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Title: Transitions in neural oscillations reflect prediction errors generated in audiovisual speech

Running title: *prediction errors and beta/gamma oscillations*

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Abstract

According to the predictive coding theory, top-down predictions are conveyed by backward connections, while prediction errors are propagated forward across the cortical hierarchy. Using MEG in humans, we show that violating (multisensory) predictions causes a fundamental and qualitative change in both the frequency and spatial distribution of cortical activity. When visual speech input correctly predicted auditory speech signals, a slow delta regime (3–4 Hz) developed in higher-order speech areas. In contrast, when auditory signals invalidated predictions inferred from vision, a low-beta (14–15 Hz) / high-gamma (60–80Hz) coupling regime appeared locally in a multisensory area (STS). This frequency shift in oscillatory responses scaled with the degree of audio-visual congruence and was accompanied by increased gamma activity in lower sensory regions. These findings are consistent with the notion that bottom-up prediction errors are communicated in predominantly high (gamma) frequency ranges, while top-down predictions are mediated by slower (beta) frequencies.

Introduction

Predictive coding and other models of perception based upon hierarchical Bayesian inference¹⁻³ assume that neural representations are optimized to reduce “prediction error”. This error is classically defined as the difference between the representations (neuronal activity) at each cortical level and the “predictions” or expectations arising from the level above, or cascading back from higher cognitive levels. Hence, the better the prediction, the smaller the prediction error. This reciprocal relationship between predictions and prediction errors is overtly or covertly exploited by several experimental paradigms (e.g., oddball, violation and adaptation paradigms) that rely on the contrast between neural responses to anticipated and unexpected stimuli, and report stronger responses to stimuli that are not or incorrectly anticipated.

There is also growing evidence that perception involves coordinated slow and fast brain oscillations, typically theta/gamma nesting⁴⁻⁶, and novel hypotheses suggest that bottom-up information could be propagated forward on a gamma frequency channel from superficial cortical layers, whereas top-down information would use backward propagation on a beta frequency channel from deep cortical layers⁷. How the coding of cognitive content and properties of electrical signaling articulate with each other is unclear. Here, we set out to experimentally address whether the rate and distribution of neural activity depends on correct or incorrect anticipation of the stimulus, and whether sensory predictions and prediction errors are conveyed using different frequency channels.

Audio-visual speech provides an ideal setting in which to test these hypotheses⁸. Our experimental paradigm capitalizes on a natural ~150 ms temporal lag between the onset of facial movements and vocal chord vibration that naturally occurs when we speak⁹. This lag allows the observer to synthesize phonological predictions prior to auditory onset on the basis of visual information. This also gives the experimenter the opportunity to temporally distinguish the neural effects related to these visually induced predictions and the prediction errors that emerge during audio-visual integration if predictions are invalidated. Here, sensory prediction errors were induced experimentally by violating the congruence between visual and auditory information. We also exploited the specificity with which visual input predicts auditory input in order to create a gradient of perceived incongruence⁸⁻¹⁰. We thus induced graded prediction errors by varying audio-visual congruence, and expected them to be manifest at the neural level in the interaction between the amount of predictive information conveyed by the visual input (predictability) and the validity of this information with respect to incoming auditory input (audio-visual congruence). We quantified this “predictability-by-

validity” interaction on neuromagnetic event-related fields (ERFs) measured with magnetoencephalography (MEG), and determined the oscillatory processes underlying prediction error using time-frequency analyses of the MEG data. We report qualitative differences in neural dynamics as a function of the validity of visual predictions, i.e. the amount of prediction errors.

Our central hypothesis was that there should be a fundamental and qualitative change in neuronal message-passing when sensory predictions are invalidated. In particular, audiovisual mismatch detection should enhance coordinated beta and gamma activities associated with the propagation of revised predictions and the redeployment of new prediction errors, respectively. While we observed distributed slow delta activity in higher-level cortical areas during the perception of congruent stimuli, faster local cortical activity replaced these slow interactions when predictions from visual modality were invalidated by auditory inputs. In agreement with our hypothesis, beta activity appeared in regions where visual and auditory information converged, i.e. where multisensory predictions were generated, whereas gamma activity was seen in lower sensory cortices where prediction errors emerged and were propagated forward.

