Neuroscience Research 156 (2020) 165–177

Contents lists available at ScienceDirect

Neuroscience Research

journal homepage: www.elsevier.com/locate/neures

Is learning scale-free? Chemistry learning increases EEG fractal power and changes the power law exponent

Amanda Bongers[a,1], Alison B. Flynn[a], Georg Northoff[b,*,2]

[a] Department of Chemistry and Biomolecular Sciences, University of Ottawa, STEM Complex, Room 342, 150 Louis-Pasteur Pvt, Ottawa, ON, K1N 6N5, Canada

[b] Mind, Brain Imaging and Neuroethics Unit, Institute of Mental Health Research, University of Ottawa, 1145 Carling Avenue, Room 6467, Ottawa, ON, K1Z 7K4, Canada

ARTICLE INFO

Article history:
Received 25 July 2019
Received in revised form
16 September 2019
Accepted 21 October 2019
Available online 10 November 2019

Keywords:
Scale-free brain activity
Learning
Mind, brain, and education
Power-law distribution
Power-law exponent
Electroencephalography
Brain dynamics
Oscillology

ABSTRACT

Learning in chemistry and other areas of science involves developing one's mental models of invisible processes and manipulating temporal and spatial domains during visual information processing. While some aspects learning have been well studied by EEG (*e.g.,* theta and gamma oscillations), the role of spontaneous and scale-free brain activity remains unclear. We used a continuous chemistry learning EEG paradigm to explore how scale-free brain activity is related learning. We found a learning effect in participants ($N = 22$) with an increase in test accuracy (learning gain) and decrease in test question response times in a counterbalanced pre/post-test experiment. In the brain we found increased overall (mixed) broadband power (1–50 Hz) during learning compared to rest. We then used the IRASA method to separate oscillatory and fractal (*i.e.* scale-free) spectral components and observed an increase in low-frequency oscillatory band powers during learning. More importantly, we found that fractal power increased during the learning sessions relative to oscillatory power. Finally, the structure of the fractal power spectra (PLE) correlated to the individual participants' learning gains. These findings support the importance of scale-free activity for learning from a complex visual paradigm. We tentatively hypothesize that this fractal component is involved in integrating the different time scales of the learning material with those of the spontaneous activity during learning and mental model shaping.

1. Introduction

1.1. *Science and chemistry learning – mental models*

Learning in science requires the learner to visualize complex invisible processes and make connections between macroscopic and sub-microscopic domains (Johnstone, 1993; Taber, 2013; Talanquer, 2011). Students are known to have difficulties learning from scientific models and to lack sufficient mental models of the interactions of electrons and molecules in chemistry (Johnstone, 1991; Nelson, 2002; Tsaparlis, 2014). Experts appear to have general mental models of these interactions by recognizing similarities between different reaction types (Clement, 2000). These similarities are in the patterns of electron flow inherent to the reaction mechanisms (Galloway et al., 2018). Learning quickly from patterns is also often necessary for chemistry students, who are rapidly presented new material (Galloway et al., 2019; Graulich et al., 2010).

Recognizing and learning patterns requires robust mental models to integrate the new information with prior knowledge and long-term memory (Greca and Moreira, 2000). There is evidence that learners in chemistry recognize reactivity patterns in scientific models (Bongers et al., 2019; Galloway et al., 2019). However, it is still unclear how these learners develop and connect their mental models during learning, and the exact nature of these mental models remains unclear (Bongers et al., 2019). Given the fact that especially chemistry learning relies on recognizing spatial and temporal patterns of chemical representations, the mental models may themselves be shaped by such temporal-spatial dynamics.

1.2. *Learning and memory in EEG – task-related and spontaneous activity*

Learning occurs with "changes in mental representations that can manifest themselves in behavioral changes . . . an interaction

* Corresponding author.
E-mail address: georg.northoff@theroyal.ca (G. Northoff).
[1] Current address: Department of Chemistry, Queen's University, Chernoff Hall, Room 507, 90 Bader Ln, Kingston, ON, K7L 3N6, Canada.
[2] www.georgnorthoff.com.

https://doi.org/10.1016/j.neures.2019.10.011

with the environment and is initiated to adapt personal needs to the external world" (Stern, 2017, p. 1). Learning includes various components with one central component being visual information processing, which describes how the brain attends to, processes, stores, and retrieves external representations (Mayer, 2012; Stern, 2017). Visual information processing starts with sensory input of information, which involves attentional resource allocation. This information may be intentionally transferred into working memory, then organized (mental modelling), integrated with prior knowledge, and encoded into long-term memory. The speed of information processing is important to learning, and brain scanning with electroencephalography (EEG) can explore these temporal dynamics and also detect selective processing of information (van den Boomen et al., 2015).

Information processing and the neural networks underlying memory and learning have been studied using EEG to measure task-related activity with event-related potential (ERP) and spectral analysis. The latency and amplitude of the P300 ERP is a direct indicator of the speed of information processing (Duncan-Johnson and Donchin, 1982; Gevins, 2000; Steinemann et al., 2016). The P300 ERP is also used as an index for cognitive load during learning; for example, it was shown that abstract diagrams require more mental resources to process in EEG recordings (van Leeuwen et al., 2015). Studies also show event-related changes in EEG spectra are linked to memory encoding and retrieval; increased theta activity (especially frontal midline) and alpha attenuation are associated with working memory tasks and conditions of sustained attention (Gevins, 2000; Headley and Paré, 2017; Klimesch, 1999; Klimesch et al., 2005; Michels et al., 2010).

The different oscillations observed in brain activity with EEG are connected in a complex and underexplored temporal structure, with various functions for memory and cognition being proposed. For example, there is a working-memory-load dependent increase in both alpha and theta band powers during retention and retrieval tasks (Klimesch et al., 2005). More recent studies show the important role of synchronization across regions and frequency bands for processes of memory encoding and retrieval of prior knowledge, especially in relation to theta and gamma band powers (Fell and Axmacher, 2011; Klimesch et al., 2008). The phase- and power-coupling of different oscillations represents spatiotemporal continuity that is possibly important to the perception of stimuli (Canolty and Knight, 2010; Fell and Axmacher, 2011; Sauseng and Klimesch, 2008).

In addition to task-related processes, like working memory, learning also involves the brain's endogenous activity related to consciousness and metacognitive awareness. The latter is represented continuously in the brain as spontaneous activity (Huang et al., 2017, Northoff, 2018a), which is measured over longer timescales than ERP studies. The brain's spontaneous activity exhibits a complex spatial and temporal structure of various frequencies (Buzsáki et al., 2013; Mantini et al., 2007; Northoff, 2018a; Sadaghiani et al., 2010). Studies have linked ongoing spontaneous activity to measures of task performance, personality, and self (He et al., 2010; Huang et al., 2016; Scalabrini et al., 2017; Wolff et al., 2019), and also psychiatric disorders (Northoff, 2018a). The impact of the brain's spontaneous activity on learning remains yet unclear.

Spontaneous activity appears to play a role in how the brain interacts with the environment, as evidenced from a non-additive response in to stimuli (Huang et al., 2017), and it is believed to give rise to information processing and thought in the brain (Langer et al., 2017; Lehmann et al., 1998). However, there are few studies into learning with continuous EEG measurement, where the participant is learning over longer time periods than traditional stimulus presentation (Dahlstrom-Hakki et al., 2019). Such measurement over the length of a learning activity includes both short-term task-evoked activity and also the brain's ongoing spontaneous activity; both are likely to contain indicators for learning (Sadaghiani et al., 2010). A continuous learning paradigm is much closer to the actual learning process than a discontinuous paradigm, since learning involves the shaping and reorganization of the brain's continuously ongoing neuronal activity; that is also in line with the recently suggested shift from discontinuous to continuous paradigms and brain activity analysis (Huk et al., 2018).

1.3. Spontaneous activity is scale-free – fractal and oscillatory components

The brain's spontaneous activity constitutes a complex temporal structure which, in large part, can be characterized by the balance between slower and faster frequencies. This activity features different frequencies ranging from infraslow (0.01–0.1 Hz), slow (0.1–1 Hz), and fast (1–40 Hz) to ultrafast (40–180 Hz) (Buzsáki, 2006; Buzsáki and Draguhn, 2004). Power is strongest in the infraslow range with decreasing power in slow, fast and ultrafast ranges following power law distribution (He, 2014, 2011; He et al., 2010; Hiltunen et al., 2014; Huang et al., 2017). Herein we focus on this temporal structure and not on the spatial structure of spontaneous activity (Bullmore and Sporns, 2009; Cole et al., 2014).

The relationship between slow and fast frequencies operates at different temporal (and spatial) scales and can therefore be characterized as scale-free activity. Scale-free activity describes the fractal, i.e. self-similar, organisation of the power between the different frequencies and is distinct from the activity of rhythmic brain oscillations (He, 2014; Sadaghiani et al., 2010). This organisation is a kind of temporal nestedness: the longer and more powerful slower frequencies nest and contain the shorter and less powerful faster frequencies. Such nestedness amounts to long-range temporal correlation (LRTC) which operates across different time scales, i.e., are scale-free (Hardstone et al., 2012; He, 2014; He et al., 2010; Huang et al., 2017; Linkenkaer-Hansen et al., 2001). While LRTCs reflect continuous (rather than discontinuous) neuronal activity relevant to arousal state and task-evoked response, their relationship to more continuous forms of behavior, like continuous learning, remains unclear.

LRTC can be measured and expressed by the power law expression $P \propto 1/f^{\beta}$ where P is power, f is frequency, and β is the power-law exponent (PLE) (He, 2014; He et al., 2010). A high PLE value indicates relatively stronger power in slow frequencies and relatively less power in the faster ones, whereas the opposite is the case in a low PLE value. Alternatively, LRTC can also be measured on the basis of the fluctuations in the amplitude present in the oscillations as it is done by detrended fluctuation analysis (DFA) (Chialvo, 2010; Hardstone et al., 2012; He et al., 2010; Linkenkaer-Hansen et al., 2001; Manning et al., 2009; Miller et al., 2009a; Palva et al., 2013). DFA thus operates in the time domain by measuring the variance in the amplitude, whereas PLE is distinguished in that it presupposes the frequency domain.

