Instructor-learner neural synchronization during elaborated feedback predicts learning transfer

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Abstract

The provision of feedback with complex information beyond the correct answer, i.e., elaborated feedback, can powerfully shape learning outcomes such as transfer. However, an understanding of neurocognitive mechanisms that support elaborated feedback during instructor-learner interactions remains elusive. Here, a two-person interactive design is used during simultaneous recording of functional near-infrared spectroscopy (fNIRS) signals from adult instructor-learner dyads. Instructors either provided elaborated feedback (i.e., correct answer and an example) or simple feedback (i.e., correct answer only) to learners during a concept learning task. Our results showed that elaborated feedback produced comparable levels of retention to simple feedback, however, transfer was significantly enhanced by elaboration. We also noted significant instructor-learner neural synchronization in frontoparietal regions during the provision of elaborated feedback, especially when examples were provided. Further, interpersonal neural synchronization in the parietal cortex successfully predicted the transfer of knowledge to novel contexts. This prediction was retained for both learner-delayed and learner-preceding neural synchronization, supporting the interpretation that deeper-level representations of knowledge, such as abstract structure and personal interpretation, may promote the transfer of learning. These findings point toward interpersonal neural synchronization as a key neurocognitive mechanism that supports learning transfer effects, and may have important implications for real-world learning and pedagogical efficacy.

Keywords: elaborated feedback, transfer, instruction and learning, interpersonal neural synchronization, fNIRS hyperscanning

Educational Impact and Implications Statement

Feedback provides the information regarding the gap between what is achieved and what is aimed to be achieved, and thus plays a critical role in any learning processes. In real-world settings, feedback is oftentimes provided and received during social interactions, and contains complex information beyond the correct answer, that is elaborated feedback. This study sought to investigate neurocognitive mechanisms that support elaborated feedback during instructor-learner interactions using fNIRS hyperscanning. It was revealed that providing learners with elaborated feedback enhanced the transfer of knowledge to novel contexts relative to simple feedback. Instructor-learner neural synchronization was detected in frontoparietal regions during the provision of elaborated feedback, especially for examples. Parietal instructor-learner neural synchronization predicted the transfer. This study provides a novel lens, i.e., interpersonal neural synchronization, for people to understand more about how elaborated feedback takes effects on learning transfer, and may have critical implications for real-world learning and pedagogical efficacy.

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Introduction

As we navigate the world, knowledge and skills are often acquired on the basis of feedback from others during social interaction. Feedback provides the information regarding the gap between what is achieved and what is aimed to be achieved, and thus plays a critical role in any learning processes (Hattie & Timperly, 2007; Mory, 2004). Prior research has identified feedback as a significant factor in student achievement and learning motivation (e.g., Lepper & Chabay, 1985; Narciss & Huth, 2004). Although it is of great power, feedback has been regarded as one of the least understood features in the instructional design (Cohen, 1985; Gagne, 1970). In real-world settings, feedback is oftentimes provided and received during two-person interactions, and contains complex information beyond the correct answer such as illustrative examples (Hattie & Timperly, 2007). Any type of feedback supplying more complex information than correct answer is generally considered as elaborated feedback (Kulhavy & Stock, 1989). Elaborated feedback has been found to deepen the understanding and promote the transfer to novel contexts (Bangert-Drowns et al., 1991; Butler et al., 2013; Finn et al., 2018; Kulhavy & Stock, 1989). However, a scientific understanding of the how elaborated feedback takes effects on learning during social interaction, remains largely elusive.

Using single-subject experimental designs, a number of studies have established that frontoparietal brain regions including medial prefrontal cortex (mPFC), dorsolateral prefrontal cortex (DLPFC), and parietal lobules were implicated in the process of feedback messages such as yes-no verification and correct answer, which is regarded as simple feedback (Cavanagh et al., 2011; Crone et al., 2008; Luft et al., 2013;

Mars et al., 2005; van Duijvenvoorde et al., 2008; Zanolie et al., 2008). Specifically, mPFC was responsible for basic functions such as error detection and conflict monitoring (Cavanagh et al., 2011; Luft et al., 2013; Mars et al., 2005), while superior parietal lobule was engaged in more complex processes such as error correction and performance adjustment (Crone et al., 2008; van Duijvenvoorde et al., 2008; Zanolie et al., 2008). Brain activation in these regions had connections with feedback-based learning outcomes (Arbel et al., 2013; Luft, 2014; McCormick and Telzer, 2018; Peters et al., 2017). To understand more about the neurocognitive mechanisms that support elaborated feedback during social interaction, the simultaneous investigation of brain signals from interactive dyads is essential but lacked.

The recent decade has witnessed a paradigm shift toward the concurrent measurement of multiple individuals engaging in social interaction (Kingsbury & Hong, 2020; Redcay and Schilbach, 2019; Schilbach et al., 2013; Wheatley et al., 2019), including infant-adult dyads (Leong et al, 2017; Santamaria et al, 2020; Wass et al, 2020) and individuals with neuropsychiatric disorders (Bilek et al, 2017; Leong & Schilbach, 2019). Relevant research indicated interpersonal neural synchronization (INS) might underlie social interaction, and underpin successful communication and learning from early life (for reviews, Hasson et al., 2012; Redcay & Schilbach, 2019; Wass et al, 2020). Stephens et al. (2010) addressed that when communication was successful, the information provider's brain activity was spatiotemporally coupled with the information receiver's; INS also showed provider- or receiver-preceding patterns, indicating the provider's dominance and the receiver's prediction, respectively.

Moreover, INS has been found to hold implications of effective learning and instruction (Bevilacqua et al., 2018; Dikker et al., 2017; Holper et al., 2013; Pan et al., 2018; 2020; Zheng et al., 2018). Based on the simultaneous recording of fNIRS signals

from multiple individuals during learning and instruction without the strict restraint of movement (Boas et al., 2014; Pinti et al., 2018), research has identified INS associated with learning outcomes. For instance, INS in frontal cortex during educational interactions served as a correlate of learners' performance on singing (Pan et al., 2018) and on statistics (Liu et al., 2019). Besides, instructor-preceding neural synchronization in temporoparietal areas predicted the learners' performance on numerical reasoning (Zheng et al., 2018). Once feedback is combined with more complex information beyond the correctness, it becomes intertwined with instruction (Hattie & Timperley, 2007). Thence, synchronized brain activity in instructor-learner dyads may offer a new lens into how elaborated feedback takes effects on learning in naturalistic educational settings.

