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# Cortical electrophysiological network dynamics of feedback learning

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**Understanding the neurophysiological mechanisms of learning is important for both fundamental and clinical neuroscience. We present a neurophysiologically inspired framework for understanding cortical mechanisms of feedback-guided learning. This framework is based on dynamic changes in systems-level oscillatory synchronization, reflecting changes in synaptic plasticity between stimulus-processing and motor areas that are modulated in a top-down fashion by different areas of the prefrontal cortex. We make new and testable predictions for how large-scale cortical networks support learning from feedback. Testing these predictions may provide new insights into the basic mechanisms underlying learning and how these mechanisms may be impaired in clinical disorders in which feedback learning is compromised.**

## Understanding feedback-guided learning

Learning to adapt behavior according to changes in the environment is a fundamental ability seen even in animals not typically thought of as being intelligent, such as slugs [1]. And yet, learning from feedback is a hallmark of human social and emotional development, and impairments in learning are implicated in some of the most vexing societal ailments, including substance abuse and schizophrenia [2–5]. A better understanding of the neural circuits and mechanisms underlying feedback learning has the potential both to bridge neuroscience research across a range of species and theoretical and methodological frameworks, and to help gain insight into brain disorders.

Feedback processing and learning are fast neurocognitive processes that likely rely on integrating information across multiple spatially disparate brain systems. In the past decade, over 300 papers have been published about the electrophysiological processes underlying feedback-guided learning (PubMed search for the terms 'feedback negativity' or 'EEG feedback learning', October 2011). Nevertheless, as we discuss below, significant gaps remain in our knowledge concerning how large-scale brain networks interact to support learning from feedback.

We argue that deeper insights into the neural mechanisms of learning require a new and more physiologically inspired perspective that is centered on large-scale brain networks and how they interact through synchronized electrophysiological oscillations (see Glossary). We first describe briefly previous work in the field and then present our framework and ensuing hypotheses that are amenable to confirmation or falsification using magnetoencephalography (MEG) and electroencephalography (EEG). M/EEG have a temporal resolution that matches that of neurocognitive feedback processing and learning (milliseconds), and allow investigation of complex oscillatory dynamics that are putative neurobiological mechanisms for neural information coordination and integration [6].

## Major themes in research on the electrophysiological mechanisms of feedback-guided learning in humans

Although a comprehensive review of this literature would be useful to the field, it is outside the scope of the present article. We outline instead the major themes that this literature has addressed in order to contextualize our new perspective.

*Basic EEG characteristics of feedback processing*. Several articles in the field characterize the experimental

### Glossary

**Electroencephalography (EEG)**: a technique that measures voltage changes at scalp level stemming from electrical currents inside the brain. The voltage changes are thought to reflect an addition of extracellular postsynaptic potentials (EPSP), the changes in voltage outside populations of neurons.
**Event-related potential (ERP; time-domain EEG averaging)**: an increase or decrease in the EEG signal time-locked to the occurrence of an event. Signals are averaged in the time-domain over multiple experimental trials containing the same event to increase the signal-to-noise ratio and improve the distinctness of the ERP.
**Feedback-related negativity (FRN)**: an ERP in the EEG signal 200-300 msec after the presentation of (performance) feedback. The peak of the FRN is relatively more negative after negative feedback than after positive feedback.
**Frequency band**: comprises oscillations within a certain frequency range. The most commonly identified bands in neurocognitive processes are the delta band (2-4 Hz), theta band (4-8 Hz), alpha band (8-12 Hz), beta band (15-30 Hz) and gamma band (> 30 Hz), but precise definitions vary.
**Magnetoencephalography (MEG)**: a technique that measures magnetic fields outside the scalp induced by electrical currents in the brain. Magnetic fields are thought to reflect summation of intracellular currents. Because magnetic fields are orthogonal to the direction of current flow, the same brain process will cause changes in EEG and MEG signals at different scalp locations.
**Oscillation**: rhythmic signal fluctuation with a sinusoidal shape.
**Oscillation frequency**: the number of oscillation cycles per second. The unit of measurement is called hertz (Hz). Raw EEG and MEG signals can be deconvolved into numerous oscillations with different frequencies.
**Oscillation phase**: the angle of the oscillation at a specific time point. Because oscillations have a continuous, sinusoidal shape, phases are circular with a higher (top of the wave) and lower (trough of the wave) limit. Synchronization of oscillatory phases across neural networks is thought to reflect functional connectivity between groups of neurons.
**Oscillation power**: the amplitude of the oscillation or the peak deviation of the wave from its center. Oscillatory power is thought to represent the magnitude of activation in a group of neurons.
**Time-frequency representation**: the deconvolved EEG/MEG signal presented as changes in oscillatory dynamics per frequency over time.