Results

We presented 15 subjects with stimuli in one of three conditions: videos (audio-visual: AV condition) of a speaker pronouncing different syllables, /pa/, /ʒa/, /la/, /ta/, /ga/ and /fa/, an auditory track of these videos combined with a still face (auditory: A condition), or a mute visual track (visual: V condition). The videos could be either natural or a random combination of auditory and visual tracks, entailing a condition where auditory and visual tracks were congruent (AVc condition) and one where they were incongruent (AVi condition; see Methods and **Supplementary Fig. 1**). Incongruent combinations yielding combination of fusion illusory percepts, i.e. McGurk stimuli, were excluded^{8, 11}. Subjects performed an unrelated target detection task on the syllable /fa/ that was presented in A, V or AVc form in 13% of the trials (97% correct detection). These trials were subsequently excluded from the analyses. The five other syllables were chosen because they yielded graded recognition accuracy when presented visually (**Fig. 1a**), resulting from an increasing *predictability*¹⁰. The phonological prediction conveyed by mouth movements (visemes), varies in specificity depending on the pronounced syllable. Typically, syllables beginning with a consonant that is formed at the front of the mouth (/p/, /m/) convey a more specific prediction than those formed at the back (/g/, /k/, /r/, /l/)⁸. Our second experimental factor pertained to the validity

of the visual prediction with respect to the auditory input. Physically, the audio-visual stimuli could be either congruent (valid prediction) or incongruent (invalid prediction), while perceptually, the level of incongruence varied gradually as a function of visual predictability, e.g. the strongest perceived incongruence was reported for the most predictable visemes in incongruent stimuli (see **Supplementary Data**).

Predictability-by-validity interaction was tested in a number of different data features to establish when and where in the brain prediction errors were expressed. We used the amplitude of event related fields over auditory regions to produce statistics as a function of predictability and validity across the peristimulus timecourse (**Supplementary Fig. 2a**). This indicates when ERFs are modulated by i) visual prediction validity (main effect of audio-visual congruence), ii) visual predictability separately under valid and invalid conditions, and iii) when prediction errors emerged (predictability-by-validity interaction). We went on to characterize the specific time-frequency patterns underlying ERF amplitude variations reflecting prediction error, by exploring time-frequency data in a way that is constrained by the time course of ERFs. This original methodological approach exploits inter-individual - stimulus ERF variability to specifically probe time-frequency phase-locking and power effects that are sensitive to the experimental factors (**Supplementary Fig. 2b**). This method thus enhances the temporal sensitivity of the time-frequency analysis by revealing stimulus-induced and/or phase-locked oscillatory patterns underlying ERF modulations (see ¹², Methods and **Supplementary Fig. 2b**). This finally permits us to precisely identify the key frequencies, phase-locking and nesting principles that specifically underlie the expression of prediction error. Finally, to establish the regional specificity of these findings, we broadened the correlations between neuromagnetic indices of prediction error and time-frequency responses to all MEG channels.

Late ERF oscillatory regime reflects prediction errors

Our first analysis step was to correlate the amplitude of ERFs (AV-A, i.e. audio-visual integration index, see Methods) in response to each of the five syllables with their corresponding predictability value, i.e., the recognition level they yielded when presented as visemes (**Fig. 1a**), over the whole peristimulus timecourse (-100 to 600 ms relative to auditory onset; **Supplementary Fig. 2a**). The first two ERF components evoked by audio-visual syllables on the sensors that responded best to auditory stimuli correspond to feed-forward visual and auditory responses ¹³. We refer to these components as M170V and M100A, respectively. Reflecting the natural delay between visual and auditory onsets, M170V and M100A were separated by approximately 100 ms. A main effect of visual prediction validity (audio-visual congruence) was detected after M100A peak in 4 distinct ~20

ms time-windows (**Fig. 1b**). Critically, we detected an effect of predictability ($p < 0.01$, shaded windows in **Fig. 1b** and **c**) on the M170V preceding auditory onset (Window 1) and on M100A (Window 2) in both AVc and AVi conditions (**Fig. 1c**). The parametric effect on M100A responses confirms that the independently assessed behavioral gradient is recovered by early physiological signals despite an un-related task instruction. A further late predictability effect was observed in AVi stimuli only, at around 350–500 ms (solid line in **Fig. 1c**, Window 3). Accordingly, the predictability-by-validity interaction emerged within this third window (**Fig. 1c**, interaction: $p < 0.001$). These data confirm that prediction errors only occurred late, after cross-modal prediction had emerged at cortical levels higher than auditory cortex, presumably at the superior temporal sulcus (STS) level, and possibly above.