Here, we applied functional near-infrared spectroscopy (fNIRS) to simultaneously record brain signals from adult instructors and learners during an ecologically valid yet experimentally controlled educational interaction. Learners studied psychology concepts and received elaborated feedback or simple feedback from instructors. Elaborated feedback contained the correct answer and an example, illustrating the concepts in concrete and real-world situations, while simple feedback only contained the correct answer. Post-learning, learners were assessed for the retention of knowledge and the transfer of knowledge to novel contexts. We hypothesized that elaborated feedback enhanced the learning performance, especially on the transfer measure, relative to simple feedback. Providing and receiving elaborated feedback would synchronized instructor-learner dyads' brain activity, potentially in frontoparietal regions. Considering parietal lobules have been engaged in complex processes such as error correction rather than the basic function of error detection (Crone et al., 2008; van Duijvenvoorde et al., 2008; Zanolie et al., 2008), instructor-learner neural

synchronization in parietal regions would likely predict learning performance. As elaborated feedback is theorized to facilitate the transfer of knowledge to novel contexts (Butler et al., 2013; Finn et al., 2018), we further hypothesized parietal instructor-learner neural synchronization would specifically predict the transfer. The effect of elaborated feedback on transfer may be due to it develops learners represent the knowledge at deeper levels, e.g., abstract structure and personal interpretation, instead of surface levels, e.g., specific words and syntax (Graesser et al., 1997; Kintsch, 1998). If knowledge was represented into abstract structure and thus promoted the transfer, it would be expected that learner-delayed neural synchronization predicted the transfer, because the extraction of abstract structure demands a sufficient amount of information, which takes time to transmit from instructors to learners (Stephens et al., 2010; Tatler et al., 2003). If knowledge was represented into personal interpretation which enabled learners successfully predict the upcoming information before it was completely provided (DeVault et al., 2011; Pickering & Garrod, 2013) and thus promoted the transfer, it would be expected that learner-preceding neural synchronization predicted the transfer.

Methods

Ethics statement

This study was carried out according to the guidelines in the Declaration of Helsinki. The study procedure was approved by Human Research Protection Committee at East China Normal University (Number HR 043-2018). All participants gave their written informed consent prior to the experiment. Participants were financially compensated for their participation.

Participants

Twenty-four healthy, female, right-handed participants were recruited as instructors. They were required to major in psychology and complete at least one of teacher education courses. Besides, forty-eight healthy, female, right-handed participants were recruited as learners. They were required to not major in psychology. Twelve instructors were randomly assigned into elaborated feedback group (age M = 21.75, SD = 2.42), while the other twelve into simple feedback group (age M = 21.25, SD = 2.93, $t_{(22)}$ = 0.46, p = 0.65). Each instructor was randomly matched with up to two learners and instructed each of the learners one by one at two adjacent days, resulting in forty-eight dyads composed of one instructor and one learner. The age of learners did not differ between elaborated feedback group (M = 19.63, SD = 1.95) and simple feedback group (M = 19.79, SD = 1.77, $t_{(46)}$ = 0.31, p = 0.76). We merely recruited female dyads to control for the potential impacts of gender difference (Baker et al., 2016; Cheng et al., 2015; see also Hu et al., 2018; Pan et al., 2018; 2020 for similar settings). All participants were naïve with respect to the purpose of the study.

Materials

Materials used for instruction and learning were about a set of ten psychology concepts from the topic of judgement and decision making (Rawson et al., 2015). Each concept has a term, a one-sentence definition and two examples (view details in Table S1). Examples illustrated the target concepts in concrete and real-world situations. Examples used in current study were adapted from psychology textbooks (Hou, 2018; Pastorino & Doyle-Portillo, 2008; Zimbardo et al., 2012) and materials used by previous studies on feedback-based learning (Finn et al., 2018; Rawson et al., 2015). The specific usages of materials were described together with the experimental procedures as follows.

Experimental protocol

The experiment was carried out over two visits to the laboratory, with the interval of one or two days (Figure. 1a).

During visit 1, learners completed a pre-learning test (< 15 min) assessing their prior knowledge relative to those ten psychology concepts. Specifically, learners were required to match 10 definitions with 10 terms from provided 12 terms (c.f. Allen and Brooks, 1991; Finn et al., 2018; Murphy, 2004). The extra two terms were also from the same topic of judgement and decision making (view details in Table S1). The prior knowledge was quantified in forms of accuracy on pre-learning test (i.e., dividing the number of correctly matched concepts by the number of all concepts). As expected, learners had comparable prior knowledge in elaborated vs. simple feedback group ($M \pm SD$, 0.58 ± 0.19 vs. 0.58 ± 0.26, $t_{(46)} = 0$, $p = 1$). Besides, learners completed a battery of scales with regard to learning and motivation: (*i*) Achievement Goal Orientation (Button et al., 1996); (*ii*) Academic Self-efficacy (Pintrich & Groot, 1990); (*iii*) Learning Engagement (Schaufeli et al., 2002). No significant differences on scales for two feedback groups were detected (ts < 1.60, ps > 0.10). During visit 1, instructors underwent a standardized training on the instructional procedure and content (~ 30 min). Afterwards, instructors were required to make further preparations at home. Upon coming back to the laboratory for visit 2, instructors were required to correctly recall the instructional procedure, together with the definitions and examples of two randomly selected concepts by the experimenter. Instructors were not allowed to carry out formal instruction until they met those requirements.

Visit 2 consisted of two sessions: fNIRS hyperscanning and post-hyperscanning. During the first session, instructors and learners sat face-to-face approximately 1 meter apart, wearing the fNIRS equipment. This session consisted of three phases: rest,

introduction and feedback.

In the rest phase (300 s), both instructors and learners kept their eyes closed, motion restrained and mind relaxed. In the introduction phase, instructors introduced 10 concepts one by one with the term and definition orally presented twice. The introduction order of the concepts was self-decided by instructors in advance. In this phase, learners listened to the introduction with the permission of requesting the repetition of unclear parts. This phase was self-paced and instructor-learner dyads in elaborated vs. simple feedback group spent comparable time (337.77 s ± 62.02 vs. 330.78 s ± 66.86, $t_{(46)} = 0.38$, $p = 0.71$).

In the feedback phase, learners re-studied the 10 concepts based on the instructor's feedback. The flow relevant to one concept, i.e. one trial, could be split into four periods: question, answer, feedback and confidence. Specifically, instructors first presented a definition and questioned learners which term corresponded to the definition. Then, learners gave an answer. Next, instructors provided elaborated or simple feedback to learners depending on which feedback group she was assigned in. Simple feedback merely involved the correct answer, which consisted of the term and the definition, while elaborated feedback involved the correct answer and an additional example. Finally, learners judged the confidence that they would correctly answer the relevant questions in the post-hyperscanning session via number keyboards (0–9, *very low* to *very high*). One trial for elaborated feedback group was exemplified as follows.

Instructor: The tendency, once an event has occurred, to overestimate one's ability to have foreseen the outcome. Which term did this definition correspond to?

Learner: Hindsight bias.

Instructor: The correct term is hindsight bias, whose definition is the tendency, once an event has occurred, to overestimate one's ability to have foreseen the outcome. Here is an example. Some students will pat the thighs after the teacher announces the correct answer and say "I

know this is the choice!"

Learner: (press one number).

