Title Note-taking Across Modalities: Improving Learning in Science Lectures

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Abstract

When students take notes during undergraduate lectures today, they are often typing on their computers or drawing in their notebooks. Effective notetaking requires active organization of the presented information, as opposed to non-generative processes such as copying or simply reading material. However, these effects remain unclear in disciplines that depend on visual models and thus rely on verbatim copying of visuals. To investigate this, we conducted a study into the effects of integrated note-taking on learning during a video lecture. Participants were prompted to take verbatim (copying visuals) or generative (pre-emptive manipulation or transformation of visuals) notes using a tablet at intervals during an organic chemistry lecture, while their behavioral (duration), ocular (eye-tracking) and neural activity (EEG) was measured. We found that participants in the generate condition took longer reading instructions, were faster to complete tasks, and had lower Shannon entropy in pupil diameter during tasks. During the lecture videos, participants in the generate condition had a higher relative increase in alpha (8-13Hz) band power during the latter part of the lecture, and greater increases in scale-free neural activity throughout the lectures. Together, these findings suggest greater learning and performance in the generate compared to the copy condition. Overall, pausing and prompting generative notetaking is recommended to sustain learners' engagement with the lecture content.

Keywords note-taking, EEG, eye-tracking, active learning, scale-free, performance

Conflict of interest

All authors state no known conflicts of interest.

Data sharing and accessibility

The data that support the findings of this study are available on request from the first, [AW], or last author [AB]. The data are not publicly available due to restrictions from the research ethics committee which granted approval for the research study.

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Introduction

The learning experience in today's higher education is intricately linked with the integration of technology. As of 2024, computer-assisted lectures and slide decks have become ubiquitous in undergraduate science courses, reflecting the ever-evolving nature of teaching methodologies. This technological shift has driven students to adapt their note-taking strategies, embracing the use of computers - or other technological devices - to capture and organize information effectively.

With their greater prevalence of technology use for note-taking, it is crucial to understand how students are adapting their note-taking practices to this change. Effective note-taking is a critical skill that supports comprehension, retention, and academic success.[1-3] In fact, the note-taking effect shows that note-taking is attributed to sustained attention, increased retention, and increased test performance.[4] Most recent note-taking studies rely on generative strategies, specifically summarization of the text or lecture, which involves selecting and modifying relevant information. This contrasts with verbatim transcription, which is word-for-word copying of the text in the lecture.

However, the application of generative learning principles becomes more nuanced in scientific disciplines that heavily rely on visual information and models. Summarization is not possible in disciplines which rely on conveying visual information through models,[5] along with explanations of these visual models. For example, in organic chemistry, verbatim copying of visual information (i.e., molecular chemical models) could provide more benefits than verbatim copying of text or the lecture.[6] Undergraduate chemistry students are still learning how to draw these visual models, so copying them verbatim could be important practice of their drawing skills and learning model syntax and conventions.

Despite the importance of this topic, research on note-taking in science education – particularly regarding the handling of visual information – has been limited. Furthermore, many existing studies have relied on trial-based experimental designs rather than more naturalistic experimental paradigms that more closely mirror actual classroom experiences.

To address this gap, we compared the effects of verbatim note-taking (copying visual information) and generative note-taking (pre-emptive manipulation or transformation of visual information) on learning and task performance. We designed our study to be more naturalistic than the standard discrete, event-related experimental designs[7] in order to examine behavior and neural activity during continuous stimuli (video lectures) and tasks.

Theoretical background, research questions and hypotheses

Generative learning theory provides alternative note-taking strategies to verbatim copying. According to Wittrock's Generative Learning model,[8,9] a connection between prior knowledge and new stimuli must be established for there to be understanding associated with learning. This transfer, or generation, of meaning from prior knowledge to new stimuli is the central aspect of generative learning theory and requires additional cognitive effort through deeper 'levels of processing'.[10] The theory states that meaningful learning consists of generation, motivation, attention and memory, and strategies that achieve this are summarizing, mapping, drawing and self-explaining.[8,9]

So how does this apply to learning visual information such as molecular structures? Generative learning strategies for visual information could involve other ways of processing the learning material, for example selecting or modifying the molecular structures.[11,12] Learning chemistry requires understanding how the visual models of chemicals transform and change (i.e., rotation, varying viewpoints, changing structures, bonds forming and breaking, etc.). Thus, generative note-taking could allow students to depict those changes themself.