Brain activity measured in fMRI and EEG contains both fractal and oscillatory components (Wen and Liu, 2016). Oscillatory components are regular across time while fractal components are more irregular in that different time scales within the signal are nested or integrated within each other. True scale-free activity thus applies to the fractal component but not the oscillatory components of the spectrum. Therefore, relying on the method established by Wen and Liu (2016), one can separate fractal and oscillatory components in order to apply analysis (calculation of PLE or DFA) specifically to the fractal component. Prior studies in learning, memory, and cognition focus on task-related oscillatory activity and connections between different frequency bands without studying the underlying continuously ongoing scale-free structure including how it is shaped and reorganized by the continuous learning process. It thus remains unclear how the oscillatory and fractal signal components are related to behavioral function and the recruitment of mental models as in learning. We hypothesize that, due to its continuous nature with the integration of different time scales, the fractal component of the brain's spontaneous activity may play a central role in integrating and embedding the stimuli, or new learning material, in chemistry learning.

1.4. Aims and hypotheses

The general aim of this exploratory study was to explore and identify neuronal markers from continuous EEG data for chemistry learning through scientific models and building of mental models. Multiple processes are involved in learning (*e.g.*, attention, memory, cognitive load, and pattern recognition) with some known neuronal markers, as described above. Memory is only one part of information processing though, and perception of stimuli accurately and incorporation into the brain's ongoing spontaneous activity are also necessary. Rather than identifying specific cognitive or sensory components implicated in the outputs of learning and measured by task-related activity, we here aimed to take a broad look at the changes and organization of the more continuously ongoing activity during the process of learning process itself. For that purpose, we applied a more continuous paradigm (Huk et al., 2018) of specifically chemistry learning, and measured the EEG-based ongoing activity in a continuous way during both resting state and the learning process. This allowed us to investigate how the chemistry learning process shapes and reorganizes the spontaneous activity's temporal structure, like its oscillatory and fractal power as well as its scale-free structure as measured with the power law exponent. This approach made it possible, at least in part, to infer about the nature of the learners' mental models which may be shaped in a fractal way as related to the need to integrate different time scales during the chemistry learning process.

The first specific aim consisted in investigating the behavioral effects such as learning gains during a complex visual continuous chemistry learning paradigm. Applying a paradigm with two subsequent learning sessions, we hypothesized large learning gains during the first learning activity but smaller or no gains in the second learning activity.

The second specific aim was to investigate broadband power changes in EEG during the resting state as well as during the subsequent learning sessions. Based on previous data during more discontinuous learning paradigms, we hypothesized an overall power increase and specifically theta band power increases during the learning activities thus reflecting learning gains.

The third specific aim consisted in separating fractal and oscillatory signal components to test which one is more related to chemistry learning; for that purpose, we also determined the PLE over specifically the fractal component. Since there are no previous data at all, we were not able to formulate a specific hypothesis on whether learning is mediated by mainly the fractal or oscillatory signal component.

More generally, we expected that fluctuations in oscillations during learning may be linked to behavioral measures of learning from scientific models. Specifically, we predicted an increase in theta band power during learning compared to rest, and a complementary attenuation of alpha oscillatory power, based on prior work implicating these frequencies in learning functions (see above). In addition, given the need for the participant to integrate different time scales during the chemistry learning process, we expected that fractal power and the scale-free activity during learning (*e.g.,* the power law exponent applied to the fractal spectrum) would possibly be related to individual differences in learning gains.

2. Materials and methods

2.1. Participants and setting

Prior to recruiting participants and conducting the study, ethics approval was granted by the institutional Research Ethics Board (University of Ottawa Institute of Mental Health Research). Participants were students from a bilingual public research university in Canada who voluntarily participated in the study, were either enrolled in or had completed an organic chemistry course, and had no clinically significant non-correctable sensory impairment ($N = 22$, 13 female).[3] All but one participant were right-handed. All participants gave written informed consent prior to participation in the study and were compensated for their time.

2.2. Experimental paradigm and outcome measures

The experiment consisted of a computerized learning activity with brain-scanning (EEG). At the start of the session each participant was assigned a successive code and placed into one of two groups (even code = Group 1, odd code = Group 2). The experiment began with an eyes-open resting state measurement (7 min) followed by a series of consecutive continuous learning tasks on the computer consisting of Tests and Learn Blocks (Fig. 1). Learn Blocks 1 and 2 were either static or animated, following a switching replications design, to study the effect of stimulus type and the progression of learning. The Learn Blocks were 12 min in length plus two self-timed breaks, giving three sections of continuous data, each 4 min in length. More details of the Tests and Learn Blocks are provided in the Appendix (Fig. 8), and an earlier version of this experiment was used in an educational research context to study and show the development of mental models in chemistry students (Bongers et al., 2019).

PsychToolbox v3 and MATLAB v2018a (MathWorks) software were used to design and run the experiment, including recording test accuracy and response time (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). Examples of the animations are provided in the Appendix. The complementary static images were created using ChemDraw software. Stimuli were displayed on a desktop computer with a 19 inch monitor. All stimuli and text were shown in black with a grey background. Research participants were seated approximately 20 in. from the bottom of the stimulus, as per their comfort. Each stimulus was preceded by a black fixation cross.

The Rest EEG measurement and behavioral data from Test 1 are considered in this study as “pre-learning” measurements. The Block 1 and 2 EEG measurements, and Test 2 and 3 behavioral data are considered as “during learning” and “post-learning”, respectively. Learning was measured with four behavioral variables (Fig. 1): 1) Test accuracy (acc, %); 2) Test response time (RT, s); 3) Learning Gain (LG) which is the change in test accuracy (%) before and after each Learn Block; 4) Change in test response time (dRT) which is the change in the mean test response time (s) before and after each Learn Block.

2.3. EEG data acquisition and pre-processing

EEG activity was recorded using a 64-channel actiCAP (Brain Products GmbH, Germany) with electrodes at Fp1, Fp2, AF7, AF3, AF4, AF8, F7, F5, F3, F1, Fz, F2, F4, F6, F8, FT9, FT7, FC5, FC3, FC4, FC6, FT8, FT10, T7, C5, C3, C1, Cz, C2, C4, C6, T8, TP9, TP7, CP5, CP3, CP1, CPz, CP2, CP4, CP6, TP8, TP10, P7, P5, P3, P1, Pz, P2, P4,

[3] The demographic questionnaire asked “What is your gender?” with options “Male”, “Female”, “Prefer not to answer”, and “These options do not apply to me, I identify as: _”.

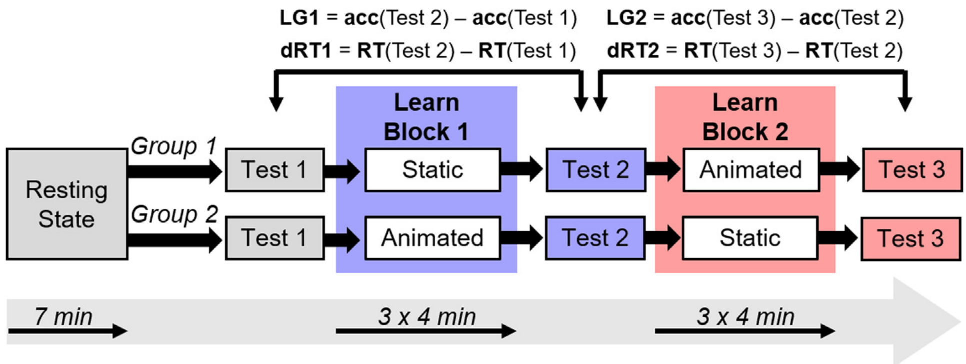

Fig. 1. Experimental paradigm. After eyes-open resting state measurement (7 min) the participants were randomly divided into two groups for a counterbalanced pre/post-test design with static and animated learning blocks. Learn Blocks were 12 min in length with two self-timed breaks, giving three sections each 4 min in length (*min* = minutes). Formulas for calculating learning gain (LG) from test accuracy (acc), and change in test response time (dRT) from test response time (RT), are shown for Block 1 (LG1, dRT1) and Block 2 (LG2, dRT2).

P6, P8, PO9, PO7, PO3, POz, PO4, PO8, PO10, O1, Oz, and O2, reference electrode at FCz and ground electrode at AFz according to the extended International 10–20 Systems. The impedance of all channels was measured at less than 5 kΩ before recording was initiated and remained below this level for the duration of the recording. The signal was amplified (actiCHamp) and data recorded at a sampling frequency of 1000 Hz using the EEG BrainVision Recorder (Brain Products GmbH, Germany) with a 400 Hz anti-aliasing filter.

All EEG data preprocessing was completed using EEGLAB (Delorme and Makeig, 2004), which required MATLAB v2018a (MathWorks). The data for each participant consisted of one set for each of Rest, Block 1, and Block 2. The sets for Block 1 and Block 2 were then cut to remove the self-timed breaks, providing three sub-sets (early, mid, late) for each. All 7 sets were then cut to the same length of 244 s using event markers included in the data from recording. Pre-processing for all datasets then followed Makoto's pipeline (Miyakoshi, 2019) for continuous data in EEGLAB, as described below.

The continuous data was resampled to 500 Hz using EEGLAB's zero-phase antialiasing *pop_resample* function, then was low- and high-pass filtered (FIR filter) from 1.0 Hz to 50 Hz, which eliminated 60 Hz electrical line noise. The data was then visually inspected for bad channels and non-stationary artifacts, which were removed using the *clean_rawdata* EEGLAB plugin (Mullen et al., 2015). Channels were removed if flat longer than 5 s, had less than 0.80 correlation with neighboring channels, or had a standard deviation of over 5 (for removal of bursts by ASR). All removed channels (average of 8 out of 63) were then spherically interpolated. The data was then re-referenced to the average of the channel values.