In this phase, the order of 10 concepts was also self-decided by instructors in advance, but should be different from that in the introduction phase. As expected, instructor-learner dyads in elaborated vs. simple feedback group spent longer time in the feedback period (339.54 s ± 48.42 vs. 137.13 s ± 28.38, $t_{(46)} = 17.67$, $p < 0.001$). To note, instructor-learner dyads in elaborated feedback group spent 136.042 s ± 22.217 and 203.500 s ± 30.062 for the correct answer and example part, respectively. The whole process of the fNIRS hyperscanning session was also recorded via a digital video camera (Sony, HDR-XR100, Sony Corporation, Tokyo, Japan).

Post hyperscanning, learners completed a post-learning test (< 15 min) measured both the retention of knowledge and the transfer of knowledge to novel contexts. On the retention measure, learners were required to match 10 definitions with 10 terms from provided 12 terms, which was identical with the pre-learning test. On the transfer measure, learners had to match 10 novel examples with 10 terms from provided 12 terms (c.f. Finn et al., 2018). To note, the selection of examples for the usage in elaborated feedback vs. transfer sub-test was previously decided by the experimenters without replacement.

fNIRS data acquisition and preprocessing

Instructors' and learners' brain activity was simultaneously recorded during the hyperscanning session of visit 2 using an ETG-7100 optical topography system (Hitachi Medical Corporation, Japan). Two optode probes were used for each participant: a 3×5 probe covering frontal areas (eight transmitters and seven detectors resulting in 22 measurement channels, i.e., CH1–22) and a 4×4 probe covering left temporoparietal areas (eight transmitters and eight detectors resulting in 24 measurement channels, i.e.,

CH23–46), see Figure 1b for the reference and channel locations. The probes were placed over frontal and temporoparietal areas because these regions have been implicated in feedback-based learning (Crone et al., 2008; Luft, 2014; van Duijvenvoorde et al., 2008) as well as learning and instruction (Liu et al., 2019; Pan, et al., 2018; Zheng et al., 2018). The temporoparietal areas were focused on the left hemisphere rather than the right hemisphere due to the former is dominant for the language functions (Ojemann et al., 1989; Vigneau et al., 2006), which is an essential component of concept learning. The correspondence between the NIRS channels and the measured points on the cerebral cortex was determined using the virtual registration approach (Singh et al., 2005; Tsuzuki et al., 2007; see details in Table S2).

The optical data were collected at the wavelengths of 695 and 830 nm, with a sampling rate of 10 Hz. The preprocessing of fNIRS data was performed using custom MATLAB (MathWorks, Natick, MA, USA) scripts and Homer2 toolbox (version 2.2, Huppert et al., 2009). The raw optical intensity data series were first converted into changes in optical density (OD). Channels with very low or high OD, which exceeded 5 SDs, were marked as unusable and removed from analysis. Next, the OD time series were screened and corrected for motion artifacts using channel-by-channel wavelet-based method. The Daubechies 5 (db5) wavelet was chosen (Molavi & Dumont, 2012) and the tuning parameter was set to 0.1 (Cooper et al., 2012). A band-pass filter with cut-off frequencies of 0.01–1 Hz was applied to the OD data in order to reduce the slow drift and high frequency noise. The OD time data were then converted into oxyhemoglobin (HbO) and Deoxyhemoglobin (HbR) concentration changes based on the modifier Beer-Lambert Law (Cope & Delpy, 1988). In the current study, we mainly focused on HbO concentration change, which was considered as an indicator of the change in regional cerebral blood flow with higher signal-to-noise ratio (Hoshi, 2007)

and has been more widely used in fNIRS hyperscanning research (e.g., Cheng et al., 2015; Hu et al., 2017; Jiang et al., 2015; Pan et al., 2017; Dai et al., 2018; Yang et al., 2020).

Data analysis

Behavioral data analysis

Learning performance was assessed by post-learning test and quantified in forms of accuracy (i.e., dividing the number of correctly answered items by the number of all items). Besides, learners' knowledge immediately before feedback (i.e., on the answer period of the feedback phase) was also quantified in forms of accuracy, which was comparable between simple feedback group ($M \pm SD$, 0.67 ± 0.21) and elaborated feedback group (0.62 ± 0.15, $t_{(46)} = 0.82$, $p = 0.41$).

First, we sought to verify whether conceptual knowledge was promoted by elaborated feedback. Because each instructor was randomly assigned to teach two learners, learners were nested within instructors. A linear mixed model (West et al., 2014) was thus fitted on learners' accuracy including fixed effects of test time (pre-learning vs. post-learning), plus random effects on learner and instructor identity. Accuracy on the answer period of the feedback phase and the duration of elaborated feedback were additionally entered in the model to control for their potential effects.

Next, we investigated whether elaborated feedback promoted the learning relative to simple feedback. A linear mixed model was fitted on learners' accuracy on the retention measure, including a fixed effect of feedback type (elaborated vs. simple), plus random effects of learner and instructor identity. Accuracy on the pre-learning test, accuracy on the answer period of feedback phase and the duration of feedback were additionally entered in the model to control for their potential effects. Besides, a parallel

model was fitted on learners' accuracy on the transfer measure.

Finally, an additional linear mixed model was conducted on confidence ratings including a fixed effect of feedback type (elaborated vs. simple), plus random effects of learner and instructor identity.

All behavioral analyses were computed using functions implemented in MATLAB (R2018a, MathWorks). Linear mixed models were constructed using *fitlme* function. Restricted maximum likelihood was used to estimate the models. *F* and *p* values were derived using *anova* function based on Satterthwaite approximation.

fNIRS data analyses

WTC analysis. Interpersonal neural synchronization (INS) between instructors and learners was computed by a wavelet transform coherence (WTC) algorithm, which estimates the correlation of a pair of time series as a function of frequency and time (Grinsted et al., 2004; Torrence & Compo, 1998). First, we extracted preprocessed HbO time series from homogeneous regions (following previous studies, e.g., Cui et al., 2012; Hu et al., 2018; Jiang et al., 2012; Liu et al., 2019; Pan et al., 2018; 2020). For instance, two signals (*i* and *j*) could be respectively extracted from instructors' CH45 and the learners' CH45 (Figure 1b). Then, WTC of signals was computed by following formula:

$$\mathrm{WTC}(t,s) = \frac{|\langle s^{-1}W^{ij}(t,s)\rangle|^2}{|\langle s^{-1}W^{i}(t,s)\rangle|^2|\langle s^{-1}W^{j}(t,s)\rangle|^2}$$

where *t* denotes the time, *s* indicates the wavelet scale, $\langle\cdot\rangle$ represents a smoothing operation in time and scale, and *W* is the continuous wavelet transform. Then, a 2-D (time × frequency) WTC matrix was generated (Figure 1b, see more details in Chang & Glover, 2010; Grinsted et al., 2004).