We addressed a potential divergence in neural dynamics between the processing of correctly and incorrectly anticipated stimuli by comparing the time-frequency structure of evoked responses in valid and invalid conditions (see Methods). Consistent with the ERF data, time-frequency correlation maps (**Fig. 2a**) show that while AVc and AVi conditions evoked similar early (–100 to 300 ms) phase-locking increases in the delta-theta band (2–9 Hz), diverging patterns occurred during the latest time-window (350–550 ms). When visual prediction was valid, the amplitude of late ERFs correlated with an increase in slow delta (3–4 Hz) phase-locking (**Fig. 2a** and **b**, left panel, 350–500 ms, $p < 0.001$, interaction: $p = 0.04$), and a decrease in theta phase-locking. Conversely, when the prediction was invalidated by auditory input (**Fig. 2a** and **b**, right panel), ERF variations were associated with an increase in phase-locking factor (PLF) in a low-beta band (14–15 Hz, 400–550 ms, $p = 0.045$, interaction: $p = 0.13$), and a PLF decrease in the theta range (5–6 Hz, 350–500 ms, $p = 0.018$, interaction: $p = 0.05$). That predictability-dependent phase-locking departed from the theta band to either adopt a lower rate regime when predictions were valid, or a higher one when they were not, supports our hypothesis that visual prediction validity determines a transition in neural dynamics.

Beta and delta regimes show distinct spatial dynamics

To check whether these two distinct phase-locking modes were implemented through spatially distinct neural networks, we broadened the analysis to the whole scalp surface while focusing on the two time-frequency clusters reflecting the difference between valid and invalid conditions (black arrows, in **Fig. 2a**). We computed Pearson correlations at each sensor, between their PLF values in these time-frequency windows and the ERF amplitude of auditory sensors (**Supplementary Fig. 2b**). Scalp topographies of correlation values show diverging spatial patterns of stimulus phase-locked oscillatory activity depending on the validity of visual prediction (**Fig. 2c**). When prediction was valid, phase-locked delta activity

(3–4 Hz) emerged across regions usually involved in high-order language processing, i.e., the ventral temporal cortex and the angular gyrus¹⁴ (**Fig. 2c**, left).

When visual prediction was invalid, the phase-locked pattern in the beta band (14–15 Hz) remained confined to the posterior middle temporal region (**Fig. 2c**, right), presumably the STS that is often described as a convergence point of visual and auditory (speech) inputs¹⁵⁻¹⁷. The location of this effect strongly converges with fMRI results obtained in an independent study in which we also probed predictability-by-validity interaction using a similar experimental design (**Supplementary data** and **Supplementary Fig. 3** and **4**). The transition in frequency regime when predictions were invalidated was thus associated with a drastic change in response topography, presumably reflecting a change in message-passing mode emphasizing top-down processing.

Prediction invalidation increases beta PLF and gamma power

An important implication of predictive coding^{1,3} is that the brain dedicates more resources to unexpected than to anticipated events. As high-frequency oscillations are energetically more demanding than slow oscillations¹⁸⁻²⁰, we checked whether oscillations in the gamma range could explain late ERF amplitude modulations associated with prediction errors (Window 3 in **Fig. 1b** and **c**). This analysis hence focused on late prediction error effects, i.e. 350 ms after auditory onset. We performed the same correlation analysis as above, using the sensors (n=10) that showed the strongest validity effect at the group level. These sensors were situated over posterior superior and middle temporal regions. Whereas low-frequency (< 30 Hz) phase-locking and power correlation maps showed the same patterns for these sensors as for “auditory” sensors, we detected several clusters showing significant correlations between ERF amplitude and high-frequency power. The largest effect occurred in the AVi condition between 350 and 500 ms in the 70–90 Hz range (**Fig. 3a**, black arrow in right panel, $p < 0.001$, interaction: $p = 0.01$). Prediction invalidation hence increased late gamma power.

We further tested for a possible coordinated activity (see Methods) between low-frequency phase-locking and high-frequency gamma power (**Fig. 3b**). When prediction was invalid (AVi), late (350–500 ms) mid- and high gamma power distinctly correlated with the two low-frequency phase-locking patterns shown in the right panels in **Figures 2a** and **b**. Prediction error resulted in *i*) a joint increase in mid-gamma (60–70 Hz) power and PLF in low beta frequencies (14–15 Hz) suggestive of oscillation hierarchical coupling (nesting)⁴⁻⁶, and *ii*) an increase in high-gamma (70–90 Hz) power with a PLF decrease in the theta band (5–6Hz) (**Fig. 3b**). The transition to a beta phase-locked mode likely gated an increase in mid-gamma

oscillation power, while the increase in high gamma power was accompanied with a dissolution of phase-locked oscillations in the theta band.

