dreammachine

SYSTEMS ARCHITECTURE FOR THE HUMAN MIND

HALLUCINATION AUDIT

EMPIRICAL TRACEABILITY LOG

Permalink · dreammachine.systems/audit/sec12-1-4

LOG ID	BOOK REFERENCE	RCT FILTER	CONFIDENCE TIER
SEC 12.1.4	CHAPTER 12: DATA SOVEREIGNTY & GLOBAL OS (Production Environment)	**OFF**	**CONSENSUS**

AUDITED CLAIM

PROCEDURAL RENDERING ENGINE (PREDICTIVE PROCESSING)

SYSTEMS MODEL — AS STATED IN THE BOOK

> The brain does not passively render a high-fidelity objective universe. According to Predictive Processing, it generates **top-down statistical models** to save bandwidth, using raw sensory data primarily to detect **Prediction Errors** and update its **active inference**.

VALIDATION QUERY

Does the human brain utilize predictive processing and active inference to generate perceptual models, only processing bottom-up sensory data to resolve prediction errors?

EMPIRICAL FINDING

Cognitive neuroscience heavily supports the **predictive processing** framework. To conserve metabolic bandwidth, the brain acts as an inference engine, continuously projecting **top-down expectations** about the environment. While the claim that bottom-up data is exclusively residual error is contested, the brain relies heavily on calculating **prediction errors** (mismatches between expected and actual sensory data) to actively update its perceptual models.

PRIMARY ANCHORS

→ Clark, 2013, Behavioral and Brain Sciences

→ Friston, 2010, Nature Reviews Neuroscience

ABOUT THIS RECORD

Each claim in the book is decompiled from its IT metaphor into a naked, falsifiable scientific claim, then anchored to a **primary peer-reviewed source**. Claim and anchor are queried against the Consensus academic database (200M+ papers) under a fixed protocol — top-tier **Q1/Q2 journals only**, preprints excluded, human studies only. If a hypothesis fails the audit, the build is rejected: the AI generates the syntax; the peer-reviewed grid validates the physics.

CONFIDENCE TIERS

- **CONSENSUS ◀ this log** — broadly established, highly replicated mechanics.
- **EMERGING** — plausible, actively researched; no universal consensus yet.
- **EXPERIMENTAL** — contested, extrapolated, or purely theoretical.

RCT FILTER — Controlled Studies is ON for interventions (a forced action must beat a control) and OFF for mechanisms (so foundational neuroscience isn't blocked).

Yes, the **human brain uses predictive processing**; **active inference** is plausible, but evidence is more indirect.

1. Introduction

Predictive processing is a well-supported framework for human perception: many studies indicate that the brain combines prior expectations with incoming sensory input to build perceptual hypotheses, and that mismatches are propagated as prediction errors to update those hypotheses. Foundational reviews describe perception in exactly these terms, with descending predictions and ascending error signals operating across cortical hierarchies (Walsh et al., 2020; Sedley et al., 2016; Keller & Mrsic-Flogel, 2018). Human experiments also show direct neural signatures of both prediction templates before stimulation and trial-wise prediction-error responses after violations, which goes beyond a purely feedforward feature-detection account (Kok et al., 2017; Stefanics et al., 2018; Sedley et al., 2016).

At the same time, the strongest evidence supports predictive processing more than the strictest version of predictive coding. Several reviews argue that the brain is not simply “only processing bottom-up data to resolve errors,” because predictions can be embedded in bottom-up pathways, prediction and error may not map cleanly onto distinct neural populations everywhere, and some findings fit recurrent network or sharpening accounts better than a strict hierarchical residual-only architecture (Teufel & Fletcher, 2020; Greco et al., 2024; Furutachi & Hofer, 2026). Evidence for active inference in perception-action loops exists, but in humans it is still less direct than evidence for perceptual prediction and error signaling (Seth & Friston, 2016; Hodson et al., 2023).

Does the human brain utilize predictive processing and active inference to generate perceptual models, only processing bottom-up sensory data to resolve prediction errors? N = 7

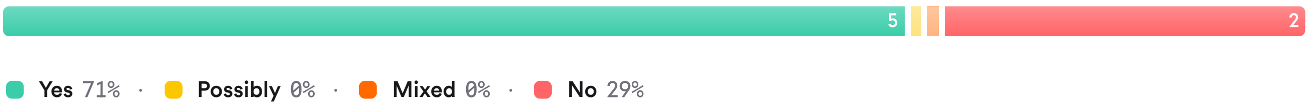

FIGURE 1 Research consensus on predictive processing in human perception

The literature strongly supports predictive perceptual modeling, but not the narrow claim that bottom-up traffic is only residual error. Bottom-up signals often include sensory evidence shaped by embedded constraints, and active inference remains more established theoretically than empirically in humans (Teufel & Fletcher, 2020; Tabas & Von Kriegstein, 2023; Hodson et al., 2023).

