. Future research needs to further integrate computational psychiatric methods to clarify the differences in the regulation of prediction errors and their precision at different levels in health and disease, thereby enhancing the PC theory's ability to explain perceptual reality and its pathological deviations.

4. Discussion

PC provides a unified and powerful framework for understanding visual consciousness. Its core insight is that the brain actively constructs visual perception through a hierarchical generative model, continuously comparing top-down predictions with bottom-up sensory inputs and minimizing prediction errors. Baker found that early visual cortex retains stimulus information even when the stimulus is completely invisible [21]. van Rhijn et al. revealed that vMMN components automatically generated during the pre-attentive phase reflect prediction error signals [25]. Bastos et al. directly demonstrated that feedback and feedforward information flows are carried by low-frequency (alpha/beta) and high-frequency (gamma) oscillations, respectively, confirming the frequency separation hypothesis of PC theory [4]. These lines of evidence collectively suggest that neural signals of prediction and prediction error are closely linked to perceptual dynamics, and that conscious content essentially corresponds to generative model states in which prediction errors are fully minimized. Accuracy weighting plays a key regulatory role by regulating the gain of error signals.

However, PC theory still faces significant challenges. Whittington and Bogacz demonstrated that PC can be mathematically approximated by the backpropagation algorithm [5]. This, while strengthening its status as an effective inference model, also exposes challenges in its neural implementation. The brain clearly cannot achieve error minimization through pure backpropagation. This implies that establishing PC as a realistic model of brain function requires the introduction of more biologically plausible mechanisms, such as Hebbian plasticity and local inhibition-excitation balance to enable hierarchical predictive learning in the absence of a global error signal, thereby strengthening the connection between computational theory and biological implementation [35, 36]. Furthermore, Seth pointed out that PC's reliance on "controlled hallucinations" can lead to circularity in interpretation, particularly the lack of a clear operational definition for distinguishing normal perception from pathological hallucinations [32]. This theoretical limitation suggests that future research urgently needs to develop quantifiable and operational computational metrics, such as precision or weight parameters for different levels of expectation, to empirically distinguish normal perception from pathological perception [37].

These controversies call for future research to employ more sophisticated experimental designs to clarify these issues. For example, TMS could be applied to target specific brain regions (such as the prefrontal cortex or higher visual cortex), but the limitations of its spatial resolution should be considered to examine the causal role of the prediction stream in the integration process [38]. Furthermore, to fully capture the spatiotemporal dynamics of prediction errors, simultaneous recordings combining the high temporal resolution of EEG and the spatial localization capabilities of Functional Magnetic Resonance Imaging could be used to dissect the neural mechanisms underlying cross-hierarchical transmission of prediction errors. This is crucial for studying visual hallucinations or pathological perceptual disorders. Furthermore, future work should focus on the neural modulation underlying precision-weighted signaling, such as in transmitter systems like acetylcholine and dopamine, and promote the development of computational models that are more biologically accurate [39].

5. Conclusion

Visual consciousness is a fundamental aspect of human perception. PC theory provides an integrative explanatory framework, arguing that vision is not simply the reception of external stimuli, but rather the result of perceptual construction by the brain through a multi-layered internal model, where top-down predictions are continuously compared with bottom-up sensory signals, and errors are continuously corrected. In this process, a "precision weighting" mechanism directly influences what information enters consciousness by regulating the degree of confidence in prediction errors. This theory is supported by experimental evidence from a variety of neuroscience techniques. Findings such as the perception of invisible stimuli to induce early neural decoding, pre-attentive prediction error signals (vMMNs), and the fact that neural oscillations in different frequency bands

carry feedforward and feedback information suggest that PC is likely the core computational principle underlying visual consciousness. However, this theoretical framework still faces challenges, such as unclear biological implementation mechanisms and the risk of conceptual circularity. For example, how does the brain achieve local weight updates without relying on global error backpropagation, and how can normal perception be objectively distinguished from pathological hallucinations. Further research is required to address these challenges. In the future, researchers should strive to develop computational models that are closer to biological reality, combine neural regulation with brain imaging technology, and focus on the transmission mechanism of prediction errors between brain levels and its modulation factors.

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