Further artifacts (*e.g.,* eye movements) were reduced using Infomax Independent Component Analysis (ICA) and the EEGLAB plugin Multiple Artifact Rejection Algorithm (MARA) with visual inspection and automatic artifact rejection, with an average 60 % rejection rate (Winkler et al., 2014, 2011).

2.4. EEG data analysis

Data analysis was conducted in MATLAB v2018a (MathWorks), including the use of the Optimization, Statistics and Signal Processing Toolboxes. Statistical analysis was completed using MATLAB or SPSS v24 (IBM), with a significance value of 0.05, and where p_{GG} represents a Greenhouse-Geisser corrected p-value. Bonferroni correction was used where appropriate to correct for multiple comparisons, unless otherwise noted. For the analysis, each participant's channel data was first averaged to give the mean signal across all 63 channels (the ground electrode AFz was excluded). All calculations for the three sub-sets in Block 1 and Block 2 (early, mid, late) were done separately, then averaged to give the final value.

We used Irregular-Resampling Auto-Spectral Analysis (IRASA) as a method to calculate the mixed power spectrum signal and to separate the signal into oscillatory and fractal components (Wen and Liu, 2016). Mixed and fractal power spectral density (PSD) spectra are shown as log-log plots, while the oscillatory PSD spectra are represented as regular plots.

Broadband power (1–50 Hz) and frequency band powers ranging from delta (1–4 Hz), theta (5–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and low gamma (30–50 Hz), were calculated using the *bandpower* function in MATLAB. The PSD estimate for the mixed, oscillatory, or fractal signals was inputted and the function returned the average power computed by integrating the PSD estimate. The oscillatory spectra were corrected to baseline before band power analysis.

Topographic maps for all participants were created for each frequency band and over the entire continuous dataset (244 s) in EEGLAB using the *topoplot* function (Delorme and Makeig, 2004). These maps were created from the mixed spectral data.

The power law exponent (PLE) of the fractal component was calculated as part of the IRASA method (and with the code provided by the authors) by fitting the log-log of the fractal power spectrum to a linear function using least squares estimation (Wen and Liu, 2016). The slope of the resulting curve (β) was the PLE value.

3. Results

3.1. Behavioral findings

Test accuracies and response times were each analyzed using a mixed design ANOVA (Fig. 2), where all variables met the assumption of homoscedasticity. This revealed a significant main effect of time on test accuracy $F(2,38) = 31.2$, $\eta_p{}^2 = 0.621$, $p < 0.001$, but no effect for the between-subjects variable (group), $F(1,19) = 0.072$, $\eta_p{}^2 = 0.004$, $p > 0.5$, or the group by time interaction, $F(2,38) = 0.021$, $\eta_p{}^2 = 0.002$, $p > 0.5$. This means there was no effect of stimulus type (static or animated) on test accuracy or learning gain. There was a significant increase in accuracy from Test 1 (M = 0.496, SE = 0.028) to Test 2 (M = 0.693, SD = 0.024) (Bonferroni corrected $p < 0.001$), corresponding to a mean learning gain LG1 = 20 %, and no difference between Test 2 and Test 3 (LG2= −1 %). The learning gain demonstrates that our participants did indeed learn showing quantifiable behavioral learning effects. In contrast to the difference in test accuracy and response time between Test 1 and Test 2, no such learning gain was observed from Test 2 to Test 3 in accuracy (and test response time; see below). These behavioral findings are in

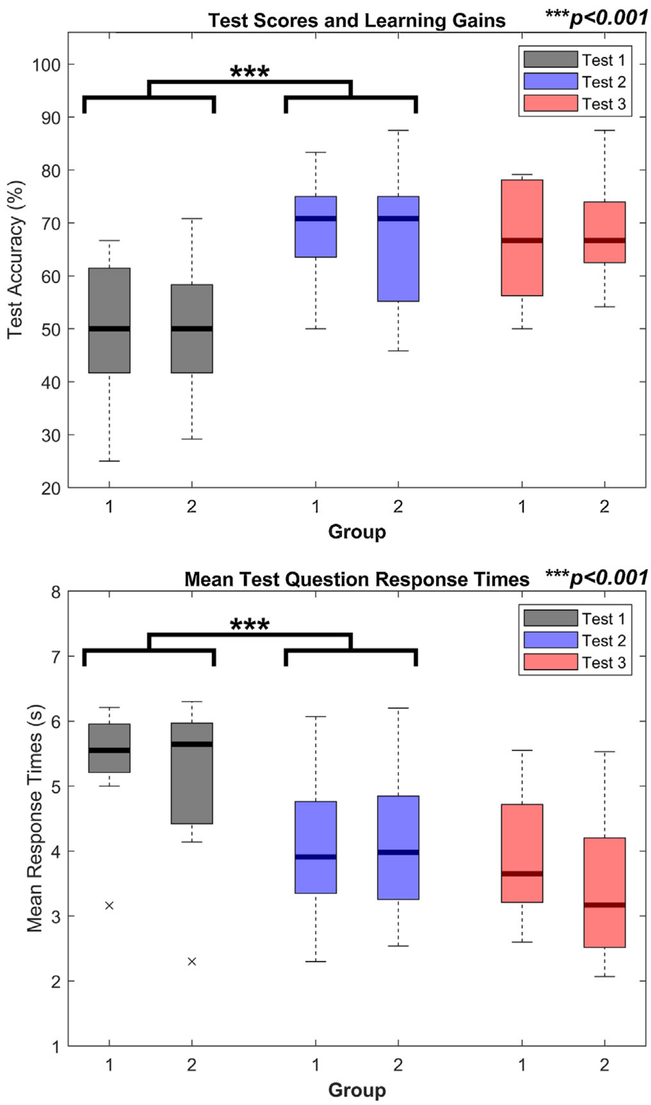

Fig. 2. Changes in test accuracy (acc) and mean test response time (RT) for chemistry learning paradigm.

alignment with our prior work, which used qualitative analysis to show chemistry students were developing dynamic mental models of the chemical reactivity (Bongers et al., 2019).

A mixed-design ANOVA for test response times revealed a significant main effect of time $F(2,38) = 36.4$, $\eta_p^2 = 0.657$, $p < 0.001$, but no effect for the between-subjects variable group, $F(1,19) = 0.603$, $\eta_p^2 = 0.031$, $p > 0.1$, or the group by time interaction, $F(2,38) = 0.244$, $\eta_p^2 = 0.013$, $p > 0.5$. This means there was no effect of stimulus type (static or animated) on test response time or dRT (see Appendix Fig. 9). There was a significant decrease in response time from Test 1 to Test 2 (MD = −1.287, SE = 0.225, Bonferroni corrected $p < 0.001$), and a smaller decrease between Test 2 and Test 3 (MD = −0.353, SE = 0.114, Bonferroni corrected $p = 0.018$).

3.2. Neuronal (EEG) findings from analysis of mixed spectra

We first started with the typical analysis of mixed power spectrum including both fractal and oscillatory components. Being the typical way in most studies, we started with the mixed signal as to render our findings comparable to others in the literature.

Power spectral density (PSD) spectra (Fig. 3A) show high individual variability in the curves for overall power, oscillatory peak amplitude, and peak frequency. The average overall power spectral density increases from Rest to Block 1, while the average alpha peak amplitude decreases. A one-way RM ANOVA (Fig. 3B) confirmed a significant increase in broadband (1–50 Hz) absolute power from rest to continuous learning task $F(2, 42) = 7.053$, $p = 0.00229$. There was a significant change (with Bonferroni correction) from Rest to Block 1 ($p = 0.0188$) and no change from Block 1–2 ($p = 0.551$) (Fig. 3B).

Further analysis of band powers with one-way ANOVA revealed overall changes in delta ($F(2,42) = 9.355$, $p = 0.000428$), theta ($F(2,42) = 7.760$, $p_{GG} = 0.00360$), beta ($F(2,42) = 6.174$, $p = 0.00446$), and low gamma ($F(2,42) = 9.266$, $p = 0.000464$) bands, but not in the alpha band ($F(2,42) = 0.701$, $p_{GG} = 0.453$) (Fig. 3C). These increases in band power were significant (with Bonferroni correction) from rest to continuous learning task, and there were again no differences between Block 1 and 2 (Fig. 3C).

Delta and theta activity are known to be linked to memory processes in the brain (Düzel et al., 2010; Headley and Paré, 2017; Sauseng et al., 2010), so we further explored these frequency band increases with spatial maps of EEG activity. A one-way ANOVA (performed in EEGLAB with FDR correction for multiple comparisons) shows a boost in delta and theta activity in the prefrontal cortex and occipital regions (Fig. 3D), and also an overall power increase in these bands across specifically prefrontal and occipital areas of the brain. Although the data was treated with MARA for rejection of ocular artefacts, we cannot completely rule out eye movement contamination for this power increase in the prefrontal cortex in the theta band (Supplementary Materials Figures S4-S9). For topographic maps of all frequency bands see the Supplementary Materials (Figure S10).

3.3. Separation of mixed spectra into oscillatory and fractal components

We used the IRASA method to separate each participant's oscillatory and fractal components of the power spectrum (Fig. 4A) in order to explore how these two components contribute to changes from rest to continuous learning task (See Methods). The average fractal component spectrum across participants ($N = 22$) showed an overall higher fractal power in Blocks 1 and 2 compared to Rest, as well as a slight change in the slope of the curve. The average oscillatory component spectrum showed a decrease in alpha oscillation band power during learning (Rest to Block 1), and an increase in delta and theta oscillation band powers.

Analysis of broadband power in the fractal and oscillatory components revealed that fractal broadband power changed from rest to continuous learning task (Rest to Block 1), while oscillatory broadband power did not (Fig. 4B-C). A one-way RM ANOVA showed an increase in mean fractal broadband power from rest to learning task ($F(2,42) = 8.1251$, $p = 0.00104$), pairwise comparison showed this change to be significant for Block 1 ($p = 0.0111$) and Block 2 ($p = 0.0250$) with Bonferroni correction (Fig. 4B), whereas there was no significant difference between Block 1 and 2. For the mean oscillatory broadband power there was no significant overall change (Fig. 4C).