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 1364-6613/$ – see front matter  doi:10.1016/j.tics.2011.10.004 

conditions that modulate the amplitude of the feedback-related negativity (FRN), a time-domain trial-averaged event-related potential (ERP) component (Figure 1). Because the FRN has been hypothesized to reflect a reward prediction error [7], researchers have investigated whether FRN amplitude correlates with feedback magnitude (e.g., big vs. small reward) or the probability of negative feedback. Unfortunately, the literature is not entirely consistent: whereas several studies provide empirical support for the FRN reflecting the magnitude or probability of feedback [8–18], several other studies fail to support this conclusion [19–24], suggesting instead that the FRN reflects a binary 'good-bad' evaluation [19].

It is possible that this discrepancy is due to differences across studies in the significance of feedback for learning. Although many studies do not explicitly test for a link between the FRN and learning, there is evidence that the FRN reflects the evaluation of the significance of feedback for future behavior [7,16,25–30] or the relevance of feedback for task performance [28,31,32].

FRN magnitude also correlates with personality constructs, such as extraversion [33], and is modulated by social factors (e.g., watching a friend win/lose money) [34,35]. These and related studies show that the FRN has external validity and correlates with real-world behaviors.

*The FRN as a marker for aging or pathological conditions*. FRN magnitude decreases as a function of age [36–39] and is modulated by depression, substance abuse, attention deficit hyperactivity disorder and schizophrenia [40–43]. These studies suggest that the FRN might be a useful biological marker for disease risk, severity, and treatment success.

*Neural generators and mechanisms of the FRN*. Although the brain generators of scalp EEG activity cannot be unambiguously localized, consensus from dipole and distributed source modeling studies that provide mathematical estimations of the putative generators of scalp-recorded EEG activity suggest that the anterior cingulate and overlying medial frontal cortex are the major contributors to the FRN [25,44–47], along with right prefrontal [48] and posterior cingulate [25,45,46].