Finally, to address whether high gamma power modulations in the AVi condition reflected the level of prediction error, and in such a case where this occurred at the scalp level, we averaged power values in the time-frequency window defined by the interaction above (350–500ms; 70–90 Hz; **Fig. 3a**, black arrow in right panel) and computed Pearson correlations with visual predictability at each sensor. As shown in **Figure 3c**, the highest correlation values were visible over the left occipital and temporal sensors, mainly distributed between early visual areas, auditory areas and the STS. When visual prediction was both strong and invalid, high-gamma power increased in low-level sensory regions. The increase in beta phase-locking in the STS was seen conjointly with an increase in gamma activity locally and in lower-tier sensory areas. This supports the proposal that the beta range is involved in inter-areal coupling^{17, 21-23}, and more specifically used in feedback projections^{24, 25}, and further suggests that the gamma range serves to propagate prediction error forward.

Discussion

Our results support theoretical models assuming that the brain uses prediction estimation procedures to construct percepts^{1, 3, 26-28} and control action²⁹. In sensory perception, the general idea is that the brain continuously uses available information to update internal estimates that are used to predict the subsequent input. In this view, the information that is propagated forward reflects the difference between incoming input and expectation (i.e., what remains to be explained), whereas predictions are propagated backward. In our experimental setting, the temporal precedence of visual signals allows for the generation of predictions that are then confronted with incoming auditory signals⁸. Consistent with predictive models, detectable correlates of prediction error were confined to late responses (~350 ms). This is because they are most strongly manifest after auditory and visual signals have converged on the STS, where phonological predictions generated on the basis of the visual input are effective (see **Supplementary Data**).

We hypothesized that prediction validity at the origin of prediction errors induces a qualitative shift in neural dynamics that determines the message-passing mode. As expected, in the case of visual prediction validation, we observed stimulus-locked slow neural activity in a large high-order integrative network. In contrast, visual prediction invalidation induced the dissolution of distributed low-frequency oscillations and the emergence of higher-frequency

activity in the STS. Consistent with previous studies ^{19, 20}, this increased high frequency activity co-localized with an increase in the BOLD signal (see **Supplementary Fig. 4**). The oscillatory pattern involved low beta and gamma activity locally in the STS and high gamma (70–90 Hz) activity in early auditory and visual processing systems. In other words, we observed a transition from a smooth distributed flow of information to a fast local processing, presumably aiming at i) resolving the conflict at the stage where audio-visual phonological incongruence is registered by forming new plausible sensory predictions, and ii) estimating these predictions in lower processing stages.

Superficial layers of the cortex are the predominant source of gamma oscillations ³⁰ and the notion that prediction error is indexed by increased gamma power in lower-tier sensory areas is therefore consistent with the proposal that superficial pyramidal cells, that originate forward projections in cortical hierarchies, report prediction error ¹ (see **Supplementary Fig. 5**). That low beta activity increased in the STS, a higher hierarchical stage, also fits with the idea that deeper layer pyramidal cells, notionally representational units originating backward predictions ³¹, are associated with beta activity ^{7, 24, 25, 32}. Given that superficial pyramidal cells receive their input from layer IV and project back on deep layers ³³, an increase in prediction error enhancing superficial gamma activity likely strengthens connections across superficial and deep cortical layers. This coupling between superficial and deep layers generates a low beta rhythm (15Hz) that changes the nature of message-passing ^{34, 35}. Functionally, the emergence of this common rhythm across superficial and deep layers could reflect i) the convergence of error and representation units on a new representational solution (prediction error minimization) and ii) top-down propagation of this solution to hierarchically lower regions. A slower frequency channel for top-down than for bottom-up signal propagation could reflect that top-down predictions result from the accumulation of bottom-up prediction errors. The emergence of low beta activity (14–15Hz) in the STS and increased high gamma activity locally and in lower-tier sensory areas could signal the redeployment of prediction errors due to alternative prediction testing operations (**Supplementary Fig. 5**).