2. Methods

This deep search synthesized evidence from Consensus, which searches over 170 million research papers across Semantic Scholar, PubMed, and other sources. The workflow identified 133,508 initially relevant papers for the exact query, expanded through targeted alternate-term and empirical searches plus citation crawling, screened 230 papers with machine-learned relevance filtering, judged 148 as eligible after deduplication and relevance review, and included the top 50 most relevant papers for this synthesis.

Search Strategy

40.1M Retrieved	1.7K Eligible	50 Included
21 searches 1 citation graph use All papers retrieved from 21 searches and 1 citation graph use.	Papers meeting relevance and quality criteria, after deduplication	Top papers selected to be included in the final analysis

FIGURE 2 Deep search screening and inclusion flow

Searches combined predictive processing, predictive coding, active inference, Bayesian perception, hierarchical inference, and top-down versus bottom-up sensory processing.

3. Results

3.1 Key Papers

A small set of papers anchors this corpus because they either directly evaluate the neurophysiological evidence, provide direct human evidence for predictions or errors, or synthesize the architecture-level debate. The 2020 review by Walsh et al. is the clearest empirical stocktake, while human MEG, EEG, intracranial, and fMRI studies by Kok, Sedley, Chennu, and others supply the strongest mechanistic evidence (Walsh et al., 2020; Kok et al., 2017; Sedley et al., 2016).

Paper	Summary
(Walsh et al., 2020)	Balanced review of core predictive-processing claims (Walsh et al., 2020)
(Seth & Friston, 2016)	Direct human signatures of prediction, surprise, precision (Sedley et al., 2016)
(Noppeney, 2021)	Prestimulus sensory templates support proactive prediction (Kok et al., 2017)

FIGURE 3 Key foundational papers in this corpus

3.2 Human Evidence for Predictions

Human data support actual prediction signals, not just error responses. MEG decoding showed stimulus-specific sensory templates before expected visual gratings appeared, indicating proactive preactivation of expected content (Kok et al., 2017). Intracranial auditory recordings identified separable oscillatory signatures for prediction updating, surprise, and precision, providing rare direct evidence for multiple computational variables proposed by generative models (Sedley et al., 2016). Omission paradigms further isolate top-down prediction because a response appears even when expected sensory input is absent, and dynamic causal modeling linked these omission responses to the same forward-backward architecture as mismatch responses (Chennu et al., 2016).

Conceptual and associative knowledge can also generate sensory predictions. The hippocampus represented predicted visual shapes from auditory cues even when visual cortex tracked the presented shape, and stronger hippocampal prediction tracked stronger facilitation in visual cortex (Kok & Turk-Browne, 2018). Recently acquired conceptual associations likewise produced category-specific suppression throughout ventral visual cortex, implying that abstract priors can reach sensory systems (Yan et al., 2022).

3.3 Prediction Errors and Architecture

Dimension	Evidence
Trial-wise mismatch	Visual mismatch responses track precision-weighted prediction errors better than categorical change detection (Stefanics et al., 2018)
Oscillatory routing	Beta-band activity aligns with top-down predictions, gamma with bottom-up prediction errors (Van Pelt et al., 2016; Arnal et al., 2011)
Laminar support	Tactile temporal prediction errors differentially modulate deep versus superficial layers in S1 (Yu et al., 2021)
Attention and precision	Attention increases encoding of mismatch information, consistent with precision-weighting of error units (Smout et al., 2019)
Multilevel predictions	Auditory pathway responses reflect combined task-informed and statistics-informed predictions at all stages (Tabas & Von Kriegstein, 2023)

FIGURE 4 Evidence for prediction error computations across levels

These findings support prediction-error signaling, but they also complicate a simple residual-only feedforward story. Some work finds distributed synergistic error coding across networks rather than isolated local error computation at each level (Greco et al., 2024). Meta-analysis also found no clean network-level separation between prediction and error processing, favoring a broader predictive network over a strict modular mapping (Ficco et al., 2021).