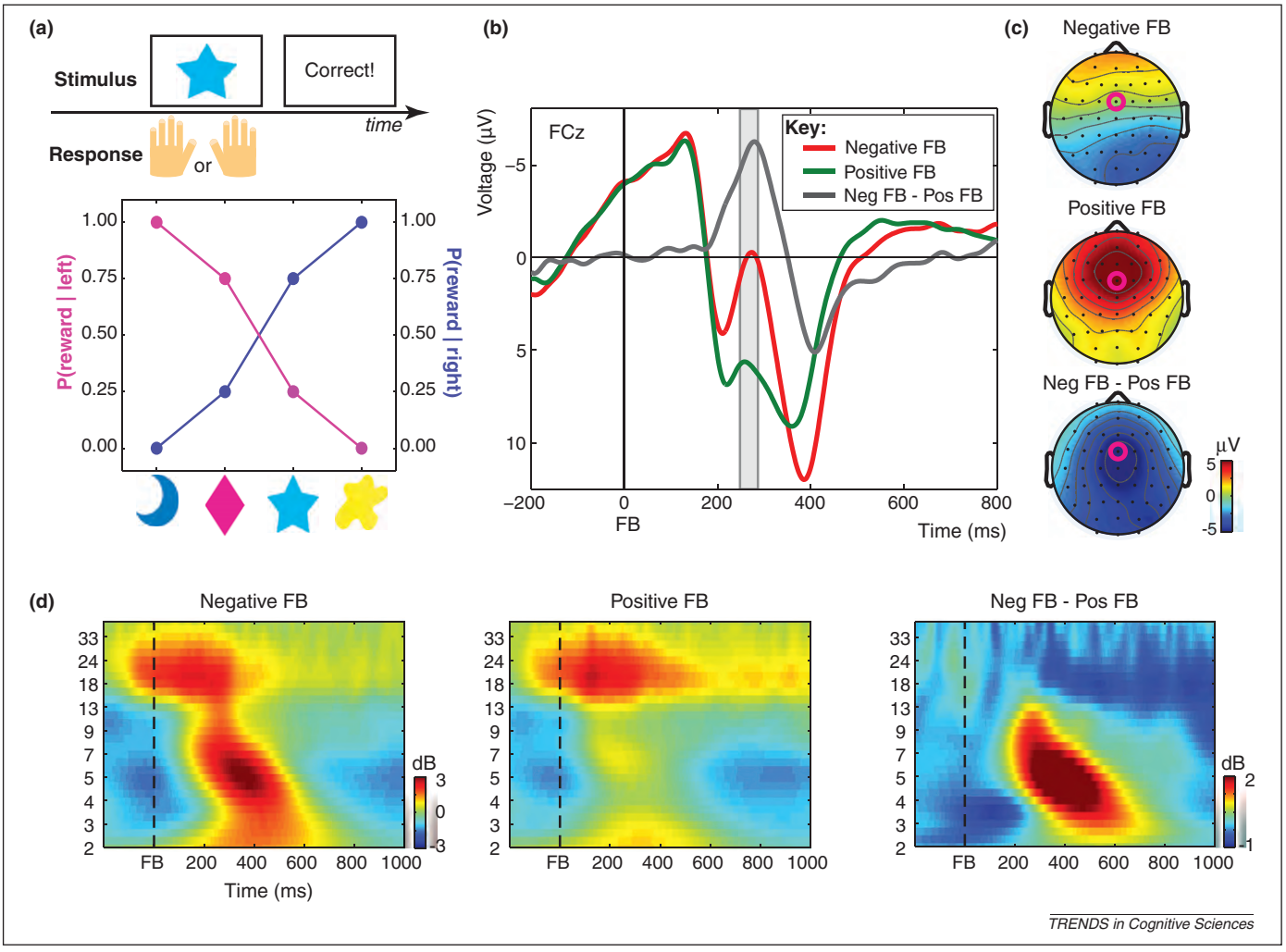


**Figure 1**. Typical experimental design and results from a feedback learning study. **(a)** In most studies, subjects learn which response option leads to positive feedback for a particular stimulus. Stimuli are often probabilistic (lower panel) such that correct answers do not always lead to positive feedback. **(b)** Most EEG studies on feedback learning focus on the feedback-related negativity (FRN, also sometimes called a feedback error-related negativity or medial frontal negativity). The FRN is a positive deflection in the time-domain averaged EEG potential, time-locked to visual onset of performance feedback (FB), and is relatively less positive following negative compared to positive feedback. These ERPs differentiate positive from negative feedback starting at around 200 ms, and the difference is maximal over midfrontal scalp sites (panel **(c)**). The rhythmic activity seen after negative feedback (note the peaks and troughs of the red line) can be quantified through time-frequency decomposition, which shows that negative (positive) feedback elicits increased theta-band (beta-band) activity compared to positive (negative) feedback (panel **(d)**). Adapted, with permission, from [54] (without spatial filtering for ERPs and with spatial filtering for time-frequency plots).

In terms of neurophysiological mechanisms, growing evidence suggests that the FRN may be the time-domain reflection of oscillatory activity [47,49–54]. Oscillations in EEG data reflect rhythmic fluctuations of populations of neurons and may be a fundamental mechanism for organizing and coordinating information processing [55–57]. As discussed below, conceptualizing the feedback-related EEG response not as an ERP component with one peak but rather as a temporal-spatial-frequency landscape of oscillatory dynamics has two significant advantages [6]: it allows results to be linked to known neurophysiological phenomena, including population-level neuronal activity, and also allows for in-depth data analyses aimed at uncovering how the prefrontal cortex interacts with other brain systems to support learning.

## Why a fresh perspective on electrophysiological mechanisms of feedback learning is needed

*Theoretical considerations.* The dominant theoretical model for understanding the FRN (and the response-locked error-related negativity, a theoretically related ERP that is time-locked to response errors) was proposed in 2002 by Holroyd and Coles [7]. This model predicts that the FRN reflects the impact of phasic (in)activation of the midbrain dopamine system, which reflects a reward prediction error [58], on anterior cingulate neurons. The appeal of this account stems from its simple, computationally-based and neurobiologically inspired framework. Our considerations below are not meant to disprove this theory but rather to highlight the need for a new perspective on feedback learning that incorporates the past decade's developments in neuroscience.

Several key predictions of the Holroyd and Coles model have not received empirical confirmation or are difficult to test in humans. The neural generators of the FRN appear to be distributed throughout frontal cortex [25,44–48] instead of being confined to a focal source in the anterior cingulate cortex. Empirical studies provide mixed support for the prediction that the FRN reflects a reward prediction error, as discussed earlier. There is no strong evidence regarding whether the FRN reflects phasic dopamine signaling because measuring and manipulating the human dopamine system in a precise way is difficult: positron emission tomography (PET) with dopamine agents is not readily accessible; dopaminergic pharmacological manipulations have complex and poorly understood effects on several neurochemical systems that depend on the dosage, the subject's metabolism, hormonal state, etc.; and reducing dopamine medication, for example in Parkinson's patients, induces other symptoms ranging from motor impairments to depression and impulsivity [59,60]. We do not suggest that dopamine is unrelated to the FRN – indeed, pharmacological [61] and genetic [53] studies demonstrate correlations between overall dopamine system activity and FRN magnitude. Rather, we argue that the hypothesis that the FRN reflects phasic changes in midbrain dopamine activity that directly modulate anterior cingulate neurons is difficult to falsify or confirm.

Furthermore, by restricting analyses to a fixed-latency ERP component from one electrode, most studies on feedback learning address a putative mechanism by which the need for learning is signaled, but these studies do not address the putative mechanisms by which that learning takes place nor do they address the nature of representations that are being learned (although some studies have examined learning-related changes in stimulus processing [62]). In our framework below, we address both the mechanisms by which the need for learning is signaled and the neural network-level manifestations of learning and task-specific representations.