In this study, we specifically investigated INS associated with elaborated feedback

(for general instruction and learning, see Liu et al., 2019; Pan et al., 2018; 2020; Zhang et al., 2018). To this end, time points corresponding to the start and the end of feedback (i.e., the feedback period, Figure 1b) were marked based on the recorded videos and was adjusted for the delay-to-peak effect by 6 s (Cui et al., 2009; Jiang et al., 2015). Accordingly, elaborated feedback could be further segmented into two parts (i.e., correct answer and example, Figure 1b).

Cluster-based permutation test. Interpersonal interactions as opposed to resting state elicited significantly larger INS (Cui et al., 2012; Jiang et al., 2012). For each dyad and each channel combination, WTC values during the feedback period and the rest phase (leaving out first and last minutes to retain more steady data) were respectively time-averaged, and then converted into Fisher *z*-values. Accordingly, we sought to identify frequency-channel clusters showing significantly larger WTC during elaborated feedback vs. rest using a cluster-based permutation test. It is a non-parametric statistical test that offers a solution to the problem of multiple comparisons for multi-channel and multi-frequency data (Maris & Oostenveld, 2007). We conducted it following five steps. First, we ran frequency-by-frequency and channel-by-channel linear mixed models including a fixed effect of task (feedback vs. rest), plus random effects of learner and instructor identity. Considering the process of elaborated feedback was self-paced, duration was entered in the model to control for its potential effect. Next was to find channels and frequency bands, at which the task effect was significant (feedback > rest, $p < 0.05$). To note, we excluded the respiration-related band from 0.15 to 0.3 Hz and the cardiac-related band above 0.7 Hz (Nozawa et al., 2016; Zheng et al., 2018). Third was to form clusters composed of neighboring channels ($\geqslant$ 2) and neighboring frequency points ($\geqslant$ 2) and compute the statistic for each cluster by summing all *F* values. Fourth, repeat first step using permuted data and calculate the

statistics for each cluster identified in third step for 1000 times. The permutation was conducted by randomly pairing one learner's dataset with another instructor's dataset. As the length of datasets varied across dyads, the longer dataset was trimmed to the same length as the shorter one for each random pair (Reindl et al., 2018). Finally, the observed cluster statistics were compared with the results of 1000 permutations (both converted to square roots to normalize the distributions) with p value assessed by following formula (Theiler et al., 1992): $\mathrm{erfc}((\frac{|S_o - \mu_p|}{\sigma_p})/\sqrt{2})$, S_o denotes observed cluster statistic, μ_p, σ_p respectively denote the mean and standard deviation of permutation results. The clusters with p value < 0.05 were regarded as significant. Besides for elaborated feedback, the cluster-based permutation test was also conducted on each of two parts of elaborated feedback, i.e., correct answer and example, and simple feedback, i.e., correct answer only, respectively.

Contrast analysis. To further characterize brain regions more strongly synchronized by different information contained in feedback, contrast analyses were performed on the significant clusters identified by the cluster-based permutation test. To control for the individual differences, we used clusters' ΔWTC in the following analyses, which was computed by subtracting WTC (averaged by channels and frequencies contained in the cluster) during the feedback from that during the rest, and then converted into Fisher z-values. First, a linear mixed model was fit on ΔWTC associated with two parts of elaborated feedback, including a fixed effect of feedback information (example vs. correct answer), plus random effects of learner and instructor identity. Duration of the feedback information was entered in the model to control for its potential effect. Second, considering the simple feedback merely contained the information of correct answer, contrast analysis based on the linear mixed model was also performed between the example part of elaborated feedback and simple feedback.

Multiple comparisons were corrected using the false discovery rate (FDR) method (Benjamini and Hochberg, 1995) to calculate *corrected p* values.

Behavior-brain relation analyses

Next, we tested whether instructor-learner neural synchronization associated with elaborated feedback predicted learning performance. To control for the individual differences, relative accuracy was used in the following analysis, which was computed by subtracting z-score of the accuracy on pre-learning test from that on post-learning test. A machine learning algorithm, i.e., linear support vector regression (SVR), was applied to train ΔWTC for each identified cluster for the prediction of relative accuracy. To avoid the potential information loss by the trial-averaged ΔWTC value, we instead extracted trial-by-trial ΔWTC values, which was then used as up to ten features for the training. We used a leave-one-out cross-validation approach via Regression Learner APP implemented in MATLAB (R2018a, MathWorks). The prediction analysis was performed by doing such a training first on all but one dyad and then testing on the left-out dyad to examining the generalization of prediction of relative accuracy based on trial-by-trial ΔWTC. The prediction analysis was performed n times (n = total number of dyads). Prediction accuracy was quantified by the Pearson correlation coefficient (r) between the observed and predicted relative accuracy (Hou et al., 2020; Kosinski et al., 2013). The value of r ranges from -1 to 1, indicating worst to best prediction accuracy, with the value of p indicating the significance. Considering elaborated feedback unfolded over time, when the aforementioned prediction analyses showed significant results ($r > 0$ and $p < 0.05$), we added various time shifts (instructor's brain activity was shifted forward or backward relative to the learner's by 1–14 s, step = 1 s) to the re-computation of prediction analyses, with FDR method (Benjamini and Hochberg, 1995)

calculating *corrected p* values.

Results

Elaborated feedback promotes the transfer of knowledge

First, whether elaborated feedback promoted learners' conceptual knowledge was investigated. A linear mixed model was fitted on learners' accuracy in elaborated feedback group, including a fixed effect of test time (pre-learning vs. post-learning), plus random effects of learner and instructor identity. Accuracy on the answer period of feedback phase and duration of elaborated feedback were additionally entered in the model to control for their potential effects. As expected, accuracy on the post-learning test ($M \pm SD$, 0.83 ± 0.13) was significantly higher than that on the pre-learning test (0.58 ± 0.19, $F_{(1, 23)} = 58.50$, $p < 0.001$, $\beta = 0.25$, SE = 0.03, 95% confidence interval (CI) = 0.19 to 0.32). It was indicated that elaborated feedback promoted learners' conceptual knowledge.

Next, we investigated whether elaborated feedback relative to simple feedback promoted learning. A linear mixed model was fit on learners' accuracy on the retention measure, including a fixed effect of feedback type (elaborated vs. simple), plus random effects of learner and instructor identity. Accuracy on the pre-learning test, accuracy on the answer period of feedback phase and duration of feedback were additionally entered in the model to control for their potential effects. On the retention measure, learners' accuracy was comparable for elaborated feedback group (0.96 ± 0.09) and simple feedback group (0.94 ± 0.14, $F_{(1, 21.17)} = 1.90$, $p = 0.18$, $\beta = 0.04$, SE = 0.03, 95% CI = -0.02 to 0.09). However, on the transfer measure, a parallel model analysis revealed that learners' accuracy in elaborated feedback group (0.70 ± 0.21) was significantly higher than that in simple feedback group (0.59 ± 0.21, $F_{(1, 15.63)} = 5.42$, $p = 0.03$, $\beta = 0.14$, SE

= 0.06, 95% CI = 0.02 to 0.26). It was indicated that elaborated feedback relative to simple feedback promoted the transfer rather than the retention of knowledge.