3.4 Competing Mechanisms and Active Inference

Predictive influences do not always appear as pure error minimization. In speech, sharpening of expected sensory representations and higher-level semantic prediction errors coexisted at different hierarchical levels (Schneider & Blank, 2025). In face perception, expected information was sharpened in early face areas while prediction-error processing appeared across the broader face hierarchy (Garlichs & Blank, 2024). Visual object studies likewise reported expectation suppression but interpreted it as dampening rather than sharpening in object-selective cortex (Richter et al., 2017).

Active inference extends predictive coding by claiming that action changes sensory input to fulfill predictions, but direct human tests remain relatively sparse. Theoretical and review work consistently defines active inference this way (Arthur et al., 2023; Seth & Friston, 2016; Smith et al., 2020). Human evidence is emerging in domains such as sensorimotor behavior, groove-related tapping, and clinical modeling, yet reviews still conclude that formal tests against competing action theories are limited (Arthur et al., 2023; Ishida & Nittono, 2025; Hodson et al., 2023).

Results Timeline

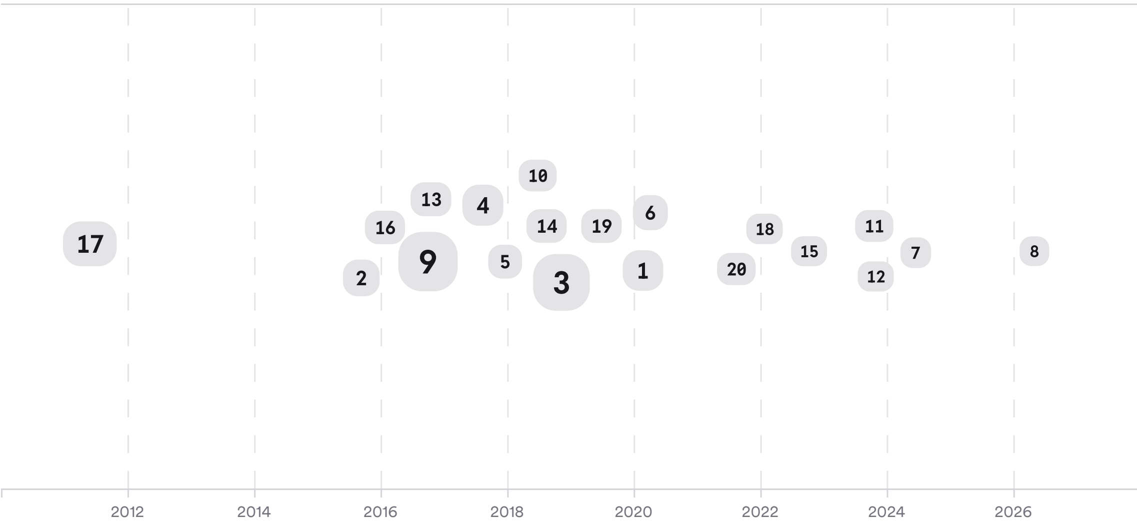

FIGURE 5 Timeline of predictive processing papers, larger markers indicate more citations

The timeline shows an early theoretical phase, a 2011-2018 phase of strong human neurophysiology and imaging tests, and a recent phase focused on architectural refinement, crossmodal prediction, and sharpening-versus-error debates. The field has shifted from asking whether prediction errors exist to asking what exactly is predicted, where, and by which circuit motifs (Walsh et al., 2020; Richter et al., 2025; Furutachi & Hofer, 2026).

Top Contributors

Type	Name	Papers
Author	F. D. de Lange	[9ba372d48a175088a56a96ab1af09f87][407abb7cc0635887af4e940ca6cfc966][bda6e3b78eef566c974f00d07e9100e7][7e940e2c3aa85750a84aca0dcdabb149]
Author	Karl J. Friston	[652a2ae40f8756028b9a178dc202189d][4b6958c7f50251c6a7f5871ea5ef041a]
Author	Helen Blank	[778a90a556095cea9364a84993aacb63][b8f6f69375bb51cda9b8929b28e024a6]
Journal	*The Journal of Neuroscience*	[ade3bbd300f6565d8f8fd8982cbf5e40][a97e3894db8a51b0b76a4c3026f8315e][9ba372d48a175088a56a96ab1af09f87][bbf47d12d47b5c02af762d872182c5b5][94a77298f4485f90b9d05da82864d712][495349df62ae5ab78ac928da75477a51][1ba3e3dfee5858a3bdcb35db6e6e4fbc]
Journal	*Nature Communications*	[360c798501485ee2ad6552e50451b8ae][b8f6f69375bb51cda9b8929b28e024a6]
Journal	*Neuron*	[7f42eb8e0cb55b36b072658b1d4f33d0][c8d682af29a55d09b82b21e5f22ec621]