The ratio of fractal to oscillatory broadband power components was found to increase significantly during learning (Blocks 1 and 2) compared to Rest (One-way RM ANOVA $F(2, 42) = 8.387$, $p = 0.000862$) (Fig. 4D). Together, these results suggest that the increase in broadband power we observed in the mixed signal (Fig. 3B) is related to an increase in the fractal power rather than the oscillatory power. Hence, learning seems to increase the broadband power of the fractal signal component, with smaller changes in power in specific bands of the oscillatory signal component.

Analysis of individual band powers for the oscillatory spectra showed an increase in only delta ($F(2,42) = 7.2237$, $p = 0.00201$) and

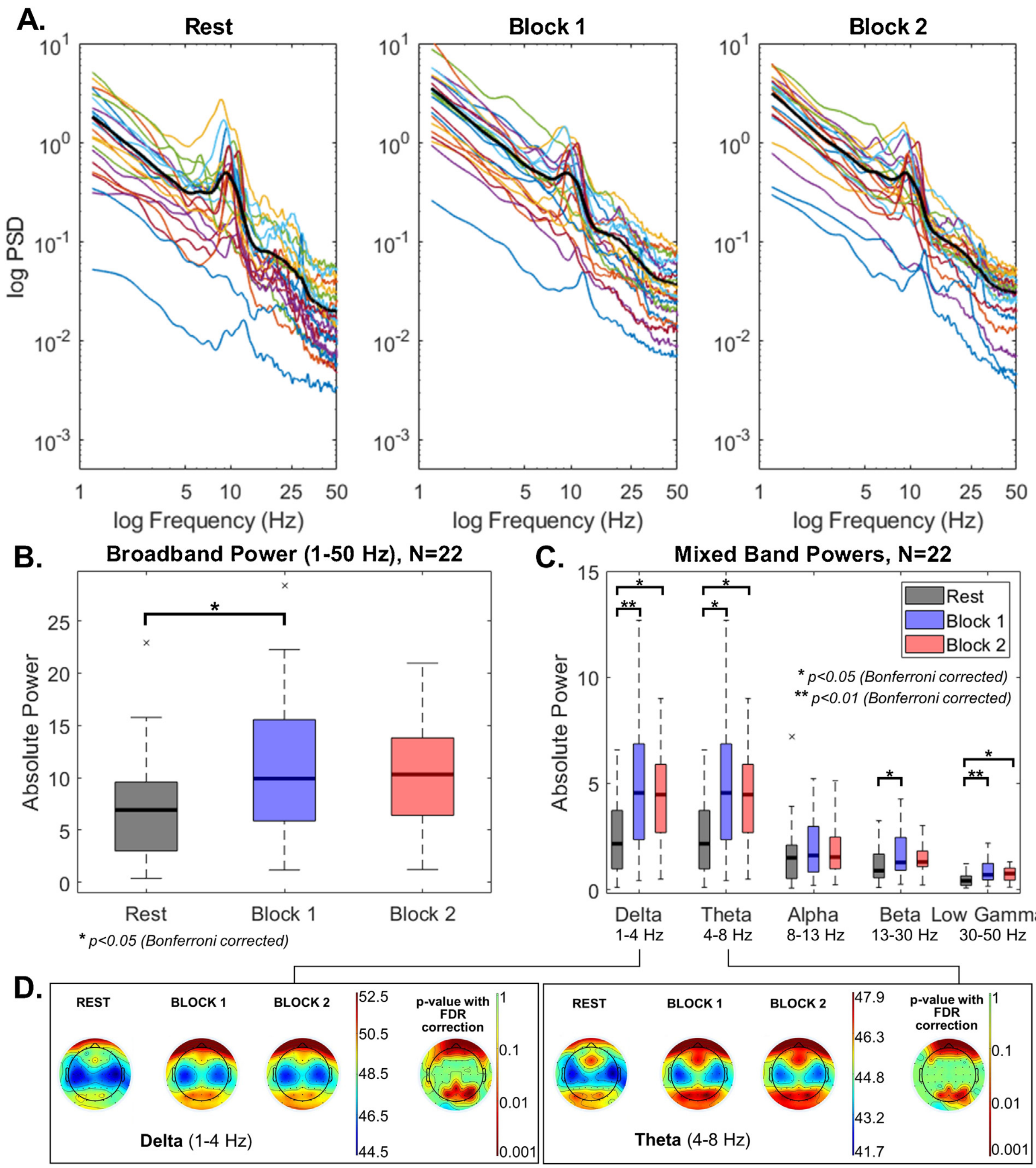

Fig. 3. (A) Power Spectral Density (PSD) Spectra for all participants in Rest, Learn Block 1, and Learn Block 2. Average = bold black line. (B) Broadband power (1–50 Hz) in Rest, Learn Block 1, and Learn Block 2. (C) Band powers (mixed spectra) in Rest, Learn Block 1, and Learn Block 2. (D) Topographic maps of the delta and theta bands from the mixed spectra.

theta ($F(2,42) = 4.3882$, $p_{GG} = 0.0349$) oscillations during learning (Fig. 4E). These band power increases were also observed in the mixed spectral data (Fig. 3C). The full oscillatory PSD spectra for all participants and blocks can be found in the Appendix (Fig. 10).

3.4. Relationship of spectral powers to behavioral data

Broadband (1–50 Hz) mixed, fractal, and oscillatory powers during learning (Block 1) were not found to have correlations to LG1 or dRT1 (Supplementary Materials, Figure S11). We also found no relationship between participants' delta and theta oscillatory band power values and LG1 or dRT1 (Supplementary Materials, Figure S12).

3.5. Fractal spectra: power-law exponent (PLE) and learning gains

We then explored how the fractal power structure was related to the observed behavioral learning effects. The fractal power spectrum is best described by the relationships across frequencies, and not by band powers, so we used the power law exponent (PLE) as a measure of the slope of the fractal curve across frequencies (Fig. 5). The PLE values ($N = 22$) for Rest ($M = 1.107$, $min = 0.739$, $max = 1.401$)

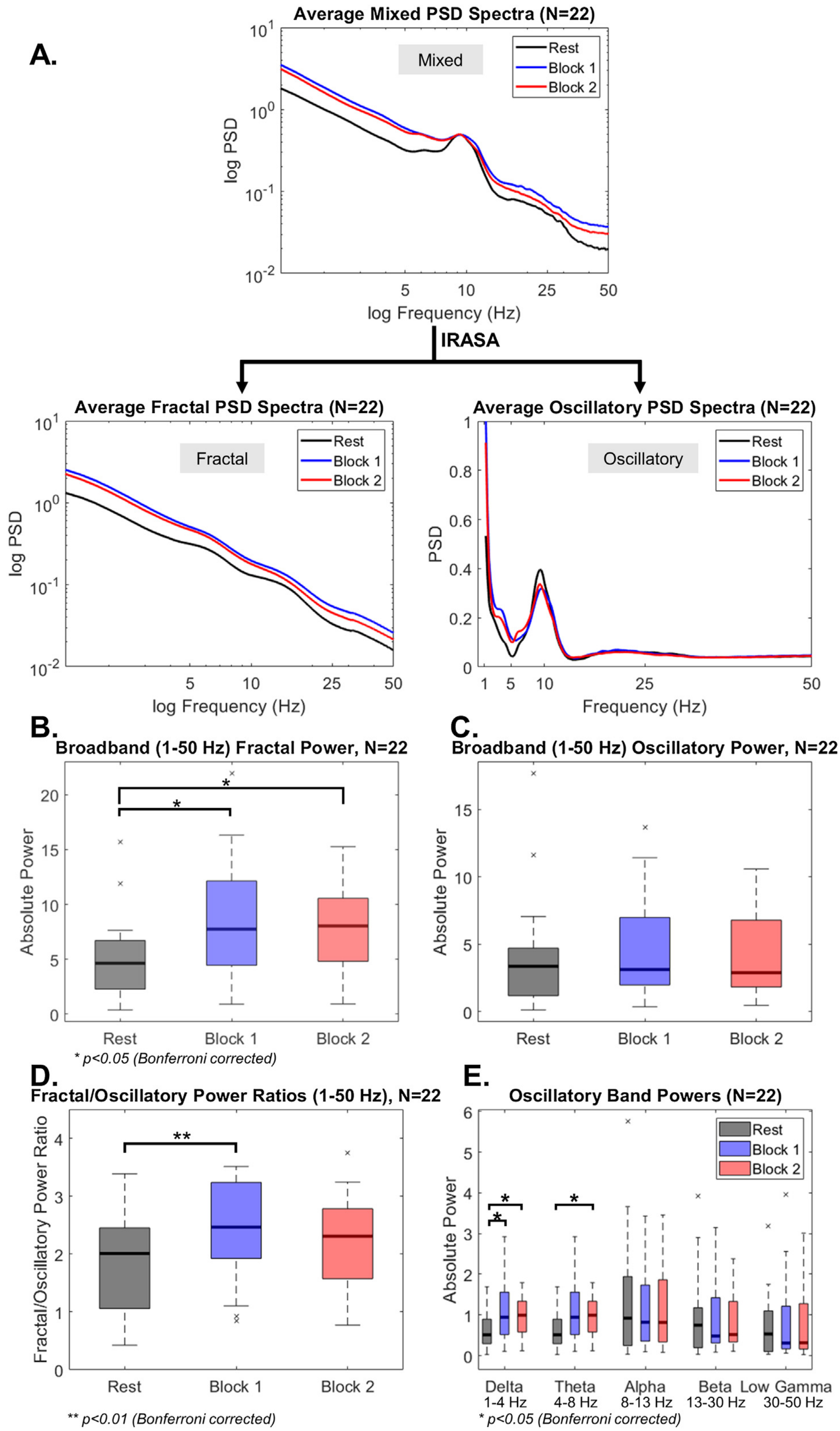

Fig. 4. (A) Average mixed, fractal, and oscillatory spectra across participants. Fractal and oscillatory components were separated computationally using IRASA. (B) Fractal and (C) Oscillatory broadband powers (1–50 Hz) in Rest, Block 1, and Block 2. (D) Broadband power ratio of the Fractal/Oscillatory components in Rest, Block 1, and Block 2. (E) Oscillatory band powers in Rest, Block 1, and Block 2.