While beta and high gamma (80Hz) activity (and BOLD response) indexed prediction error and its resolution, slower delta/theta oscillatory activity signaled further processing of correctly anticipated stimuli. Delta (3–4Hz) activity in our data localized to distributed lexico-semantic areas, suggesting that late slow stimulus-locked oscillatory activity reflects higher stages of speech processing ^{36, 37} and stabilizes sensory representations ^{38, 39}. It is unclear how slow activity precisely relates to perception. Perception is often thought to rely on synchronization of focal neuronal assemblies in the gamma range ⁴⁰⁻⁴². Delta/theta activity on the other hand has been suggested to shape gamma activity in superficial cortical layers ⁴³

that propagate information to the next hierarchical stage⁴⁴. Accordingly, we observed that gamma activity related to prediction error is accompanied by a decrease in theta phase-locking (**Fig. 3b**). The observation that mid and high gamma activity are related to the phase-consistency of beta and theta activity, respectively, extends the idea that gamma frequency variations reflect information routing^{32, 34, 45, 46}, and that message-passing is indexed by specific hierarchical combinations of slow and high frequencies (low/high frequency ratio)⁴⁷.

The current data demonstrate that violating intermodal expectations changes the neural dynamics of slow (delta/theta) brain activity, and increases the coordination between local low beta and high gamma oscillatory activity. Our data suggest that this transition occurs in brain regions where audio-visual predictions are likely updated (STS), and new prediction errors generated (auditory and visual cortices). These findings suggest a tight relationship between particular high-frequency modes of activity and prediction errors, and suggest that slow cortical activity contains a previously unappreciated wealth of information that reflects perceptual expectations.

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Author Contributions

The author(s) have made the following declarations about their contributions: Conceived and designed the experiments: LHA, ALG. Performed the experiments: LHA. Analyzed the data: LHA, VW, ALG. Contributed to analysis tools: LHA, VW. Wrote the paper: LHA, VW, ALG.

Figure legends

Figure 1. Interaction between predictability and validity in ERFs.

a. Predictability was assessed behaviorally as the recognition rate of syllables presented in the visual (V) condition. Normalized predictability of each syllable was then correlated with experimental measures. **b.** Main ERF components evoked on auditory sensors by the presentation of AVc (dashed line) and AVi (solid line) stimuli. Grey surfaces between dashed and solid lines delimit time periods showing a main effect of validity (** $p < 0.01$). **c.** Correlations between ERF (AV–A) amplitude and predictability were computed at each time bin, separately for AVc (dashed line) and AVi (solid line) conditions. ERFs and correlation lines are locked to visual onset on the left, and on auditory onset on the right of the vertical double bar, respectively (see Methods). Windows 1, 2 and 3 (shaded surfaces in **b** and **c**) indicate the timeperiods where correlation is significant (signed r^2). Black horizontal lines delimit statistical threshold $p < 0.01$ (** $p < 0.01$, * $p < 0.05$). Window 1 indicates that the visually-evoked response increased with visual predictability but was not affected by prediction validity (interaction in window 1: $p = 0.93$). Window 2 indicates that the decrease in M100A was accelerated proportionally to visual predictability, confirming that visual input hence sped up^{8, 10} and “sharpened”⁴⁸ early auditory evoked responses proportionally to its informational value, yet without prediction error computation (non-significant interaction in window 2: $p = 0.52$). Prediction errors (visual predictability-by-validity interaction) emerged in the latest Window 3 (grey surfaces between dashed and solid lines in Window 3 delimit significant interaction, $p < 0.001$).

Figure 2. Late low-frequency oscillatory patterns depend on the validity of inferences.

a. Correlation strength (signed r^2) between ERF amplitude and PLF of low (2–20 Hz) frequency bands. Time is expressed relative to auditory stimulus onset. Contours delimit statistical threshold of $p < 0.05$, $p < 0.01$ and $p < 0.001$. Arrows indicate time-frequency effects of interest, subsequently used for topographical rendering (see **c.**). **b.** Significance of the correlation strength (cluster corrected for multiple comparisons) across time in selected frequency bands, in AVc condition (delta-theta [350–500ms; 3–4 Hz]), and in AVi condition (delta-theta [350–500ms; 5–6 Hz]; beta [400–550; 14–15 Hz]). Thick lines indicate p cluster < 0.05 across time (** $p < 0.001$, * $p < 0.05$). Filled-in grey surfaces represent the mean and standard deviation of the corresponding null distributions across 1,000 permutations. **c.** Topographical renderings were obtained by computing Pearson correlations between amplitude of late ERFs (on auditory sensors) and PLF values of selected time- and frequency- windows of interest (see **a.** and **b.**) at each sensor for AVc (left topography) and AVi (right topography) conditions.