FIGURE 6 Authors and journals appearing most in corpus

4. Discussion

Overall, the corpus supports the broad predictive-processing view of perception. Multiple human paradigms show expectations biasing awareness, perception, response speed, sensory templates, mismatch responses, and hierarchical learning, across vision, audition, multisensory processing, and affective perception (Pinto et al., 2015; Garlichs & Blank, 2024; Noppeney, 2021; Strube et al., 2021). This convergence across methods is a major strength.

The main limitation is that many findings are compatible with predictive processing at a computational level without uniquely confirming a specific neural implementation of predictive coding. Reviews repeatedly note that direct tests of distinct prediction neurons, error neurons, and strict hierarchical residual passing remain limited, and some positive findings can also fit alternative feedforward or recurrent explanations (Walsh et al., 2020; Furutachi & Hofer, 2026; Hodson et al., 2023). Recent studies increasingly argue against an exclusively top-down account by showing predictions embedded in bottom-up pathways, concurrent multilevel predictions, and distributed rather than strictly linear transmission (Teufel & Fletcher, 2020; Tabas & Von Kriegstein, 2023; Greco et al., 2024).

The active-inference claim is even more nuanced. As a framework unifying action and perception, it is influential and mechanistically rich, and several papers describe action as changing the world or body to reduce prediction error (Seth & Friston, 2016; Dutta, 2025; Smith et al., 2020). But empirical reviews emphasize that human evidence directly discriminating active inference from other action-control models is still modest (Hodson et al., 2023).

Claim	Evidence Strength	Reasoning	Papers
Human perception integrates priors with sensory input to build perceptual models.	Strong	Supported across reviews, decoding, intracranial, and behavioral studies.	(Walsh et al., 2020; Sedley et al., 2016; Kok et al., 2017)
Prediction-error signals are a robust feature of human sensory processing.	Strong	Reproduced across EEG, MEG, fMRI, laminar fMRI, and meta-analysis.	(Stefanics et al., 2018; Yu et al., 2021; Corlett et al., 2022)
Bottom-up signals are only residual error signals.	Weak	Too strong; evidence favors mixed, embedded, recurrent, and distributed processing.	(Teufel & Fletcher, 2020; Greco et al., 2024; Ficco et al., 2021)
Active inference likely captures some perception-action coupling in humans.	Moderate	Mechanistically plausible, with emerging support, but few decisive tests.	(Seth & Friston, 2016; Ishida & Nittono, 2025; Hodson et al., 2023)
A strict single-mechanism predictive-coding architecture explains all perceptual prediction effects.	Weak	Sharpening, dampening, and distributed-network findings argue against a single canonical implementation.	(Schneider & Blank, 2025; Richter et al., 2017; Furutachi & Hofer, 2026)

FIGURE 7 Key claims and supporting evidence strength

5. Conclusion

The human brain appears to use predictive processing to generate perceptual models, and prediction-error signaling is strongly supported across human neuroscience. The narrower claim that bottom-up information is only residual error is not supported, because current evidence favors richer bottom-up sensory evidence, recurrent interactions, and multiple predictive mechanisms rather than a single strict architecture (Teufel & Fletcher, 2020; Tabas & Von Kriegstein, 2023; Tivadar et al., 2021).

Research Gaps

The main gaps concern architecture, causal tests, and direct validation of active inference against alternatives.

Topic/Outcome	Human causal tests	Laminar/circuit specificity	Competing-model comparison	Action-based tests
Sensory prediction templates	4	2	3	1
Prediction-error signaling	10	4	5	2
Active inference in humans	2	1	2	4
Sharpening vs dampening	3	1	4	GAP
Crossmodal and abstract priors	5	2	3	1

Open Research Questions

Future work should test which predictive architecture best explains human data, not just whether expectations matter.