Finally, a linear mixed model was fitted on the confidence ratings including a fixed effect of feedback type, plus random effects of learner and instructor identity, but found no significant effect ($F_{(1, 22)} = 0.49$, $p > 0.10$).

Elaborated feedback synchronized instructor-learner dyads' neural activity in frontoparietal regions

We investigated whether instructor-learner dyads providing and receiving elaborated feedback as opposed to resting elicited significantly larger WTC using a cluster-based permutation test. Two significant channel-frequency clusters were identified (Figure 2 and Table S3). Cluster 1 was composed of 2 spatially neighboring channels, i.e., CH42, CH45, at the frequency band of 0.017–0.025 Hz (cluster statistic = 11.54, $p < 0.001$). The channels contained in Cluster 1 were approximately located at left parietal cortex, including postcentral gyrus (PoCG) and superior parietal gyrus (SPG). Cluster 2 was composed of 3 spatially neighboring channels, i.e., CH05, CH06, CH10, at the frequency band of 0.017–0.024 Hz (cluster statistic = 6.62, $p = 0.005$). The channels contained in Cluster 2 were approximately located at left frontal cortex, including superior frontal gyrus (SFG) and middle frontal gyrus (MFG). In addition, instructor-learner synchronization on Cluster 1 and Cluster 2 exhibited temporal patterns, i.e., the learners' brain activity synchronized with instructors' with some delay or the opposite (see details in Supplementary Results, Figure S1).

Additionally, granger causality analysis was performed to explore the information flow from instructor to learner or from learner to instructor on brain regions corresponding to the identified clusters (see more details in Supplementary Methods).

Granger causality analysis revealed there existed significant and comparable bidirectional information flow between the instructor and the learner when they providing and receiving elaborated feedback (see more details in Supplementary Results, Figure S2).

Frontoparietal instructor-learner synchronization was specific to examples

To further characterize the brain regions synchronized by different feedback information, brain activity during elaborated feedback was segmented into two parts (i.e., example and correct answer) and respectively compared with that during resting using a cluster-based permutation test. For the example part of elaborated feedback, two significant channel-frequency clusters were identified (Figure 3 and Table S4). Cluster 3 was composed of 2 spatially neighboring channels, i.e., CH42, CH45, at the frequency band of 0.018–0.027 Hz (cluster statistic = 13.69, $p < 0.001$). The channels contained in Cluster 3 were approximately located at left parietal cortex, including PoCG and SPG. Cluster 4 was composed of 3 spatially neighboring channels, i.e., CH05, CH06, CH10, at the frequency band of 0.015–0.023 Hz (cluster statistic = 10.61, $p < 0.001$). The channels contained in Cluster 4 were approximately located at left frontal cortex, including SFG and MFG. To note, Cluster 1 and Cluster 3 contained identical channels, while Cluster 2 and Cluster 4 contained identical channels. In addition, the synchronized brain activity on Cluster 3 and Cluster 4 exhibited temporal patterns, i.e., the learners' brain activity synchronized with instructors' with some delay or the opposite (see details in Supplementary Results, Figure S1). However, for the correct answer part of elaborated feedback, none significant channel-frequency cluster was identified (Table S4). Simple feedback (only containing the information of correct answer) was also compared with rest using a cluster-based permutation test and none

significant channel-frequency cluster was identified (Table S5). It was indicated that instructor-learner neural synchronization on frontoparietal regions was specific to example rather than correct answer part of elaborated feedback.

Next, based on the linear mixed model, contrast analysis was performed between two parts of elaborated feedback, i.e., example vs. correct answer, on Cluster 3 and Cluster 4, respectively. Besides, as simple feedback merely contained the information of correct answer, contrast analysis based on the linear mixed model was also performed between the example part of elaborated feedback vs. simple feedback on Cluster 3 and 4, respectively. On Cluster 3, providing and receiving the example vs. correct answer part of elaborated feedback elicited larger ΔWTC (feedback minus rest) (0.10 ± 0.12 vs. 0.09 ± 0.11, $F_{(1, 23.70)} = 8.21$, $p = 0.009$, *corrected* $p = 0.018$, $\beta = 0.15$, SE = 0.05, 95% CI = 0.04 to 0.25, Figure 4a); providing and receiving the example part of elaborated feedback vs. simple feedback also elicited larger ΔWTC (0.10 ± 0.12 vs. 0.01 ± 0.14, $F_{(1, 26.60)} = 4.75$, $p = 0.037$, *corrected* $p = 0.049$, $\beta = 0.13$, SE = 0.06, 95% CI = 0.01 to 0.24, Figure 4a). On Cluster 4, providing and receiving the example vs. the correct answer part of elaborated feedback elicited comparable ΔWTC (0.12 ± 0.13 vs. 0.11 ± 0.13, $F_{(1, 19.73)} = 2.46$, $p = 0.133$, *corrected* $p = 0.133$, $\beta = 0.09$, SE = 0.06, 95% CI = -0.03 to 0.22, Figure 4b); providing and receiving the example part of elaborated feedback vs. simple feedback elicited larger ΔWTC (0.12 ± 0.13 vs. 0.03 ± 0.17, $F_{(1, 45)} = 9.39$, $p = 0.004$, *corrected* $p = 0.016$, $\beta = 0.20$, SE = 0.06, 95% CI = 0.07 to 0.32, Figure 4b).

Parietal instructor-learner neural synchronization predicts the transfer of knowledge

Next, we tested whether instructor-learner neural synchronization during

providing and receiving elaborated feedback could predict learning performance. A SVR was trained on ΔWTC associated with the example part of elaborated feedback on Cluster 3 and Cluster 4 to respectively predict learners' accuracy on the post-learning test relative to pre-learning test. To avoid the potential information loss by the trial-averaged ΔWTC value, we instead extracted trial-by-trial ΔWTC values, which was then used as up to ten features for the training. It was revealed in Figure 5a that trial-by-trial ΔWTC on Cluster 3 could successfully predict out-of-sample learners' relative accuracy on the transfer measure ($r = 0.57$, $p = 0.004$) but not on the retention measure ($r = 0.25$, $p = 0.24$); trial-by-trial ΔWTC on Cluster 4 could not predict learning performance (rs < -0.09, ps > 0.05). A similar prediction pattern was seen for synchronized neural activity associated with elaborated feedback (see more details in Supplementary Results, Fig. S3a).

Moreover, when time shifts were added to re-perform the prediction analyses based on trial-by-trial ΔWTC associated with the example part of elaborated feedback on Cluster 3, the prediction accuracy on the transfer measure was significant when instructors' brain activity preceded learners' by 1–10 s and when learners' preceded the instructors' by 1–13 s (*corrected* ps < 0.05, Figure 5b). With time shifts, the prediction accuracy on the retention measure remained insignificant (*corrected* ps > 0.05, Figure 5b). With time shifts, a similar prediction pattern was seen for synchronized brain activity associated with elaborated feedback (see more details in Supplementary Results, Figure. S3b).