were on average lower than in the learning activities (One-way RM ANOVA $F(2, 42) = 6.400$, $p = 0.0037$). There were similar mean PLE values ($N = 22$) for Block 1 ($M = 1.174$, $min = 0.919$, $max = 1.500$) and Block 2 ($M = 1.183$, $min = 0.861$, $max = 1.417$). The PSD plots (Fig. 5) show individual variability in PLE that is the highest during Rest ($SD = 0.172$), followed by Block 1 ($SD = 0.127$), and is lowest in Block 2 ($SD = 0.121$), and an analysis of within-subjects variance with Mauchly's test failed to reject the null hypothesis that the variances

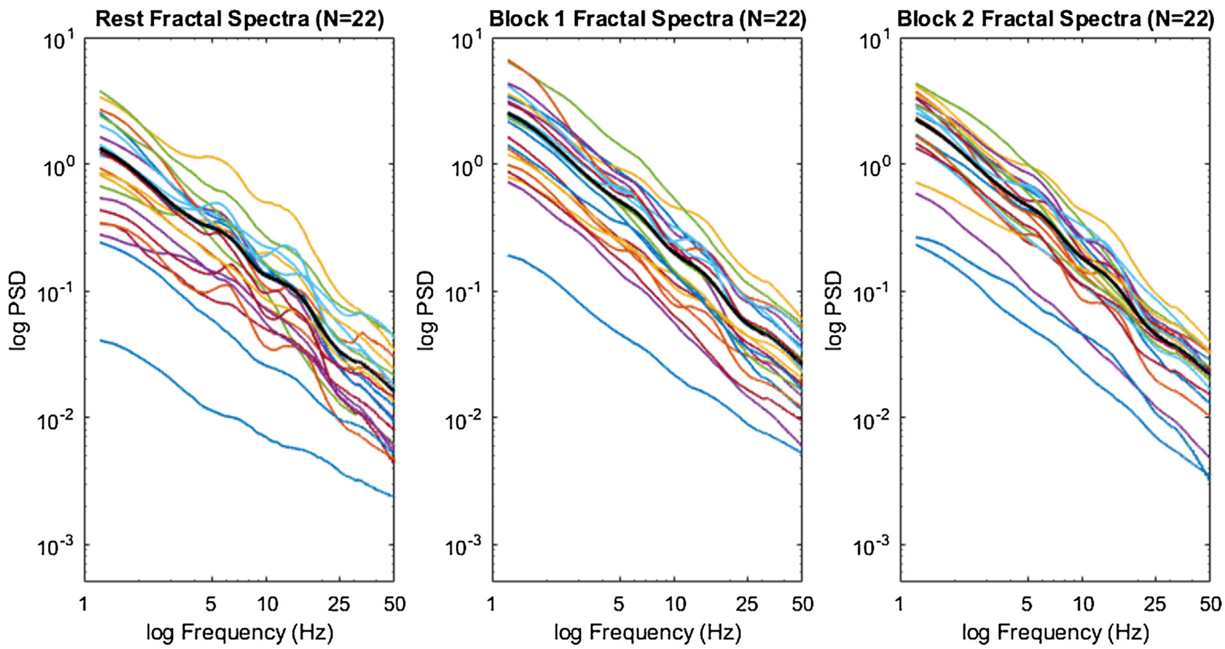

Fig. 5. Fractal power spectra for all participants in Rest, Block 1, and Block 2. The mean is represented by a bold black curve. The PLE value is the slope of curve in the fractal power spectrum.

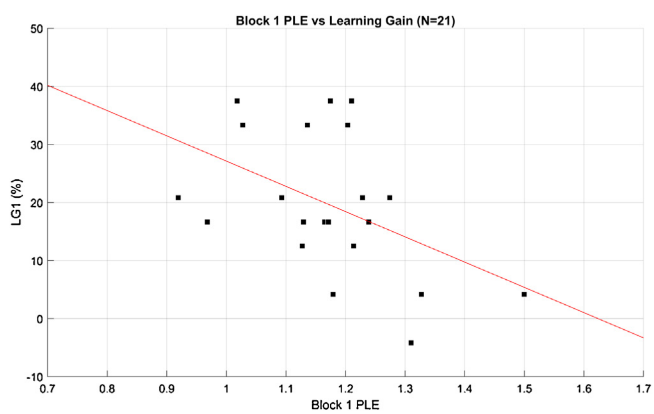

Fig. 6. Correlation of Power Law Exponent (PLE) with learning gain (LG1) for Block 1 in the chemistry learning paradigm. The regression line is shown in red.

are equal. This indicates that while between-subjects variability is high and changes depending on the condition, there is consistency within-subjects.

We were interested in whether the individual variabilities in PLE during the continuous learning tasks were related to learning gains. Correlation analysis and visual inspection found that Block 1 PLE did have a linear relationship with LG1 (Fig. 6), while Block 2 PLE was not correlated to the small learning gains (Mean LG2 ~ 0 %) observed in Block 2 (Supplementary Materials, Figure S13). A hierarchical linear regression was then conducted to test for the effect of Block 1 PLE and the possible confounder representation type (group) on LG1. Analysis using the backward elimination method for Block 1 indicated a negligible effect of group and it was removed from the model with no change in R^2. The resultant model showed a significant relationship between PLE and LG1 ($R^2 = 0.214$, $F(1,19) = 5.176$, $p = 0.0347$) corresponding to a negative linear correlation: a lower PLE, meaning more contribution of higher frequencies relative to lower ones, increased the learning gains in these participants.

In summary, while the mean PLE showed a small increase from Rest to Block 1, a lower PLE was linked to better learning gains. This appears to be a balance of the contribution between increased overall broadband (1–50 Hz) fractal power during learning, and the high frequency (13–50 Hz) band power increase observed during learning in the mixed spectra. Both factors are reflected in the slope of the fractal spectrum to give the participant's PLE value observed during learning (Fig. 7).

4. Discussion

In this exploratory study we investigated learning from scientific (chemistry) models with a continuous paradigm and analysis in EEG. First, we saw large learning gains (LG) and changes in test response time (dRT) in Block 1, and no overall changes in these behavioral measures in Block 2. Second, we showed that learning activities (Block 1 and 2) were associated with an increase in the mixed power of broadband (1–50 Hz) as well as delta, theta, beta, and low gamma band powers. We then demonstrated using the IRASA method to separate fractal and oscillatory components of the spectra. This showed that the observed mixed power increase reflected an overall increase in fractal power (but not the oscillatory power) during learning, as well as an increase in the ratio of fractal vs. oscillatory absolute power. Next, by examining the oscillatory spectral component we showed the hypothesized mean theta band power increase and alpha attenuation, as well as increased delta band power during learning. Finally, examining the structure of the fractal component using PLE values revealed an overall small increase in the mean PLE during learning, along with a significant relationship between individual learners' PLE values during learning and their behavioral measure of learning gains (LG).

Our behavioral results (acc, RT, LG, and dRT) provided a quantifiable measure of learning chemistry from scientific models in this study, which matched our hypothesis and aligns with prior work (Bongers et al., 2019; Hinze et al., 2013). The design of our experiment included two types of representations of these scientific models (static and animated), and we found no differences in the behavioral outcome measures for these representations types. We observed the largest mean LG and dRT in Block 1, where an increase in test accuracy was accompanied by a decrease in mean RT demonstrated the learning effect. There was small to no change,

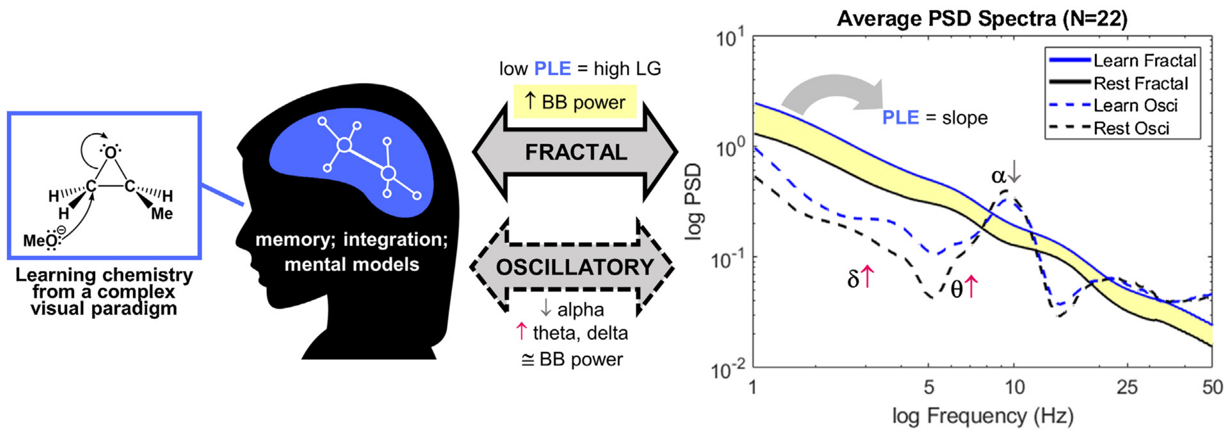

Fig. 7. Schema of the role of oscillatory and fractal spectral components to learning chemistry from a complex visual paradigm. BB = broadband (1–50 Hz). PLE = Power Law Exponent (slope of the fractal power law spectra). LG = learning gains (behavioral measure of learning). PSD = power spectral density. Osci = oscillatory. α = alpha, δ = delta, θ = theta.

on average, in LG and dRT for Block 2. Some participants did have learning gains for Block 2, but more often their test scores stayed the same. Overall, this shows that the material was learned and maintained in memory for the length of the experiment (both Blocks), and also that there may be some similar and some different learning processes occurring in the different blocks. Our findings suggest that participants reorganized and updated their mental models during the chemistry learning process as evidenced by their learning gains.