*Methodological considerations.* Most EEG studies on feedback learning report peak amplitudes of the FRN from a single electrode (as in Figure 1a). This fixed-latency FRN amplitude measure is useful as an index of general activation of a cognitive learning system, but there are two main limitations of studying the FRN (and ERPs more generally). First, measuring the amplitude of the ERP deflection at a fixed point in time is an impoverished treatment of the rich and complex nature of EEG data [6]. As discussed below, potentially task-relevant dynamics may be lost during ERP averaging. Second, for the same reason, null results (e.g., non-statistically different FRNs across conditions) can be difficult to interpret because of potential condition-discriminating EEG dynamics not present in the ERPs.

M/EEG data provide a millisecond-precision window into the rich, complex and multi-dimensional temporal landscape of cortical electrical dynamics that unfold over time, space and frequency, and are, therefore, useful methodologies for linking neural dynamics to real-world cognitive, emotional, perceptual and social behaviors [6]. Conceptualizing M/EEG as comprising oscillatory dynamics is amenable to characterizing complex local and long-range interactions, interpreting findings in the context of neurophysiological mechanisms and linking results in humans to those in invasive recording studies in animals.

There are two main advantages of time-frequency decomposition. First, these analyses are amenable to neurophysiological interpretation because the neuronal mechanisms and interactions that produce field potential oscillations are well understood [57]. In contrast, it is less clear what neuronal mechanisms would produce trial-averaged ERPs that do not result from oscillatory activity, particularly ERPs such as the FRN that contain rhythmically alternative positive and negative peaks. (Whether ERPs in general reflect oscillatory processes is an ongoing debate that is outside the scope of the present article [63–65].) Second, orthogonal to the previous point and of more practical relevance, time-frequency decomposition allows a more in-depth investigation of the EEG dynamics underlying behavior. Many potentially informative phenomena of task-relevant neural dynamics – including synchronization, cross-frequency coupling and activities that overlap in time but are separable in frequency – are difficult or impossible to extract from ERPs. It has been argued that, because a Fourier transform will necessarily account for all activity (given sufficient frequency sampling), non-oscillatory activity will be present in time-frequency representations either as a broad-band or a band-limited response [65]. However, regardless of whether activity in a particular frequency band is termed oscillatory or band-limited, the fact remains that time-frequency decomposition can

provide insights into neurocognitive processes that go well beyond what can be learned from ERP averaging.

### A new perspective: large-scale, task-specific networks based on oscillatory synchronization

Learning can be conceptualized as experience-dependent changes in synaptic weights between neural populations representing stimuli or contexts and those representing the actions that help achieve a goal in response to those stimuli [66]. These changes in plasticity can be measured at the mesoscopic level with M/EEG as changes in inter-regional oscillatory synchronization [56,67]. Note that inter-regional synchronization does not require or imply monosynaptic connections. The issue of whether inter-regional synchronization necessarily implies synaptic plasticity is addressed in a subsequent section.

Measuring changes in synaptic plasticity as changes in oscillatory synchronization leads to the first core prediction of our framework: learning stimulus-response mappings should be associated with monotonically corresponding changes in synchronization between the stimulus-processing and motor areas involved in the mapping [68]. This means that increased learning should be reflected in increased synchronization, whereas unlearning (for instance, in an extinction or reversal paradigm) should be associated with decreased synchronization. For example, as subjects learn to associate a blue circle with a left-hand response and a red circle with a right-hand response, synchronization should increase between posterior color-processing areas and the right (left) motor cortex for blue (red) circles respectively. These synchrony-learning correlations should be manifested both within-subjects across trials or blocks of trials, and across subjects or groups, such that individuals who learn better should display stronger synchronization.

Inter-regional coupling may be manifested as phase synchronization [69], spectral coherence, power-power correlations or cross-frequency coupling [70] (see below and Box 1) and, because synchronization relies on the precise temporal interactions between regions, it does not require increases in oscillation power at any localized brain region. The precise frequency ranges in which learning-related inter-regional synchronization occur may depend on stimulus modality, processing demands and response mappings, although the gamma band may have a general role in cross-modal sensory associations [71].

Although we do not make specific predictions regarding the frequency ranges of learning-related synchronization, we do make predictions for the frequency bands in which feedback and its implications are evaluated. Several research groups have observed a frequency band dissociation for feedback valence, such that negative feedback elicits midfrontal theta-band activity whereas positive feedback elicits midfrontal beta-band activity [47,49–54,72]. This frequency band dissociation suggests that different neurophysiological mechanisms underlie learning from negative versus positive feedback and leads to the second core prediction of our framework: learning-related changes in inter-regional synchronization should be modulated in a top-down fashion by frontal theta when learning from negative feedback and by frontal beta when learning from positive feedback. Although these theta and beta effects share a somewhat similar midfrontal topographical distribution, they might have distinct neural generators: as mentioned earlier, the negative feedback theta effect appears to emerge from medial prefrontal and posterior cingulate cortices [25,44–48]. Less is known about the positive feedback beta effect, but orbitofrontal cortex is a likely candidate [52] because it has consistently been implicated in reward and positive feedback [73], and electrical fields from neurons along the ventral surface of the orbitofrontal cortex may propagate to the scalp.