Figure 3. Late high-frequency activity reflects prediction error computation.

a. Correlation between ERF amplitude over sensors showing a significant effect of validity (located over the STS, see Methods section) and power of high (30–120 Hz) frequency bands for AVc (left panel) and AVi (right panel) stimuli. Black arrows indicate time- and frequency-windows of interest for subsequent analysis. Corrected r^2 for the frequency bands of clusters of interest are indicated below the right panel (AVi: high-gamma [350–500ms; 70–90 Hz], thick line indicates p cluster < 0.05, *** p < 0.001.) **b.** Correlation strength between high-frequency (30–120 Hz) power and low frequency (2–30 Hz) PLF for AVi stimuli (averaged across time between 350 and 500 ms). Contours delimit statistical thresholds of p < 0.05, p < 0.01 and p < 0.001. Significant theta/gamma and low beta/gamma correlations only occurred in the invalid condition. Corrected r^2 for the frequency bands of selected clusters of interest are indicated in right panel (theta 5–6 Hz and beta 14–15 Hz). Filled-in grey surfaces represent the mean and standard deviation of corresponding null distributions across 1,000 permutations (thick line indicates p cluster < 0.05, * p < 0.05). **c.** Scalp topography of power \times predictability correlation strength for AVi condition. Correlation strength (signed r^2) between normalized predictability rates and power (averaged across time- [350–500 ms] and frequency- [70–90 Hz] windows) were computed at each sensor.

Methods

Subjects

All subjects gave written informed consent to take part in these studies that were approved of by the local ethics committee (Comité Consultatif de Protection des Personnes se prêtant à des Recherches Biomédicales Paris-Cochin, # RBM 01-04). Thirty-four healthy French native speakers (right-handed, 19 females; age range: 20–53 years) participated in two behavioral pilot experiments (see **Supplementary Data**) and two neuroimaging experiments. Nineteen participants took part in the behavioral experiments. Fifteen other participants participated in the MEG experiment. Sixteen participants participated in the fMRI experiment. Twelve of them participated in both neuroimaging studies.

Experimental procedures.

Stimuli were excerpts from digital videos of a male speaker pronouncing consonant/vowel syllables (C/a/ syllables). Specific stimulus combinations and durations are provided in **Supplementary Figure 1**. Stimuli were presented using Presentation software (Neurobehavioral Systems). Two preliminary experiments served to i) establish a behavioral

gradient of visual predictability, which was subsequently normalized and correlated with MEG signals (see statistical analysis section below) and ii) assess how visual predictability interacts with the subjective percept as a function of audio-visual congruence (see **Supplementary data**). During the MEG experiment, participants sat at a distance of 1 m from the monitor, the movie (720×576 pixels) subtending 10.5° (horizontal) and 8.5° (vertical) visual angles. To prevent eye movements, subjects were asked to fixate a cross and blink only after giving their motor response (after the video). Thus, only few trials (less than 5%) were contaminated by eye movement artifacts and were excluded. Each stimulus was presented 54 times in a pseudo-randomized order.

MEG recordings and data processing.

Continuous cerebral activity was recorded with a whole-head MEG system (Omega 151, CTF Systems), with 151 axial gradiometers over the scalp, at a sampling rate of 1250 Hz and low-pass filtered online at 300 Hz. Data preprocessing, analysis, and visualization were performed using both in-house software (<http://cogimage.dsi.cnrs.fr/logiciels/>) and programs written in MATLAB (The Mathworks, Natick, MA). Eye movements and blinks were monitored with four ocular electrodes (Viasys Healthcare) and automatically marked when they deviated by 2 standard deviations (SDs) from the mean. This technique, however, does not detect microsaccades. One supplementary electrode was used to monitor cardiac activity. We rejected off-line trials that were contaminated by eye or head movement, muscle contractions, or electromagnetic artifacts. Artifacts related to cardiac activity were eliminated by using a heartbeat trace matched filter. Event-related fields (ERFs) and time-frequency signals (phase-locking factor and oscillatory power, see below) were analyzed on a 1200 ms interval centered on auditory onset (AO) (−600 to 600 ms) and baseline corrected (when appropriate) on the interval (−600 to −300 ms, i.e., during the presentation of a still face), to ensure that the correction occurred before mouth movement onset. High-pass (0.15 Hz) and low-pass (30 Hz) filters were applied before averaging epochs to obtain ERFs. All signals were smoothed across time using a 20 ms sliding-average window.