Question	Why
Do bottom-up cortical signals carry only residual prediction errors, or also prediction-shaped sensory evidence?	This is the central unresolved architectural claim separating strict predictive coding from broader recurrent predictive-processing accounts.
Can active inference outperform reinforcement-learning and optimal-control models in human action tasks?	Direct head-to-head tests are needed because current behavioral fits rarely establish unique support for active inference.
When do sharpening, dampening, and error signaling each dominate across cortical hierarchies?	Recent face, speech, and object studies suggest multiple mechanisms coexist, but their boundary conditions remain unclear.

In short, the evidence supports predictive perceptual modeling in the human brain, but not the strongest claim that bottom-up processing is only error correction.

References

Arnal, L. H., Wyart, V., & Giraud, A. (2011). Transitions in neural oscillations reflect prediction errors generated in audiovisual speech. *Nature Neuroscience, 14*, 797-801. https://doi.org/10.1038/nn.2810

Arthur, T., Vine, S., Buckingham, G., Brosnan, M., Wilson, M., & Harris, D. (2023). Testing predictive coding theories of autism spectrum disorder using models of active inference. *PLOS Computational Biology, 19*. https://doi.org/10.1371/journal.pcbi.1011473

Chennu, S., Noreika, V., Gueorguiev, D., Shtyrov, Y., Bekinschtein, T., & Henson, R. (2016). Silent Expectations: Dynamic Causal Modeling of Cortical Prediction and Attention to Sounds That Weren't. *The Journal of Neuroscience, 36*, 8305 - 8316. https://doi.org/10.1523/jneurosci.1125-16.2016

Corlett, P., Mollick, J., & Kober, H. (2022). Meta-analysis of human prediction error for incentives, perception, cognition, and action. *Neuropsychopharmacology, 47*, 1339 - 1349. https://doi.org/10.1038/s41386-021-01264-3

Dutta, A. (2025). Neurocomputational Mechanisms of Sense of Agency: Literature Review for Integrating Predictive Coding and Adaptive Control in Human–Machine Interfaces. *Brain Sciences, 15*. https://doi.org/10.3390/brainsci15040396

Ficco, L., Mancuso, L., Manuello, J., Teneggi, A., Liloia, D., Duca, S., Costa, T., Kovács, G., & Cauda, F. (2021). Disentangling predictive processing in the brain: a meta-analytic study in favour of a predictive network. *Scientific Reports, 11*. https://doi.org/10.1038/s41598-021-95603-5

Furutachi, S., & Hofer, S. B. (2026). Rethinking Predictive Processing.. *Annual review of neuroscience*. https://doi.org/10.1146/annurev-neuro-102124-031410

Garlichs, A., & Blank, H. (2024). Prediction error processing and sharpening of expected information across the face-processing hierarchy. *Nature Communications, 15*. https://doi.org/10.1038/s41467-024-47749-9

Greco, A., Moser, J., Preissl, H., & Siegel, M. (2024). Predictive learning shapes the representational geometry of the human brain. *Nature Communications, 15*. https://doi.org/10.1038/s41467-024-54032-4

Hodson, R., Mehta, M., & Smith, R. (2023). The Empirical Status of Predictive Coding and Active Inference.. *Neuroscience and biobehavioral reviews*, 105473. https://doi.org/10.1016/j.neubiorev.2023.105473

Ishida, K., & Nittono, H. (2025). Active Inference in Music Perception: Motor Engagement to Syncopation Modulates Rhythmic Prediction Error. *Psychophysiology, 62*. https://doi.org/10.1111/psyp.70113

Keller, G. B., & Mrsic-Flogel, T. (2018). Predictive Processing: A Canonical Cortical Computation. *Neuron, 100*, 424 - 435. https://doi.org/10.1016/j.neuron.2018.10.003

Kok, P., Mostert, P., & De Lange, F. D. (2017). Prior expectations induce prestimulus sensory templates. *Proceedings of the National Academy of Sciences, 114*, 10473 - 10478. https://doi.org/10.1073/pnas.1705652114

Kok, P., & Turk-Browne, N. (2018). Associative Prediction of Visual Shape in the Hippocampus. *The Journal of Neuroscience, 38*, 6888 - 6899. https://doi.org/10.1523/jneurosci.0163-18.2018

Noppeney, U. (2021). Perceptual Inference, Learning, and Attention in a Multisensory World.. *Annual review of neuroscience*. https://doi.org/10.1146/annurev-neuro-100120-085519

Pinto, Y., Van Gaal, S., De Lange, F. D., Lamme, V., & Seth, A. (2015). Expectations accelerate entry of visual stimuli into awareness.. *Journal of vision, 15 8*, 13. https://doi.org/10.1167/15.8.13