Thus, we predict that feedback learning occurs through a prefrontally mediated modulation of synaptic weights that functionally link stimulus-processing and motor-generating cortical regions, which can be measured through oscillatory synchronization (Box 2). This fairly simple theoretical framework (i) makes novel predictions that are testable in a variety of species using EEG, MEG, intracranial EEG, and single- and multi-cellular recordings; (ii) may help understand learning impairments in some clinical populations, e.g., substance abuse; (iii) is also amenable to development and yields auxiliary predictions (Box 2).

*Changes in local activity (oscillatory power) versus changes in inter-regional synchronization over time and trials.* Changes in local activity, measured through frequency band-specific activity recorded from specific electrodes or brain regions via source imaging, should conform to predictions made previously [7,16]: with learning, feedback-locked activity should decrease and response-locked activity should increase, reflecting a shift from learning via

**Box 1. Different measures of connectivity with M/EEG data**

- Phase synchronization or phase-locking refers to power-independent consistency of phase values across electrodes. Phase-based measures are highly sensitive to temporal information, which is well suited for tightly temporally linked processes but may be suboptimal when the precise temporal interactions are not known or may be jittered across trials.
- Spectral coherence measures frequency band-specific coupling and combines both power and phase information.
- Power-power correlations involve correlating average frequency band-specific power across trials, and can be interpreted as reflecting slower state changes rather than temporally precise interactions. This method is suitable if a precise temporal relationship between activities in two areas is not known.
- Spectral Granger causality measures the increase in variance in one electrode that can be accounted for by considering variance in another electrode previously in time (note that Granger causality is a measure of directed synchronization and does not imply or require a true causal relationship). The main advantage of Granger causality (and related measures such as partial directed coherence) is the ability to make empirically buttressed assertions about the direction of information flow across brain regions.
- Cross-frequency coupling refers to a relationship between activities in different frequency bands, which can be measured at the same electrode or over different electrodes [70]. This may indicate that activity in larger-scale networks (coordinated by relatively slower oscillations) is regulating activity in more localized networks (coordinated by relatively faster oscillations) [70].

This is not an exhaustive list of connectivity measures; many other connectivity measures exist and might be usefully applied (e.g., mutual information, phase-lag index [99], multi-variate state-space measures [100]).

**Box 2. New predictions for the neural mechanisms of feedback learning**

Core predictions (Figure Ia):

- Learning/unlearning is associated with increases/decreases in synchronization between the stimulus and/or motor areas for which associations are formed.
- These changes in synchronization are driven by a top-down influence of prefrontal cortical regions in a frequency band-specific manner:
  - ○ Learning from negative feedback engages midfrontal theta-band oscillations.
  - ○ Learning from positive feedback engages ventromedial beta-band oscillations.
- These changes in prefrontal cortex-modulated inter-area synchronization are reflected within subjects (i.e., changes during learning) and across subjects (stronger synchronization in individuals who learn better).

Auxiliary predictions (Figure Ib; note that this is not an exhaustive list):

- Dorsolateral PFC regions should become engaged if working memory is required.
- Frontopolar regions should become involved if exploration or abstract hypothesis testing is required [96].
- Amygdala should become involved if the learning involves social/emotional associations [97].
- Additional anterior cingulate cortex recruitment might be involved when learning involves uncertainty or dynamically changing learning rates [98].