Discussion

Our findings support the notion that providing learners with elaborated feedback relative to simple feedback promotes the transfer of conceptual knowledge to novel

contexts. The neurocognitive mechanisms that support elaborated feedback during instructor-learner interactions were investigated from an inter-brain perspective. When elaborated feedback unfolded overtime, we found synchronized instructor-learner dyads' brain activity in frontoparietal regions, including superior frontal gyrus (SFG), middle frontal gyrus (MFG), postcentral gyrus (PoCG) and superior parietal gyrus (SPG). Such instructor-learner synchronization was specific to the complex information, i.e., example, contained in the elaborated feedback. Based on a machine learning algorithm, instructor-learner synchronization associated with example in parietal cortex successfully predicted out-of-sample learners' ability to transfer knowledge to novel contexts. Such a prediction was retained when instructors' brain activity preceded learners' by 1–10 s and when learners' preceded instructors' by 1–13s.

Although elaborated feedback is theorized to increase the probability of error correction and the depth of knowledge comprehension (Jacoby et al., 2005; Morris et al., 1977; Tulving & Thompson, 1973), previous studies have demonstrated divergent evidence on its specific effects on learning. For example, compared with correct answer feedback, adding example or explanation to feedback promotes the learning of conceptual knowledge (for both knowledge retention and transfer, Finn et al., 2018; for knowledge transfer only, Butler et al., 2013). However, no greater effects of elaborated feedback relative to correct answer feedback on learning have also been reported (e.g. Andre & Thieman, 1998; Kulhavy et al., 1985; Mandernach, 2005). It may be due to that the added information is too lengthy or complex to be processed and even offsets the effects of correct answer (Kulhavy et al., 1985; Shute, 2008). The present study found that providing learners with elaborated feedback containing example relative to correct answer feedback resulted in comparable retention of knowledge. However, when learners' ability to transfer conceptual knowledge to novel contexts was tested,

elaborated feedback tended to be of benefit. These findings supported the superior effect of elaborated feedback on the knowledge transfer rather than the knowledge retention.

When instructor-learner dyads providing and receiving elaborated feedback, we found synchronized brain activity in frontoparietal regions. Frontoparietal regions such as mPFC, DLPFC and parietal lobules are well-localized by single-brain imaging research on feedback-based learning (Cavanagh et al., 2011; Crone et al., 2008; Luft et al., 2013; Mars et al., 2005; van Duijvenvoorde et al., 2008; Zanolie et al., 2008). Activity generated in mPFC, such as anterior cingulate cortex (ACC), tracks a basic feedback function of error detection and conflict monitoring (Cavanagh et al., 2011; Luft et al., 2013; Mars et al., 2005). DLPFC is also implicated in social interactions (Kanske et al., 2015; Schurz et al., 2014). Moreover, parietal lobules play essential role in error correction and performance adjustment (Zanolie et al., 2008; van Duijvenvoorde et al., 2008). In current study, synchronized brain activity observed approximately in SFG, MFG, PoCG and SPL, which were spatially proximal to well-defined feedback sensitive regions, may underlie the providing and receiving elaborated feedback by instructor-learner dyads in real-world educational settings. In our study, we further demonstrated that instructor-learner synchronization in frontoparietal regions was specifically associated with the complex information, i.e., example, contained in the elaborated feedback, whereas providing and receiving the correct answer failed to synchronized brain activity from instructors and learners. These results suggest that feedback information beyond the correct answer recruit separable brain activity in instructor-learner dyads, which potentially supports the superior effect of elaborated feedback on learning.

Furthermore, based on linear SVR, instructor-learner synchronization associated with example in parietal cortex rather than frontal regions successfully predicted out-

of-sample learners' ability to transfer knowledge to novel contexts. It might be due to two factors. First, feedback information tends to activate brain activity in mPFC, such as ACC, essential for the process of error detection or conflict monitoring (Cavanagh et al., 2011; Luft et al., 2013; Mars et al., 2005). However, activity generated from mPFC might not be fully captured by fNIRS technique for its limited spatial resolution on cortical areas, thence impairing the predictive effect of synchronized brain activity in frontal regions on learning. Second, in comparison with mPFC, parietal lobules mature late (Kerns et al., 2004; Peters et al., 2016) and underlie more complex cognitive functions such as error correction and performance adjustment (Zanolie et al., 2008; van Duijvenvoorde et al., 2008), which play a more critical role in knowledge acquisition.

Interestingly, prediction effect of instructor-learner synchronization associated with example in parietal cortex retained when instructors' brain activity preceded learners' by 1–10 s and when learners' preceded instructors' by 1–13 s. The processing of high-level linguistic structures such as sentences and paragraphs is at timescale of seconds, whereas that of sound-level acoustic features is milliseconds (Hasson et al., 2015). In average, each example was presented with 2.4 sentences, lasting for about 20.3 second. Therefore, the maximal temporal shifts are more likely to reflect sentence-level rather than word- or syllable-level processing. Elaborated feedback may develop learners represent the knowledge at deeper levels, e.g., abstract structure and personal interpretation, instead of surface levels, e.g., specific words and syntax, and thus promotes learning (Graesser et al., 1997; Kintsch, 1998). On the one hand, learner-delayed neural synchronization reflects that learners successively accumulate and process the information, which takes time to flow from instructors to learners. It implies a causal relationship by which feedback providers induce and shape the response in the

receivers' brain. The predictive effect of learner-delayed neural synchronization on transfer suggests that based on the complex feedback information transmitted from instructors to learners, conceptual knowledge tends to be represented at the deeper level, potentially in forms of abstract structure, and enables learners transfer knowledge to novel contexts. On the other hand, learner-preceding neural synchronization reflects learners accurately predict the upcoming information before it is completely unfolded. The ability of predicting follow-on information can be enhanced by representing the information in forms of personal interpretation (DeVault et al., 2011; Pickering & Garrod, 2013). Accordingly, the predictive effect of learner-preceding neural synchronization on transfer suggests that interpretation-based cognitive processes may support the transfer of knowledge. These findings supported the notion that complex feedback information promoted the transfer because the knowledge was represented at deeper levels. Future research may specifically address the underlying cognitive processes by experimental manipulation.

In current study, several questions deserve noting. First, frequencies of instructor-learner neural synchronization associated with elaborated feedback were roughly identified within 0.01 to 0.03 Hz, overlapping some of those identified by previous fNIRS hyperscanning studies using communication paradigms (e.g., Jiang et al., 2012; 2015) and education tasks (e.g. Zheng et al., 2018). Future research may wish to further characterize INS for its potential significance in the frequency domain as EEG signals in terms of ranges and functions (Henry, 2006; Teplan, 2002). Second, as we demonstrated the instructor-learner neural synchrony in frontoparietal regions, it is informative for future research to set the ROIs exactly on frontal and bilateral parietal regions (rather than the mere left hemisphere in current study) to make specific validation of our findings. Finally, only female dyads were tested in order to reduce the

sample variability, in accordance with previous evidence and recommendations (Baker et al., 2016; Cheng et al., 2015; Tang et al., 2019). Future studies should consolidate and generalize the current findings to male participants.