Time–frequency analyses.

Time–frequency wavelet transforms were applied to each trial at each MEG sensor using a family of complex Morlet wavelets ($m = 8$), resulting in estimates of Phase-Locking Factor⁴⁹ at each time sample and at each frequency between 2 and 30 Hz (frequency step, 1 Hz), and of oscillatory power at each time sample and frequencies ranging from low (2–30 Hz; frequency step, 1 Hz) to high (30–120 Hz; frequency step, 2 Hz) frequency bands. Baseline-corrected power was defined at each time sample and frequency, as the increase of oscillatory power relative to baseline in logarithmic units. The log-transformed data were

distributed normally, which allowed us to use standard parametric statistical tests (e.g., paired t tests, Pearson correlations).

Statistical analyses.

We first computed Pearson correlations between the magnitude of ERF amplitude and predictability (**Fig. 1c**). To measure the effect of predictability in early auditory regions, we extracted the time courses of ERFs from auditory sensors selected individually as the three sensors where M100A amplitude was maximal. Pearson correlations were computed across subjects between visual predictability and AV–A ERFs at each time bin of peristimulus time, and significance was assumed for $p < 0.01$ (a detailed description of the correlation method is illustrated in **Supplementary Fig. 2a**). To measure the interaction between validity and predictability on ERFs we computed two-sample t tests at each time bin of peristimulus time by using individual regression slopes of the predictability \times ERF amplitude correlation (**Fig. 1c**, grey surface between dashed and solid lines, significance assumed for $p < 0.05$). To correct for slight latency differences between the onsets of visual mouth movements (MO) and auditory onsets depending on the syllable (see **Supplementary Fig. 1 b**), we separated the analysis in two parts: the first part (**Fig. 1b** and **c**, left of the double vertical bar) was synchronized on MO, and the second one (**Fig. 1b** and **c**, to the right of the bar) was synchronized on auditory onset. For each syllable, MO was detected by measuring the overall color change of pixels (comprised in a 321×151 pixels rectangle surrounding center of the mouth) between successive frames of the videos. MO was therefore defined as the timepoint where the average of pixel colors of a frame deviated significantly of 2 SDs from the previous frame. The M170V component, resulting from averaging neuromagnetic fields time-locked on MO, peaked 170 ms after MO. While the M170 response to faces is classically detected in the fusiform cortex, MO elicited a specific response in motion sensitive cortex, previously identified as MT/V5¹⁰. As there was a delay of about 25 ms between responses to visual input in MT/V5 and that in auditory regions, we conclude that the component measured by auditory sensors results from direct cross-modal (lateral) input to auditory cortex¹⁰ and not from volume conduction. Importantly, we assume that this component is specifically related to visual mouth movement as we used a static face as a baseline (see **Supplementary Fig. 1**).

Pearson correlations between ERF amplitude and time-frequency signals (power or PLF) were computed after normalization across experimental conditions (i.e., zero mean and unit variance) at the single subject level to correct for a possible influence of outliers (a detailed illustration of the correlation method is provided in **Supplementary Fig. 2b**). To determine the oscillatory structure underlying modulations of ERF amplitude, we computed correlation maps (**Fig. 2a**) by correlating time-frequency signals (low-frequency [2–30 Hz] PLF and