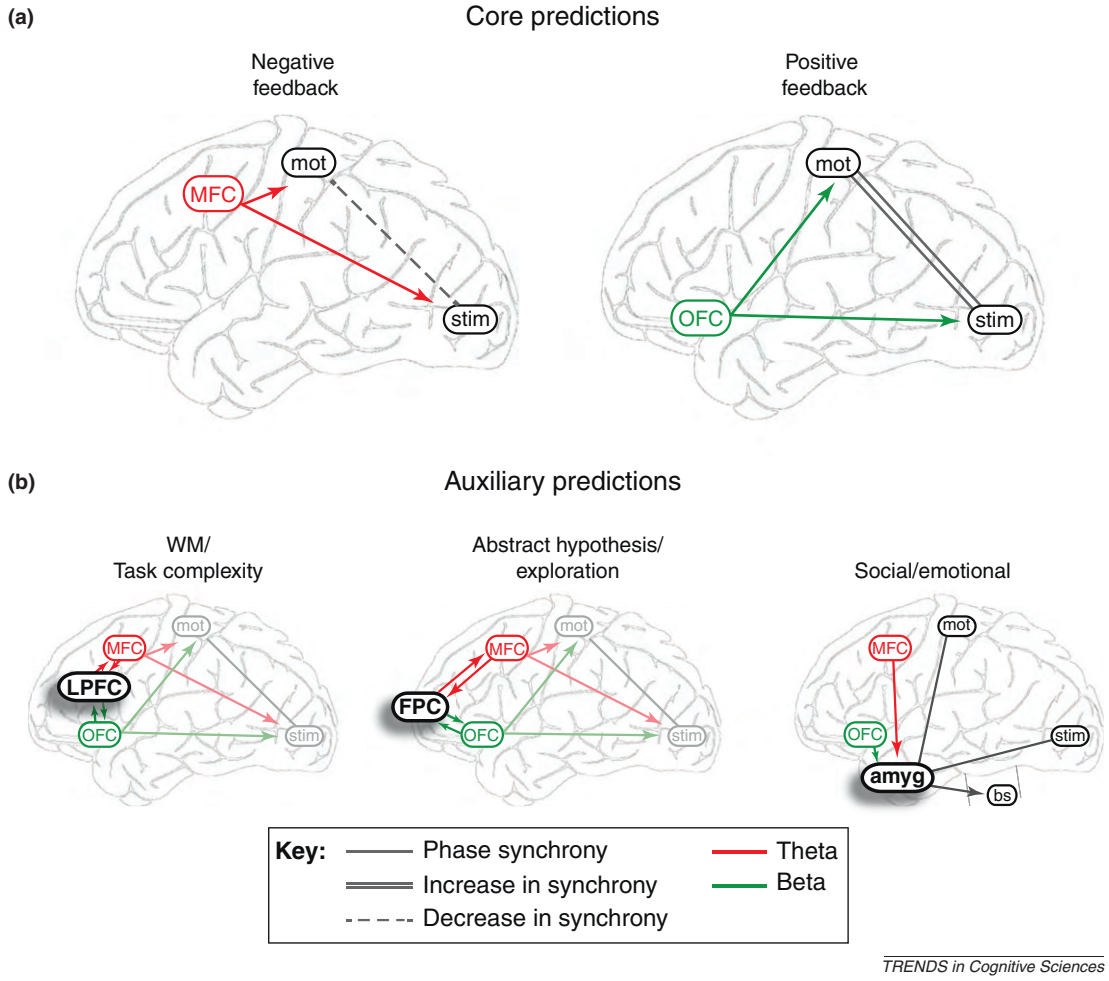


**Figure I**. Graphical illustration of new core (panel **(a)**) and auxiliary (panel **(b)**) predictions from our framework for cortical oscillatory correlates of feedback-guided learning. Note that 'stim' (stimulus representation) is here drawn towards the occipital pole but would reflect activity in any sensory area representing the task-relevant stimulus. MFC=medial frontal cortex; mot=motor areas; OFC=orbitofrontal cortex; LPFC=lateral prefrontal cortex; FPC=frontopolar cortex; amyg=amygdala; bs=brainstem.

exogenous to learning via endogenous feedback processing and consistent with temporal-difference learning mechanisms [7].

The novel predictions of our framework involve synchronization. Our model makes specific predictions about how synchronization changes over time within a trial and across trials of an experimental block. Generally, we assume that changes in synchronization elicited by performance feedback reflect the mechanism of learning – the cascade of synaptic, cellular, and systems-level restructuring based on principles of Hebbian learning – and we assume that changes in synchronization elicited by stimulus onset reflect the consequences of learning – the result of Hebbian learning such that the activation of one node (e.g., representing the stimulus) activates other nodes within the network (e.g., the associated response or other stimuli with which the stimulus has been paired). Other predictions for how changes in synchronization occur over time