In summary, the current results suggest that the feedback information beyond the correct answer could promote the learning, especially for the transfer of knowledge to novel contexts. Extending previous findings based on computer-controlled paradigms, this study used an ecologically valid yet experimentally controlled feedback-based concept learning task carried out by instructor-learner dyads with their brain activity simultaneously measured using fNIRS. As feedback information unfolded over time, instructor-learner neural synchronization was observed in frontoparietal regions, especially when examples were provided, and predicted the transfer of conceptual knowledge to novel contexts. Furthermore, such a prediction showed learner-delayed and learner-preceding patterns suggests the knowledge is represented at deep levels likely in forms of abstract structure and personal interpretation, respectively. Inter-brain dynamics may provide a novel lens for people to understand more about how feedback messages take effects on learning, thence unmasks the neurocognitive basis of elaborated feedback and contributes to the pedagogical efficacy.

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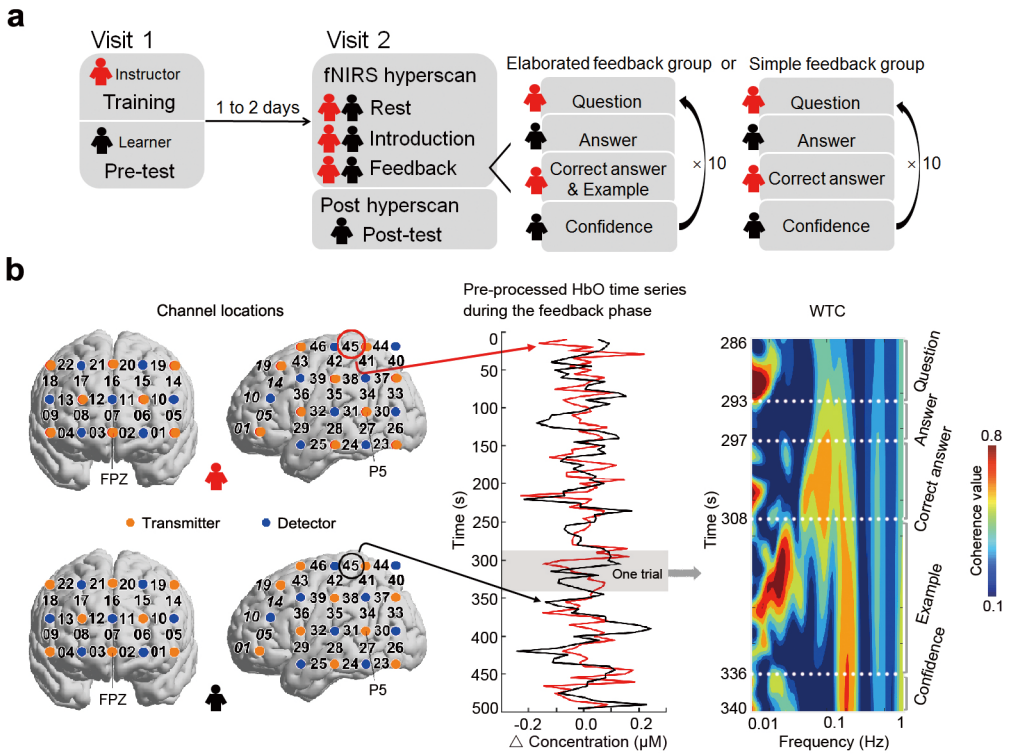
Figure 1

Experimental protocol, channel locations and WTC analysis

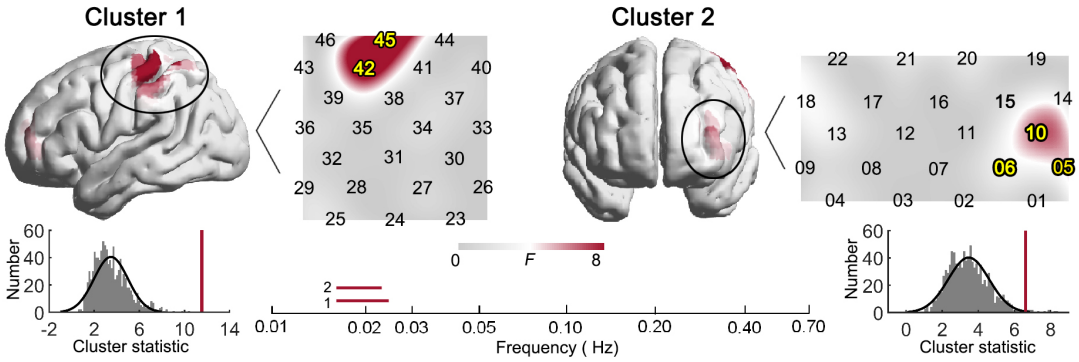


Note. (**a**) Schematic of the experimental protocol. During the first visit, instructors underwent a standardized training on the instructional procedure and content and leaners completed a pre-learning test. During the second visit, instructor-learner dyads first rested. Then instructors introduced 10 concepts, during which the term and the definition were orally presented twice. Next, learners re-studied the 10 concepts one by one based on the instructors' feedback (simple feedback of correct answer only or elaborated feedback of correct answer and example). Their brain activity was simultaneously recorded via fNIRS. Post hyperscanning, learners completed a post-learning test assessing both knowledge retention and knowledge transfer. (**b**) Locations of measurement channels and illustration of WTC analysis. On the left panel, two optode probes were placed over instructors' and learners' frontal and left temporoparietal areas, respectively. Measurement channels were located between one transmitter (orange) and one adjacent detector (blue). Location references were placed at FPZ and P5 according to the 10-10 international system. On the middle panel, sample data were one instructor-learner dyad's preprocessed HbO

time series from CH45 during the feedback phase. On the right panel, the resulting WTC matrix (frequency × time) corresponding to one trial was visualized with color bar denoting the values. HbO, oxy-hemoglobin; WTC, wavelet transform coherence.