In mixed power spectrum, we observed that broadband (1–50 Hz) power increased during learning. This is not surprising, given that broadband activity is known to increase during visual tasks and motor functions, and our paradigm contained both (Henrie and Shapley, 2005; Miller et al., 2009b). When looking at specific frequency ranges, we found delta, theta, beta, and low gamma band powers are increased during learning. We expected the increase in theta band power due to a large prior body of work on theta and memory, and found the increase in lower frequency band powers to be contained to the frontal midline region and parietal/occipital regions (Fig. 3D), although this is noted cautiously due to the spatial limitations of EEG. The observed increase in higher frequency band powers aligns with prior work on theta-gamma synchronization (Fell and Axmacher, 2011; Headley and Paré, 2017; Klimesch et al., 2008; Miltner et al., 1999). However, in the mixed spectra the mean alpha band power did not change due to a counteracting effect of the attenuation of alpha band power during attention and an overall increase broadband power. The features and changes in alpha are also known to be highly individual, which may confound our observation of the mean (Bazanova and Vernon, 2014). To elucidate how different components were contributing to the overall power spectrum, we used the IRASA method to separate the mixed spectra into oscillatory and fractal components and repeated the analysis (Wen and Liu, 2016).

We found that oscillatory band powers in the delta and theta bands were significantly different during learning when compared to rest, while beta and low gamma band powers did not change as they did in the mixed spectra. While research points to the coupling of theta and higher frequency (*e.g.,* gamma) oscillations in memory encoding and retrieval (Fell and Axmacher, 2011; Headley and Paré, 2017; Klimesch et al., 2008; Miltner et al., 1999), we did not find these band powers increasing together in the oscillatory spectra (see above). These findings suggest that the increased mixed band power observed in beta and low gamma was contributed from rather the fractal power component of the spectrum, and not from the oscillatory power component in the high frequencies. The function of theta for memory is still under investigation, but many studies suggest that theta oscillations function to integrate or synchronize brain regions used for working memory (Klimesch et al., 2008; Michels et al., 2010; Sauseng et al., 2010). We did not find any relationship between the learners' oscillatory spectra band powers and their behavioral measures of learning. Since learning involves more processes than memory, other measures, such as from the fractal component as we hypothesized, are likely also important.

The fractal component of the power spectrum was found to increase in broadband power during learning, while the oscillatory broadband power did not change. Thus, the fractal component increase is what contributed to the overall increase in mixed broadband power during learning. Accordingly, we found an increase in the ratio of fractal vs. oscillatory power from Rest to Block 1. These findings point to the importance of the fractal, or scale-free, brain activity for processes involved in learning from scientific models. However, the absolute fractal power increase did not correlate on an individual level to learning gains. Instead, the structure of the fractal component (measured by PLE) was found to be important for the learning.

We further explored the contributions of fractal power and especially its temporal structure by calculating PLE – the slope of the power spectrum curve. The PLE is a measure of the relationship of fast and slow frequencies, and the low-high frequency entrainment (*e.g.,* LRTC) as described above. The mean PLE across participants was found to increase slightly during learning (Block 1 and 2) compared to rest. Even more important, we showed that there was individual variability in PLE, and found that the PLE of the individual participant during learning was correlated to their LG1 value. Linear regression showed that a lower PLE was linked to better learning gains in Block 1, meaning that higher frequencies (>13 Hz) were contributing more to the curve of the fractal power spectrum than lower frequencies. While the effect was modest ($R^2 = 0.214$), it can be viewed as substantial in our educational context where learning at this level is difficult to fully measure.

Together, these findings show that the LRTCs measured by PLE are highly individual during rest and learning and contribute to behavioral outcomes of learning in our study. Our general hypothesis here was that scale-free activity could be related to how the external stimulus, i.e. learning material, is attended to and integrated into ongoing neural activity. This hypothesis is along similar lines to how new information is thought to be and incorporated into spontaneous activity, and the idea that this activity is relevant to features of consciousness (Deco et al., 2011; Hartmann et al., 2015; He, 2014; He et al., 2010; Huang et al., 2017; Langer et al.,

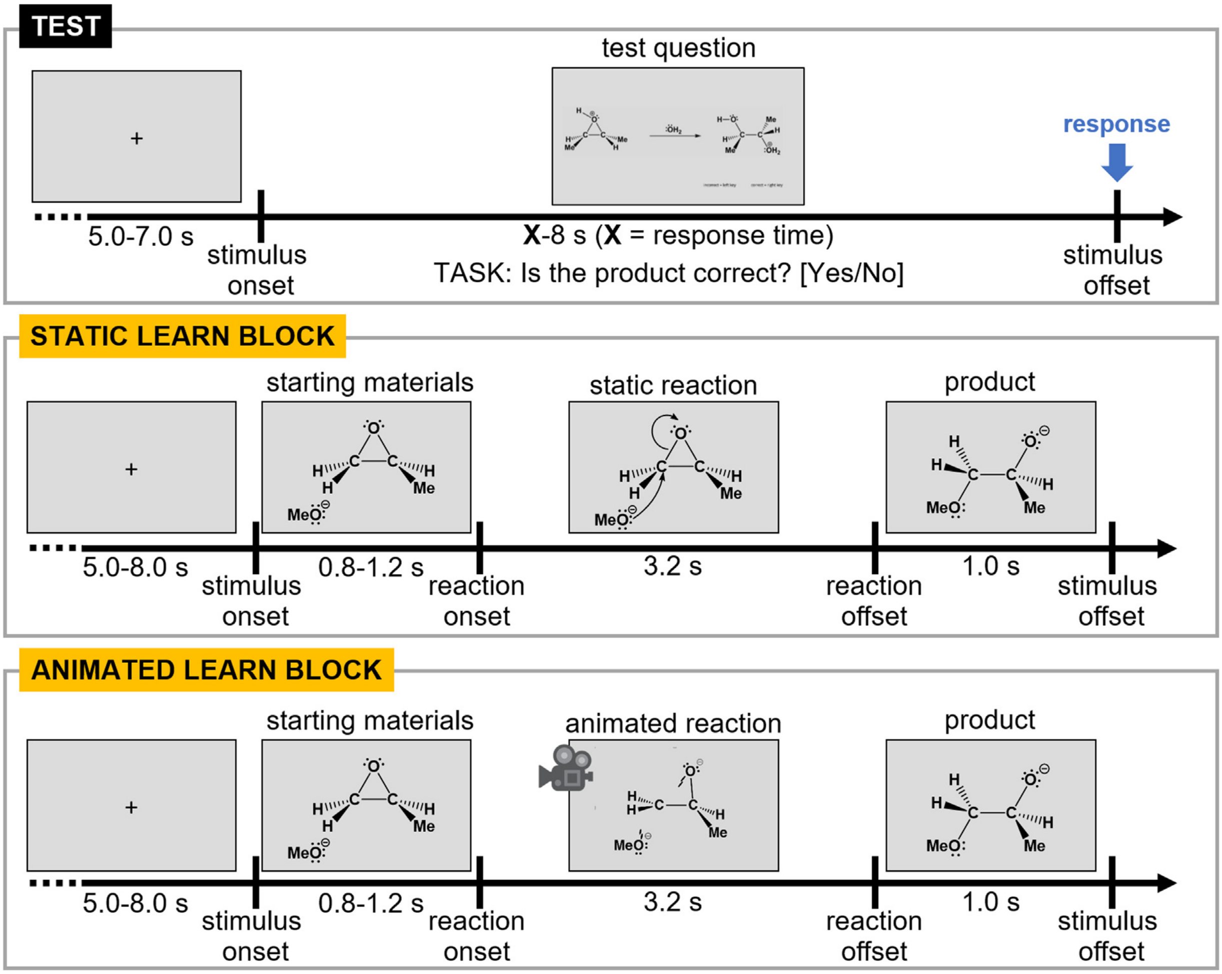

Fig. 8. Experiment details showing one example trial for the Tests and static and animated Learn Blocks. See Fig. 1 for a summary of the paradigm. For the animated Learn Block a single screenshot of the animation is shown, and the video camera denotes animation. All trials began with a fixation cross shown for a randomly variable (jittered) time, which served as the inter-trial interval.

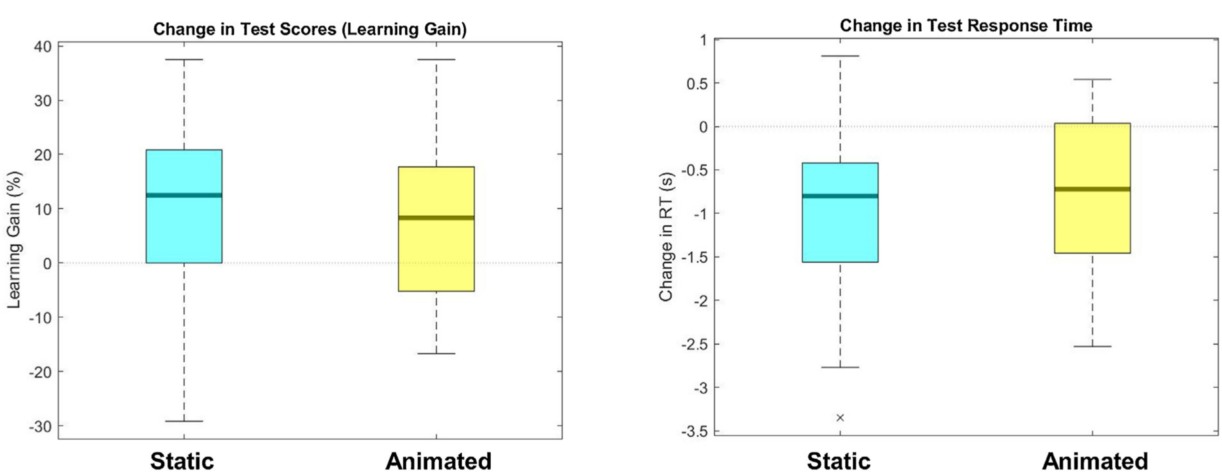

Fig. 9. Behavioral data showed no difference in learning gain (LG) or change in test response time (dRT) for the two learning material types (static or animated).