Richter, D., Ekman, M., & De Lange, F. D. (2017). Suppressed Sensory Response to Predictable Object Stimuli throughout the Ventral Visual Stream. *The Journal of Neuroscience, 38*, 7452 - 7461. https://doi.org/10.1523/jneurosci.3421-17.2018

Richter, D., Pena, P., & Ruz, M. (2025). Rapid computation of high-level visual surprise. *iScience, 28*. https://doi.org/10.1016/j.isci.2025.114121

Schneider, F., & Blank, H. (2025). Sensory sharpening and semantic prediction errors unify competing models of predictive processing in human speech comprehension. *PLOS Biology, 24*, e3003588 - e3003588. https://doi.org/10.1101/2025.07.23.666354

Sedley, W., Gander, P., Kumar, S., Kovach, C. K., Oya, H., Kawasaki, H., Howard, M., & Griffiths, T. (2016). Neural signatures of perceptual inference. *eLife, 5*. https://doi.org/10.7554/elife.11476

Seth, A., & Friston, K. J. (2016). Active interoceptive inference and the emotional brain. *Philosophical Transactions of the Royal Society B: Biological Sciences, 371*. https://doi.org/10.1098/rstb.2016.0007

Smith, R., Badcock, P. B., & Friston, K. J. (2020). Recent advances in the application of predictive coding and active inference models within clinical neuroscience. *Psychiatry and Clinical Neurosciences, 75*. https://doi.org/10.1111/pcn.13138

Smout, C. A., Tang, M. F., Garrido, M., & Mattingley, J. (2019). Attention promotes the neural encoding of prediction errors. *PLoS Biology, 17*. https://doi.org/10.1371/journal.pbio.2006812

Stefanics, G., Heinzle, J., Horváth, A., & Stephan, K. (2018). Visual Mismatch and Predictive Coding: A Computational Single-Trial ERP Study. *The Journal of Neuroscience, 38*, 4020 - 4030. https://doi.org/10.1523/jneurosci.3365-17.2018

Strube, A., Rose, M., Fazeli, S., & Büchel, C. (2021). Alpha-to-beta- and gamma-band activity reflect predictive coding in affective visual processing. *Scientific Reports, 11*. https://doi.org/10.1038/s41598-021-02939-z

Tabas, A., & Von Kriegstein, K. (2023). Multiple Concurrent Predictions Inform Prediction Error in the Human Auditory Pathway. *The Journal of Neuroscience, 44*. https://doi.org/10.1523/jneurosci.2219-22.2023

Teufel, C., & Fletcher, P. (2020). Forms of prediction in the nervous system. *Nature Reviews Neuroscience, 21*, 231 - 242. https://doi.org/10.1038/s41583-020-0275-5

Tivadar, R. I., Knight, R., & Tzovara, A. (2021). Automatic Sensory Predictions: A Review of Predictive Mechanisms in the Brain and Their Link to Conscious Processing. *Frontiers in Human Neuroscience, 15*. https://doi.org/10.3389/fnhum.2021.702520

Van Pelt, S., Heil, L., Kwisthout, J., Ondobaka, S., Van Rooij, I. V., & Bekkering, H. (2016). Beta- and gamma-band activity reflect predictive coding in the processing of causal events.. *Social cognitive and affective neuroscience, 11 6*, 973-80. https://doi.org/10.1093/scan/nsw017

Walsh, K. S., McGovern, D. P., Clark, A., & O'Connell, R. (2020). Evaluating the neurophysiological evidence for predictive processing as a model of perception. *Annals of the New York Academy of Sciences, 1464*, 242 - 268. https://doi.org/10.1111/nyas.14321

Yan, C., De Lange, F. D., & Richter, D. (2022). Conceptual Associations Generate Sensory Predictions. *The Journal of Neuroscience, 43*, 3733 - 3742. https://doi.org/10.1101/2022.09.02.506283

Yu, Y., Huber, L., Yang, J., Fukunaga, M., Chai, Y., Jangraw, D., Chen, G., Handwerker, D., Molfese, P. J., Ejima, Y., Sadato, N., Wu, J., & Bandettini, P. (2021). Layer-specific activation in human primary somatosensory cortex during tactile temporal prediction error processing. *NeuroImage, 248*, 118867 - 118867. https://doi.org/10.1016/j.neuroimage.2021.118867