Figure 2

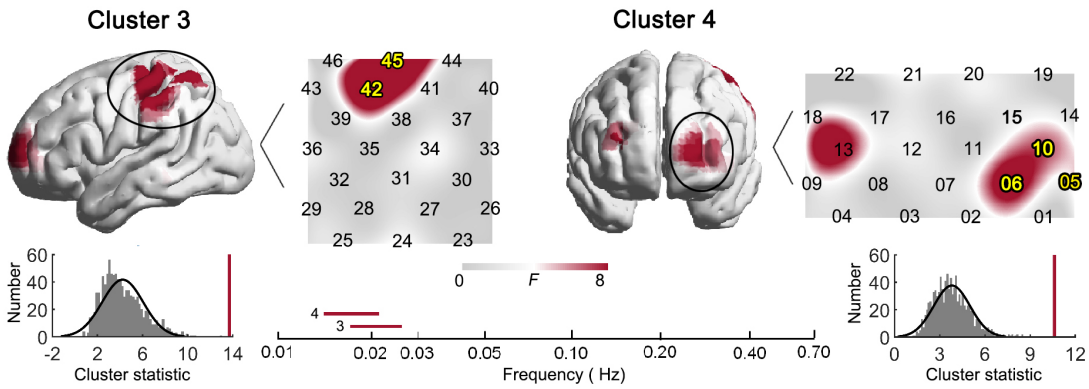
Instructor-learner neural synchronization during elaborated feedback



Note. Two significant clusters were identified. Cluster 1 was approximately located at left PoCG and left SPG within 0.017–0.025 Hz and Cluster 2 was approximately located at left SFG and left MFG within 0.017–0.024 Hz (with permutation tests, *p*s < 0.001). Spatial locations of the clusters are visualized at a representative frequency bin of 0.02 Hz. Yellow numbers denote channels contained in the clusters. Red horizontal lines denote the frequency bands. Gray histograms depict the frequent distribution of null cluster statistics, while red vertical lines denote the observed cluster statistics.

Figure 3

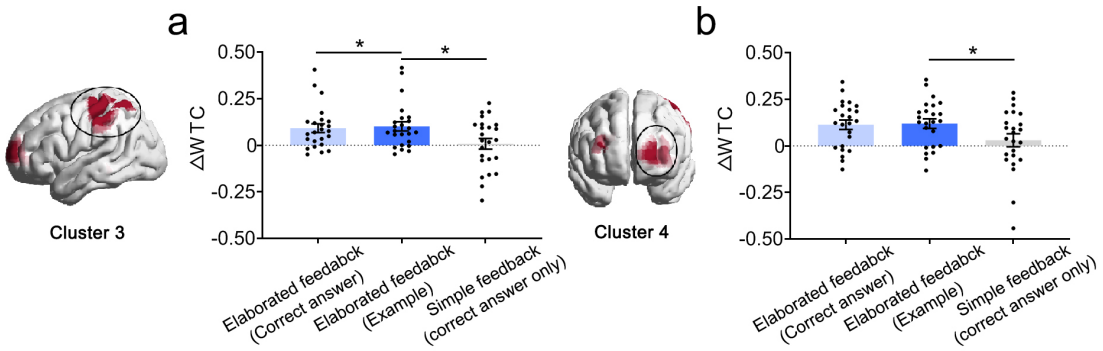
Instructor-learner neural synchronization during the example part of elaborated feedback



Note. Two significant clusters were identified. Cluster 3 was approximately located at left PoCG and left SPG within 0.018–0.027 Hz and Cluster 2 was approximately located at left SFG and MFG within 0.015–0.023 Hz (with permutation tests, *p*s < 0.001). Spatial locations of the clusters are visualized at a representative frequency bin of 0.02 Hz. Yellow numbers denote channels contained in the clusters. Red horizontal lines denote the frequency bands. Gray histograms depict the frequent distribution of null cluster statistics, while red vertical lines denote the observed cluster statistics.

Figure 4

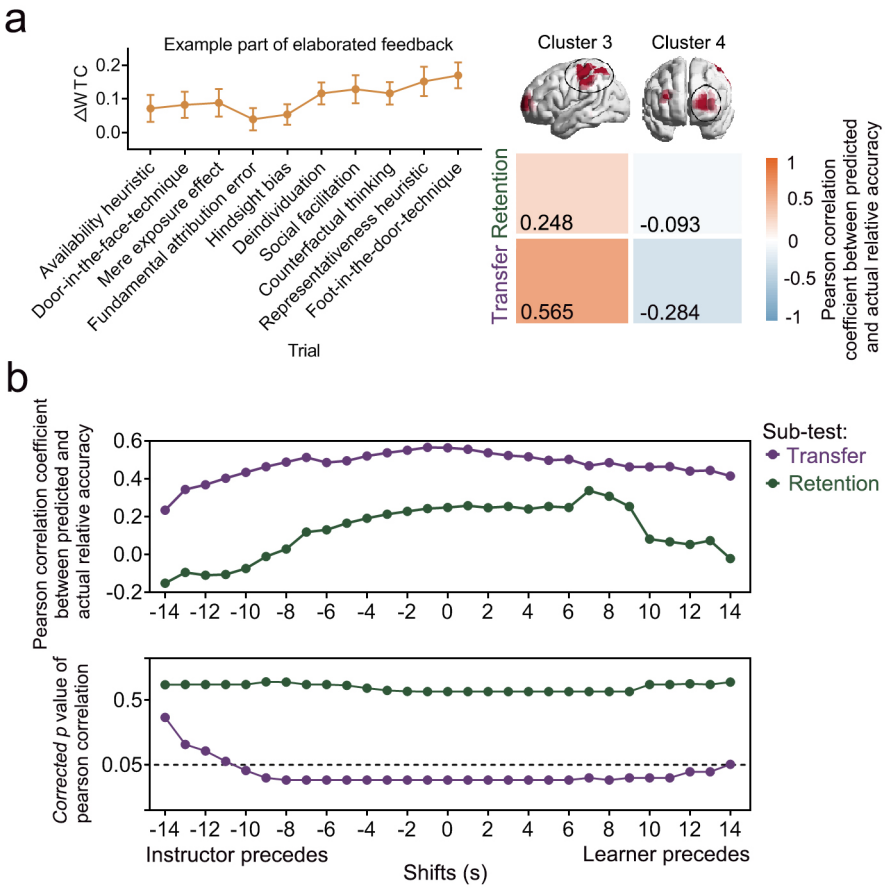
Instructor-learner neural synchronization during example vs. correct answer.



Note. (**a**) On Cluster 3, example relative to correct answer part of elaborated feedback and simple feedback elicited significantly larger ΔWTC. (**b**) On Cluster 4, example relative to correct answer part of elaborated feedback elicited comparable ΔWTC, while example part of elaborated feedback relative to simple feedback elicited larger ΔWTC. $^{*}p < 0.05$.

Figure 5

Instructor-learner neural synchronization during the example part of elaborated feedback predicts learning performance



Note. (**a**) Trial-by-trial ΔWTC on Cluster 3 could successfully predict out-of-sample learners' relative accuracy on the transfer measure but not on the retention measure. Warmer colors indicate relatively higher prediction accuracy for a given cluster; cooler colors indicate relatively lower prediction accuracy for a given cluster. (**b**). The prediction accuracy for Cluster 3 on the transfer measure was significant when instructors' brain activity preceded learners' by 1–10 s and when learners' brain activity preceded instructors' by 1–13 s (-10–13, purple).