2017; Lehmann et al., 1998; Northoff, 2018b, 2013; Wolff et al., 2019).

Accordingly, we tentatively hypothesize that, in addition to its cognitive component, the memory implicated in our chemistry learning task may also contain a dynamic and more specifically fractal component. Albeit speculatively, this suggests that the learners' mental models are reorganized and updated in a fractal and scale-free way, which may be related to the need to integrate different time scales during the learning process; that is, the different time scales of the chemistry reaction mechanisms themselves must be integrated with the different time scales of the spontaneous activity.

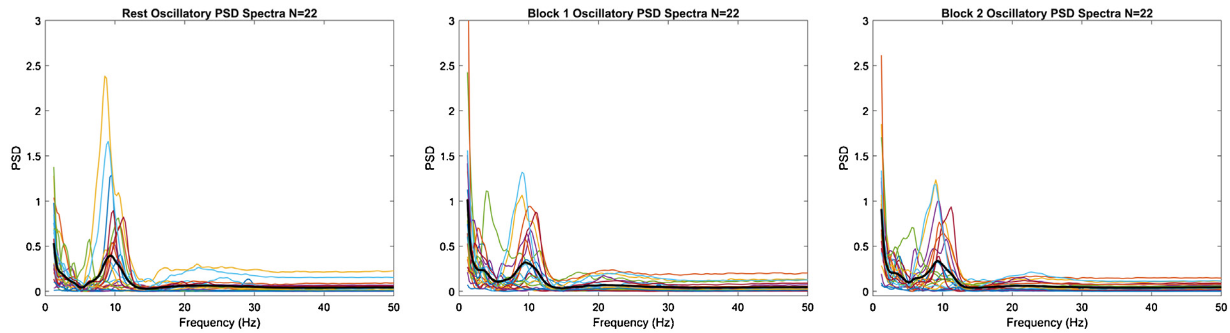

Fig. 10. Oscillatory PSD spectra for all participants ($N = 22$) in Rest, Block 1, and Block 2. The mean spectrum is shown as a bold black line.

4.1. Limitations

This is an exploratory study, therefore the number of participants ($N = 22$) is small and not representative of all learners, and we are thus cautious to extend our findings beyond this study.

This study uses a complex visual paradigm where participants freely learned from the chemistry stimuli. Although we used an established algorithm (MARA) for ocular and muscular artefact rejection, these artefacts cannot always be completely removed.

Memory and learning are broadly defined and discussed in this article, since it is not known which types of memory and learning processes (*e.g.,* associative, semantic) are involved learning from scientific models or from our paradigm. In addition, the type of learning (or memory) from these complex visual stimuli likely depends on the individual learner. Finally, learning is a complex process, and while we made attempts to validate our test and paradigm, we do not claim to have fully measured learning with our behavioral outcome measures.

5. Conclusion

We conducted an exploratory study into chemistry learning using a continuous EEG paradigm and analysis, including the IRASA method to spate oscillatory and fractal components of the power spectra. Taken together, our exploratory findings demonstrate the complex visual learning induces an increase in the power of specifically the fractal component rather than the oscillatory components. This suggests that complex learning as required by our continuous chemistry learning task or other scientific models may recruit scale-free, *e.g.,* fractal components of neuronal activity which, as we speculate, may reflect the scale-free properties of our chemistry learning task and the dynamic, *e.g.,* fractal, reorganization of the participants' mental models.

Funding

Financial support for this research was provided by eCampusOntario of Canada and the University of Ottawa, Canada.

Declaration of Competing Interest

There are no conflicts to declare.

Acknowledgments

We are grateful to eCampusOntario and the University of Ottawa for financial support for this research. We thank the participants who generously volunteered their time for our study. We also acknowledge Dr. Kelli Galloway for help in the design of an earlier version of the chemistry learning paradigm, Dr. Annemarie Wolff for helpful discussions about the chemistry learning paradigm and who provided scripts for data processing and pre-processing, Soren Waino-Theberge who provided scripts for the analysis of the fractal and oscillatory components, and Berthorie Beauvoir for help with conducting EEG sessions.

Appendix A

i. Tests

Tests 1–3 were all comprised of the same set of 24 questions (stimuli), shown to the participant in a random order. For each question, the participant was shown a chemical reaction and the task was to determine product was correct or incorrect (1/0). The participant responded on the keyboard either with the left arrow (incorrect) or the right arrow (correct) using their right hand. The participant had a maximum of 8 s to respond to each question, at which point the stimulus disappeared, and no response was marked as 0. There were 24 test questions representing 12 pairs where one question showed the correct product, and one the incorrect product. Response times and accuracy were recorded for each question, referred to in this article as "test response time" and "test accuracy", respectively. Each question was preceded by a fixation cross (5–7 s, variable jitter).

ii. Learn Blocks

The Learn Blocks included the presentation of either static or animated stimuli of chemistry reaction mechanisms (75 in total per Block) for a total time of 12 min. Each stimulus was presented for 5 s in total, preceded by a fixation cross (5–8 s, variable jitter). Participants were instructed that they were to be shown correct reaction mechanisms and products, and to try to learn the reactions. Out of 75 trails, 60 required no response from the participant, while 15 randomly spaced trials had a simple task to keep the participant engaged. For this task, the participant was prompted in text during the preceding inter-stimulus interval (in addition to the fixation cross) to press a key "as soon as they think they can predict the product of the reaction mechanism". There were two self-timed breaks during the Learn Blocks, after the first 25 and 50 trials.

We found there was no effect of stimulus type (static or animated) on the behavioral outcome measures test accuracy, learning gain, test response time, and dRT (see Results section). This is summarized visually in Fig. 9.

iii. Oscillatory spectra for all participants

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.neures.2019.10.011.

References

Bazanova, O.M., Vernon, D., 2014. Interpreting EEG alpha activity. Neurosci. Biobehav. Rev. 44, 94–110.

Bongers, A., Northoff, G., Flynn, A.B., 2019. Working with mental models to learn and visualize a new reaction mechanism. Chem. Educ. Res. Pract. Advance Ar.

Brainard, D.H., 1997. The Psychophysics Toolbox. Spatial Vision 10, 433–436.

Bullmore, E., Sporns, O., 2009. Complex brain networks: graph theoretical analysis of structural and functional systems. Nat. Rev. Neurosci. 10, 186–198.

Buzsáki, G., 2006. Rhythms of the Brain. Oxford University Press, Oxford, UK.

Buzsáki, G., Draguhn, A., 2004. Neuronal oscillations in cortical networks. Science (80-.) 304, 1926–1929.

Buzsáki, G., Logothetis, N., Singer, W., 2013. Scaling brain size, keeping timing: evolutionary preservation of brain rhythms. Neuron 80, 751–764.

Canolty, R.T., Knight, R.T., 2010. The functional role of cross-frequency coupling. Trends Cogn. Sci. (Regul. Ed.) 14, 506–515.

Chialvo, D.R., 2010. Emergent complex neural dynamics. Nat. Phys. 6, 744–750.

Clement, J., 2000. Model based learning as a key research area for science education. Int. J. Sci. Educ. 22, 1041–1053.

Cole, M.W., Bassett, D.S., Power, J.D., Braver, T.S., Petersen, S.E., 2014. Intrinsic and task-evoked network architectures of the human brain. Neuron 83, 238–251.

Dahlstrom-Hakki, I., Asbell-Clarke, J., Rowe, E., 2019. Showing is knowing: the potential and challenges of using neurocognitive measures of implicit learning in the classroom. Mind Brain Educ. 13, 30–40.

Deco, G., Jirsa, V.K., McIntosh, A.R., 2011. Emerging concepts for the dynamical organization of resting-state activity in the brain. Nat. Rev. Neurosci. 12, 43–56.

Delorme, A., Makeig, S., 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J. Neurosci. Methods 134, 9–21.

Duncan-Johnson, C.C., Donchin, E., 1982. The P300 component of the event-related brain potential as an index of information processing. Biol. Psychol. 14, 1–52.

Düzel, E., Penny, W.D., Burgess, N., 2010. Brain oscillations and memory. Curr. Opin. Neurobiol.

Fell, J., Axmacher, N., 2011. The role of phase synchronization in memory processes. Nat. Rev. Neurosci. 12, 105–118.

Galloway, K.R., Leung, M.W., Flynn, A.B., 2018. A comparison of how undergraduates, graduate students, and professors organize organic chemistry reactions. J. Chem. Educ. 95, 355–365.

Galloway, K.R., Leung, M.W., Flynn, A.B., 2019. Patterns of reactions: a card sort task to investigate students' organization of organic chemistry reactions. Chem. Educ. Res. Pract. 20, 30–52.

Gevins, A., 2000. Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. Cereb. Cortex 10, 829–839.

Graulich, N., Hopf, H., Schreiner, P.R., 2010. Heuristic thinking makes a chemist smart. Chem. Soc. Rev. 39, 1503–1512.

Greca, I.M., Moreira, M.A., 2000. Mental models, conceptual models, and modelling. Int. J. Sci. Educ. 22, 1–11.

Hardstone, R., Poil, S.-S., Schiavone, G., Jansen, R., Nikulin, V.V., Mansvelder, H.D., Linkenkaer-Hansen, K., 2012. Detrended fluctuation analysis: a scale-free view on neuronal oscillations. Front. Physiol. 3, 450.

Hartmann, C., Lazar, A., Nessler, B., Triesch, J., 2015. Where's the noise? Key features of spontaneous activity and neural variability arise through learning in a deterministic network. PLoS Comput. Biol. 11, 1–35.

He, B.J., 2011. Scale-free properties of the functional magnetic resonance imaging signal during rest and task. J. Neurosci. 31, 13786–13795.

He, B.J., 2014. Scale-free brain activity: past, present, and future. Trends Cogn. Sci. (Regul. Ed.) 18, 480–487.

He, B.J., Zempel, J.M., Snyder, A.Z., Raichle, M.E., 2010. The temporal structures and functional significance of scale-free brain activity. Neuron 66, 353–369.