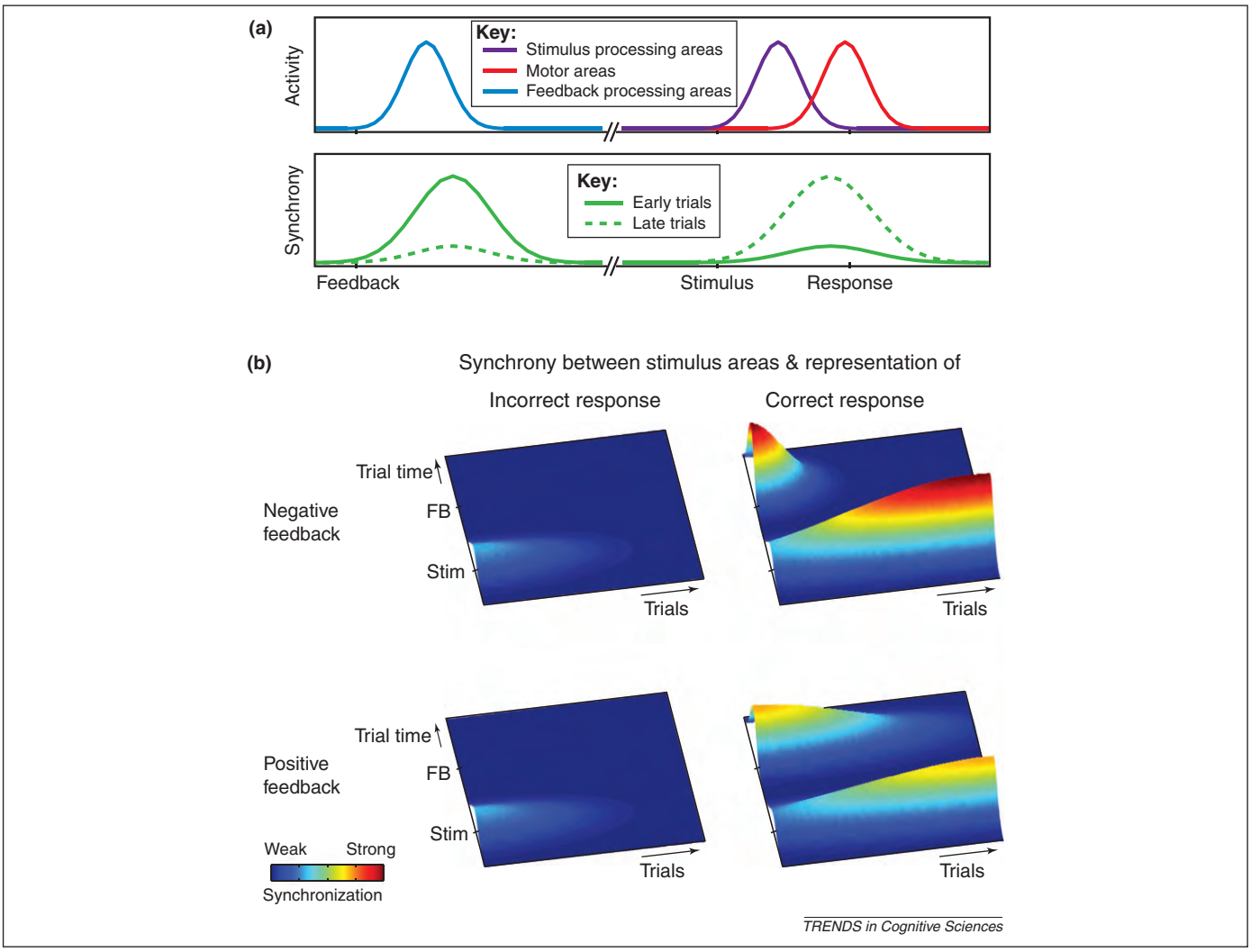


**Figure 2**. Graphical illustration of predicted temporal dynamics of local activity and inter-regional synchrony with learning. **(a)** Activity within feedback, stimulus and response processing areas is expected to increase only during the related event, but synchrony between stimulus processing areas and the representation of the correct response is expected to increase both as a result of feedback (mechanism of learning) and after stimulus presentation (manifestation of learning). This increase in synchrony after feedback presentation between stimulus processing areas and the representation of the correct response is expected to decrease over trials as the association is learned, whereas the increase in synchrony with the representation of the correct (incorrect) response after stimulus presentation is expected to increase (decrease). **(b)** Three-dimensional renderings of predicted synchronization over trials and time within a trial. Changes in synchrony as a result of learning are expected to be larger and faster (over trials) after negative than after positive feedback. This illustration assumes valid feedback; probabilistic feedback would modulate local landscape features.

and across trials, separately for positive vs. negative feedback and for the correct and incorrect response, are illustrated in Figure 2.

*If changes in synaptic plasticity lead to synchronization, does synchronization imply changes in synaptic plasticity*? Unfortunately, the answer is no. Changes in task-related inter-regional synchronization can also result from changes in attention or motivation [74–76], which likely change over the course of an experiment along with learning.

Inferring synaptic plasticity from inter-regional synchronization should therefore rely on additional considerations to rule out alternative hypotheses. Here we discuss three criteria that would help dissociate synchrony due to changes in synaptic weights from synchrony due to changes in attention or task engagement. First, changes in synchronization should occur dynamically within blocks of trials (see Figure 2), whereas effects due to attention should decline steadily over the course of the experiment. One could also record subjective ratings of attention/arousal/motivation/engagement or use inter-trial-interval posterior alpha power as an indirect measure of attention. Second, presentation of the learned stimulus after the learning session ends (and without requiring a response) should elicit synchronization patterns observed during learning (in this case, electromyographic activity should be recorded to ensure that subjects are not making covert responses with the stimulus-associated hand). Third, this 'reactivation' of the synchronization pattern should occur in the absence of attention (e.g., if the stimuli are masked to preclude conscious awareness of its presentation or if attention is overtly directed elsewhere). These patterns of results would be difficult to attribute to task-related, but plasticity- or learning-independent, mechanisms.