power, respectively) with the amplitude of ERFs on individually selected auditory sensors. Because ERF-by-power and ERF-by-PLF maps did not qualitatively differ, and because there was no significant cluster above 20 Hz, we restricted the presented results to ERF-by-PLF maps between 2 and 20 Hz. We then focused on window 3 to determine the spectral signature of the predictability-by-validity interaction. From AVc and AVi maps in **Figure 2a**, we selected two time-frequency windows overlapping with window 3 and showing significant positive correlation strengths during time periods exceeding 100 ms (**Fig. 2a**: AVc [350–500 ms; 3–4 Hz] and AVi [400–550 ms; 14–15 Hz]). In each of these time-frequency windows, we measured the interaction between predictability and validity by computing two-sample *t* tests using individual regression slopes between PLF values and predictability. Note that this interaction was not significant for the (14–15 Hz) cluster shown in Figure 2a ($p = 0.13$), but was significant when extending the frequency range to 12–15 Hz ($p = 0.017$), consistent with the spread of the beta-gamma ‘nesting’ cluster shown in **Figure 3b**. Scalp topographies in **Figure 2c** were obtained by correlating PLF values (averaged across time- and frequency-windows of interest) at each sensor of the scalp with the amplitude of ERFs extracted on auditory sensors (averaged across the same time-window). The following analysis aimed at determining the high-frequency (30–120 Hz) spectral signature of late prediction error effects. Correlation maps in **Figure 3a** were obtained by correlating high-frequency power with the amplitude of ERFs extracted from “validity sensors” (the $n = 10$ occipito-temporal sensors selected at the group level as exhibiting a significant [$p < 0.01$] main effect of validity on ERF amplitude). The predictability-by-validity interaction was measured by computing two-sample *t* tests using individual regression slopes between predictability and power values (averaged across time [350–500 ms] and frequencies [70–90 Hz]). Hierarchical coupling across frequencies (reflecting nesting) (**Fig. 3b**) was obtained by computing, for each participant, correlations between low-frequency PLF and high-frequency power (averaged across time [350–500 ms] and frequencies [70–90 Hz]). While previous studies investigated nesting by looking at power changes in one frequency related to the phase of another frequency, we explored whether low oscillatory activity time- and phase-locked to the stimulus (irrespective of the relative phase value) was consistently associated with power increase. Finally, scalp topography in **Figure 3c** was obtained by correlating high power values (averaged across time [350–500 ms] and frequencies [70–90 Hz]) at each sensor with normalized visual predictability of syllables.

To assess the strength of the observed effects and correct for type-I errors potentially arising from multiple comparisons performed at single time points within each frequency band, we used non-parametric cluster statistics⁵⁰. This analysis consists in clustering adjacent time samples that exhibit similar modulations between conditions, or similar correlations with event-related fields. As a first step, we selected all time samples in a variable of interest

(ERF amplitude or PLF or power in specific frequency bands) which r-square difference exceeded $p < 0.05$. Then, the selected samples were clustered in connected sets on the basis of temporal adjacency. Cluster selection criterion in **Figure 3b** was based on the extraction of contiguous samples in PLF frequency-bands of interest. A cluster-level statistic was then computed by taking the sum of the r-squares within a cluster.

Non-parametric statistics were computed by performing permutation tests. To assess the null distribution, the syllable labels were randomly intermixed within each subject and the r-square difference was computed and a $p < 0.05$ threshold was applied. This procedure was repeated 1,000 times. For each of these permutations, the maximum cluster-level statistic was extracted. The non-parametric p -statistic was computed by comparing the null distribution of cluster-level statistics to the original cluster-level statistic. It is important to note that cluster-corrected p -statistics were computed with respect to the null distribution of the maximum cluster-level statistics: this statistical test hence controls the false alarm rate for all clusters. All reported results and p values were corrected at the cluster level following this procedure, and correlations maps in **Figures 2** and **3** only display clusters that reached a corrected p value < 0.05 .

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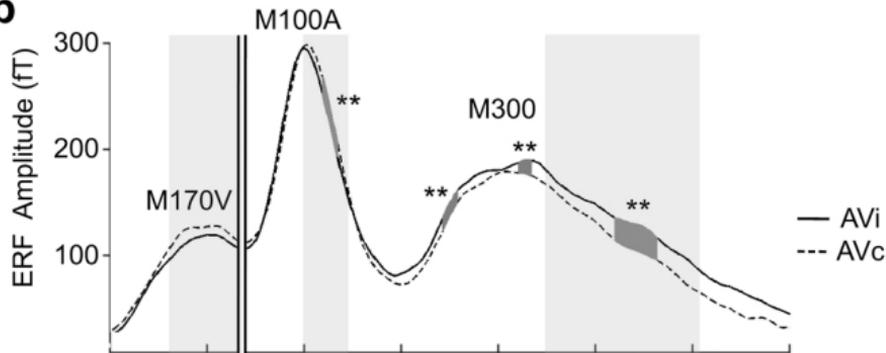
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a

Visual syllables	/ga/ V	/ta/ V	/la/ V	/βa/ V	/pa/ V
Normalized recognition rates (mean ± SD)	-1.61 ± 0.18	0.01 ± 0.38	0.18 ± 0.39	0.7 ± 0.16	0.72 ± 0.15

b**c**