Headley, D.B., Paré, D., 2017. Common oscillatory mechanisms across multiple memory systems. NPJ Sci. Learn. 2, 1.

Henrie, J.A., Shapley, R., 2005. LFP power spectra in V1 cortex: the graded effect of stimulus contrast. J. Neurophysiol. 94, 479–490.

Hiltunen, T., Kantola, J., Abou Elseoud, A., Lepola, P., Suominen, K., Starck, T., Nikkinen, J., Remes, J., Tervonen, O., Palva, S., Kiviniemi, V., Palva, J.M., 2014. Infra-slow EEG fluctuations are correlated with resting-state network dynamics in fMRI. J. Neurosci. 34, 356–362.

Hinze, S.R., Rapp, D.N., Williamson, V.M., Shultz, M.J., Deslongchamps, G., Williamson, K.C., 2013. Beyond ball-and-stick: students' processing of novel STEM visualizations. Learn. Instr. 26, 12–21.

Huang, Z., Obara, N., Davis, H.(Hap), Pokorny, J., Northoff, G., 2016. The temporal structure of resting-state brain activity in the medial prefrontal cortex predicts self-consciousness. Neuropsychologia 82, 161–170.

Huang, Z., Zhang, J., Longtin, A., Dumont, G., Duncan, N.W., Pokorny, J., Qin, P., Dai, R., Ferri, F., Weng, X., Northoff, G., 2017. Is there a nonadditive interaction between spontaneous and evoked activity? Phase-dependence and its relation to the temporal structure of scale-free brain activity. Cereb. Cortex 27, 1037–1059.

Huk, A., Bonnen, K., He, B.J., 2018. Beyond trial-based paradigms: continuous behavior, ongoing neural activity, and natural stimuli. J. Neurosci. 38, 7551–7558.

Johnstone, A.H., 1991. Why is science difficult to learn? Things are seldom what they seem. J. Comput. Assist. Learn. 7, 75–83.

Johnstone, A.H., 1993. The development of chemistry teaching: a changing response to changing demand. J. Chem. Educ. 70, 701.

Kleiner, M., Brainard, D., Pelli, D., et al., 2007. What's new in Psychtoolbox-3? Perception 36 (14), 1–16.

Klimesch, W., 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain Res. Rev. 29, 169–195.

Klimesch, W., Freunberger, R., Sauseng, P., Gruber, W., 2008. A short review of slow phase synchronization and memory: evidence for control processes in different memory systems? Brain Res. 1235, 31–44.

Klimesch, W., Schack, B., Sauseng, P., 2005. The functional significance of Theta and upper alpha oscillations. Exp. Psychol. 52, 99–108.

Langer, N., Ho, E.J., Alexander, L.M., Xu, H.Y., Jozanovic, R.K., Henin, S., Petroni, A., Cohen, S., Marcelle, E.T., Parra, L.C., Milham, M.P., Kelly, S.P., 2017. A resource for assessing information processing in the developing brain using EEG and eye tracking. Sci. Data 4, 170040.

Lehmann, D., Strik, W., Henggeler, B., Koenig, T., Koukkou, M., 1998. Brain electric microstates and momentary conscious mind states as building blocks of spontaneous thinking: I. Visual imagery and abstract thoughts. Int. J. Psychophysiol. 29, 1–11.

Linkenkaer-Hansen, K., Nikouline, V.V., Palva, J.M., Ilmoniemi, R.J., 2001. Long-range temporal correlations and scaling behavior in human brain oscillations. J. Neurosci. 21, 1370–1377.

Manning, J.R., Jacobs, J., Fried, I., Kahana, M.J., 2009. Broadband shifts in local field potential power spectra are correlated with single-neuron spiking in humans. J. Neurosci. 29, 13613–13620.

Mantini, D., Perrucci, M.G., Del Gratta, C., Romani, G.L., Corbetta, M., 2007. Electrophysiological signatures of resting state networks in the human brain. Proc. Natl. Acad. Sci. 104, 13170–13175.

Mayer, R.E., 2012. Information processing. In: Harris, K.R., Graham, S., Urdan, T., McCormick, C.B., Sinatra, G.M., Sweller, J. (Eds.), APA Educational Psychology Handbook, Vol 1: Theories, Constructs, and Critical Issues. American Psychological Association, Washington, pp. 85–99.

Michels, L., Bucher, K., Lüchinger, R., Klaver, P., Martin, E., Jeanmonod, D., Brandeis, D., 2010. Simultaneous EEG-fMRI during a working memory task: modulations in low and high frequency bands. PLoS One 5, e10298.

Miller, K.J., Sorensen, L.B., Ojemann, J.G., den Nijs, M., 2009aa. Power-law scaling in the brain surface electric potential. PLoS Comput. Biol. 5, e1000609.

Miller, K.J., Zanos, S., Fetz, E.E., den Nijs, M., Ojemann, J.G., 2009bb. Decoupling the cortical power Spectrum Reveals real-time representation of individual finger movements in humans. J. Neurosci. 29, 3132–3137.

Miltner, W.H., Braun, C., Arnold, M., Witte, H., Taub, E., 1999. Coherence of gamma-band EEG activity as a basis for associative learning. Nature 397, 434–436.

Miyakoshi, M., URL https://sccn.ucsd.edu/wiki/Makoto's_preprocessing_pipeline (Accessed 3.1.18) 2019. Makoto's Preprocessing Pipeline [WWW Document].

Mullen, T.R., Kothe, C.A.E., Chi, Y.M., Ojeda, A., Kerth, T., Makeig, S., Jung, T.-P., Cauwenberghs, G., 2015. Real-time neuroimaging and cognitive monitoring using wearable dry EEG. IEEE Trans. Biomed. Eng. 62, 2553–2567.

Nelson, P.G., 2002. Teaching chemistry progressively: from substances, to atoms and molecules, to electrons and nuclei. Chem. Educ. Res. Pract. 3, 215–228.

Northoff, G., 2013. What the brain's intrinsic activity can tell us about consciousness? A tri-dimensional view. Neurosci. Biobehav. Rev. 37, 726–738.

Northoff, G., 2018a. The brain's spontaneous activity and its psychopathological symptoms – "Spatiotemporal binding and integration.". Prog. Neuro-Psychopharmacol. Biol. Psychiatry 80, 81–90.

Northoff, G., 2018b. The Spontaneous Brain : From the Mind-body to the World-brain Problem. The MIT Press, Cambridge, MA.

Palva, J.M., Zhigalov, A., Hirvonen, J., Korhonen, O., Linkenkaer-Hansen, K., Palva, S., 2013. Neuronal long-range temporal correlations and avalanche dynamics are correlated with behavioral scaling laws. Proc. Natl. Acad. Sci. 110, 3585–3590.

Pelli, D.G., 1997. The VideoToolbox software for visual psychophysics: Transforming numbers into movies. Spatial Vision 10, 437–442.

Sadaghiani, S., Hesselmann, G., Friston, K.J., Kleinschmidt, A., 2010. The relation of ongoing brain activity, evoked neural responses, and cognition. Front. Syst. Neurosci. 4, 20.

Sauseng, P., Griesmayr, B., Freunberger, R., Klimesch, W., 2010. Control mechanisms in working memory: a possible function of EEG theta oscillations. Neurosci. Biobehav. Rev. 34, 1015–1022.

Sauseng, P., Klimesch, W., 2008. What does phase information of oscillatory brain activity tell us about cognitive processes? Neurosci. Biobehav. Rev. 32, 1001–1013.

Scalabrini, A., Huang, Z., Mucci, C., Perrucci, M.G., Ferretti, A., Fossati, A., Romani, G.L., Northoff, G., Ebisch, S.J.H., 2017. How spontaneous brain activity and narcissistic features shape social interaction. Sci. Rep. 7, 9986.

Steinemann, N.A., Moisello, C., Ghilardi, M.F., Kelly, S.P., 2016. Tracking neural correlates of successful learning over repeated sequence observations. Neuroimage 137, 152–164.

Stern, E., 2017. Individual differences in the learning potential of human beings. Npj Sci. Learn. 2, 2.

Taber, K.S., 2013. Revisiting the chemistry triplet: drawing upon the nature of chemical knowledge and the psychology of learning to inform chemistry education. Chem. Educ. Res. Pract. 14, 156–168.

Talanquer, V., 2011. Macro, Submicro, and Symbolic: the many faces of the chemistry "triplet.". Int. J. Sci. Educ. 33, 179–195.

Tsaparlis, G., 2014. Linking the macro with the submicro levels of chemistry: demonstrations and experiments that can contribute to Active/Meaningful/Conceptual learning. In: Devetak, I., Glažar, S.A. (Eds.), Learning With Understanding in the Chemistry Classroom. Springer, pp. 41–62.

van den Boomen, C., Jonkman, L.M., Jaspers-Vlamings, P.H.J.M., Cousijn, J., Kemner, C., 2015. Developmental changes in ERP responses to spatial frequencies. PLoS One 10, e0122507.

van Leeuwen, T.H., Manalo, E., van der Meij, J., 2015. Electroencephalogram recordings indicate that more abstract diagrams need more mental resources to process. Mind Brain Educ. 9, 19–28.
Wen, H., Liu, Z., 2016. Separating fractal and oscillatory components in the power Spectrum of neurophysiological signal. Brain Topogr. 29, 13–26.
Winkler, I., Brandl, S., Horn, F., Waldburger, E., Allefeld, C., Tangermann, M., 2014. Robust artifactual independent component classification for BCI practitioners. J. Neural Eng. 11, 035013.
Winkler, I., Haufe, S., Tangermann, M., 2011. Automatic classification of artifactual ICA-Components for artifact removal in EEG signals. Behav. Brain Funct. 7, 30.
Wolff, A., Di Giovanni, D.A., Gómez-Pilar, J., Nakao, T., Huang, Z., Longtin, A., Northoff, G., 2019. The temporal signature of self: temporal measures of resting-state EEG predict self-consciousness. Hum. Brain Mapp. 40, 789–803.