*How inter-regional synchronization can be measured in the human brain.* There are several different measures of synchronization, each with its own interpretation and advantages/limitations. Box 1 provides a brief overview of several different methods along with their interpretations. Measuring inter-regional synchronization is hindered by volume conduction – the spread of electrical

fields from one brain source to multiple electrodes/sensors. It is important to demonstrate that changes in synchronization between two electrodes do not simply reflect the spread of one neural source to multiple electrodes. Spatial filtering techniques such as surface Laplacian [77], independent components analysis [78] and distributed source imaging [79] help minimize the contribution of volume conduction, but may not entirely eliminate the problem. Changes in synchronization in the absence of power or uncorrelated with power, and non-zero phase lag synchronization help distinguish true synchronization from volume conduction. In short, there are several methods for quantifying the time- and frequency-varying interactions between brain regions. Each method has its advantages and limitations, and important potential methodological concerns must be taken into consideration for each method.

*Neurocomputational mechanisms*. Feedback learning in humans is likely supported by a prediction error-like mechanism. Indeed, models based on Rescorla-Wagner principles have been successful at capturing some aspects of behavior and EEG activity during learning tasks [7,25,29,80]. However, informal post-experiment debriefings consistently reveal that subjects generate and test sometimes very complex hypotheses, even when instructed that the task contains no complex higher-order patterns. A simple example is that negative feedback can be a strong positive prediction error (i.e., an early predictor of a reward) if subjects test the hypothesis that response '1' is not associated with stimulus 'A'. Furthermore, subjects occasionally spontaneously report hypotheses about complex trial sequences that they thought were manipulated in the task and that guided their behavior, even when explicitly instructed that trial sequences are randomized. These and related observations suggest that relying on simplistic computational mechanisms may preclude a more in-depth understanding of the neurocognitive processes that support learning. This is not to suggest that computational modeling cannot inform mechanisms of feedback-driven learning; rather, we think that simplistic computational models may provide a misleading interpretational framework, and more accurate models should account for the higher-level hypothesis testing and strategizing processes in which subjects regularly engage.

*The role of neurochemistry*. Undoubtedly, neuromodulators play a role in feedback learning [81]. For example, dopamine facilitates long-term potentiation/depression [82] and regulates stability vs. flexibility of representations [83]; norepinepherine modulates system-wide arousal/attention and mood [84]; and acetylecholine is involved in neural plasticity and modulating neural oscillation characteristics [85]. In the present framework, neurochemicals, including dopamine, have a peripheral rather than central role, and interpreting results within this framework does not require invocation of difficult-to-test neurochemical causal mechanisms.

*Subcortical regions*. It may seem a surprising omission to exclude the basal ganglia/striatal system from our model. Clearly the basal ganglia play a role in learning and action selection [86,87]. However, their contribution to synchronization-based manifestations of learning is more difficult to test for two reasons: deep brain activity is not easily measured from the scalp [88] and (2) some hypothesized roles of the basal ganglia are difficult to test in humans because they involve differentiating neurons by synaptic properties (e.g., go vs. nogo pathways) or in small nuclei (e.g., internal vs. external segment of the globus pallidus). However, rare opportunities to record directly from subcortical regions in humans (e.g., for deep-brain-stimulation) support the role of synchronization between the medial frontal cortex and ventral striatum for reward learning and anticipation [89,90], and between the medial frontal cortex and subthalamic nucleus for conflict-based behavior adaptation [91]. In healthy humans, combining EEG and functional magnetic resonance imaging (fMRI) may help by uncovering correlations between scalp EEG and hemodynamic activity [92], although it is unclear what the predicted hemodynamic correlate of changes in neural synchronization without changes in overall activity is.

*Potential clinical relevance*. Several brain disorders are associated with impairments in learning as well as oscillatory dynamics, such as schizophrenia [93], substance abuse [94] and autism spectrum disorders [95]. The present framework may, therefore, be useful for studying these disorders. Following confirmation that network synchronization-level disruptions are linked to learning impairments in clinical disorders, an important avenue of research would be to test whether changes in learning-related synchronization might be used as a neural marker of treatment success.

## Concluding remarks

Conceptualizing feedback-driven learning as changes in inter-regional oscillatory synchronization driven by top-down prefrontal dynamics allows novel and falsifiable hypotheses that incorporate recent developments in understanding systems-level network interactions. We hope that this framework will facilitate new discoveries about neurophysiological mechanisms of feedback-guided learning that will be relevant for basic neuroscience, and how these systems go awry in pathologies.

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