However, when students opt to take notes in chemistry, they mainly copy the visual information verbatim, and minimally annotate their copied visuals with summary notes of the lecture. Note-taking by verbatim copying of visuals allows for sustained attention of visual information, possibly at the detriment of attention to auditory information given simultaneously.[13] In addition, the cognitive effort involved in verbatim copying for novices, who are likely less able to hold a mental image of the full structure in their head but rather take a piecemeal approach, makes it more difficult to derive learning from the action, or add annotations to the visuals.

By exploring the note-taking employed by students in the context of lectures, we can gain valuable insights into the learning processes and challenges faced by today's undergraduate science students. Understanding this can inform the development of effective pedagogical practices and technological tools to enhance the learning experience and support student success in an increasingly digital educational landscape.

We developed technology to prompt on-screen note-taking during organic chemistry video lectures. By having the note-taking occur on-screen, we can observe how students interact with, and attend to, the visuals when note-taking by copying or generating. Using eye-tracking and electroencephalography (EEG) throughout the lecture sections and the tasks, we can also analyze the effects of note-taking on learning and task performance as the lecture proceeds.

Our research questions were two-fold. We first asked how students interact with, and attend to, the visuals when note-taking by copying or generating/manipulating. We hypothesized a difference in task and instruction duration between conditions,[14] along with differences in Shannon entropy of pupil diameter.[15,16] Next, we asked how learning varies throughout a lecture with the different note-taking prompts. We expected evidence of greater learning and performance during the latter lecture segments in the generate condition.[17–20] Recent studies[21–28] have supported the idea of functional inhibition[29] during effortful[25,27] and goal-directed[21] listening mediated by the alpha[30] frequency band; increased alpha power reflects active processing related to inhibition of regions not required for a given task. With this in mind, we expect an increase in alpha power in cortical areas irrelevant for watching or listening to the chemistry lecture in the generate condition, which will show functional inhibition.[29]

Methods

Participants

Ethics approval for the study was obtained from the Health Sciences Research Ethics Board of Queen’s University (HSREB# 6039208), and the study was conducted according to their regulations. All participants provided written informed consent prior to participation.

Twenty-seven (19 female, 1 non-binary) participants (mean age = 20.5 ± 1.1 years) were included in the analysis for this study, 14 in the copy (control) group and 13 in the generate (experimental) group. All had or were completing at least one first year undergraduate chemistry course. Students ranged from undergraduate students to master's students. All participants self-reported to be right-hand dominant.

Experimental paradigm

Our study design was a simple and naturalistic paradigm with eye-tracking, EEG, and drawing data recorded throughout. Participants were randomly assigned to one of two conditions, either copy (control) or generate (experimental). Both groups watched identical video lecture segments, followed by a task with a different prompt. The first video lecture segment (video 1) was shown before any prompt or task, so no difference between groups was expected.

The experimental paradigm was presented on a 24-inch screen with a 1920 x 1080 pixel resolution while the task was done using a medium Wacom Intuos Pro drawing tablet (wacomstore.ca/product/wacom-intuos-pro-medium/). The drawing and/or writing of the participant was projected onto the right side of the screen in real time to capture eye-tracking data.

The instructions for tasks differed in the two conditions, though the number of characters in each set of instructions were approximately the same (Supplementary Table 1).

At the end of each video segment, participants were shown the last frame of the video on the left side of the screen, with the task prompt above it. Participants were to read the instructions at their own pace and press a button when they wanted to begin the task. The task was then completed at their own pace. When they finished the task, they were instructed to press another button, which started the next video segment. This cycle was done for four video segments and tasks.

EEG data acquisition and preprocessing

The EEG data was recorded using 64 active electrodes and the actiCAP from Brain Vision Solutions (https://brainvision.com). The electrodes were placed according to the 10-10 system and recorded at a sampling rate of 1000Hz. Ocular bipolar electrodes were placed above and below (VEOG) the eyes and at the outer canthi of one eye (HEOG) to capture blinks and saccades.

Preprocessing of the EEG data was done using EEGLAB v2024.0[31] with MATLAB

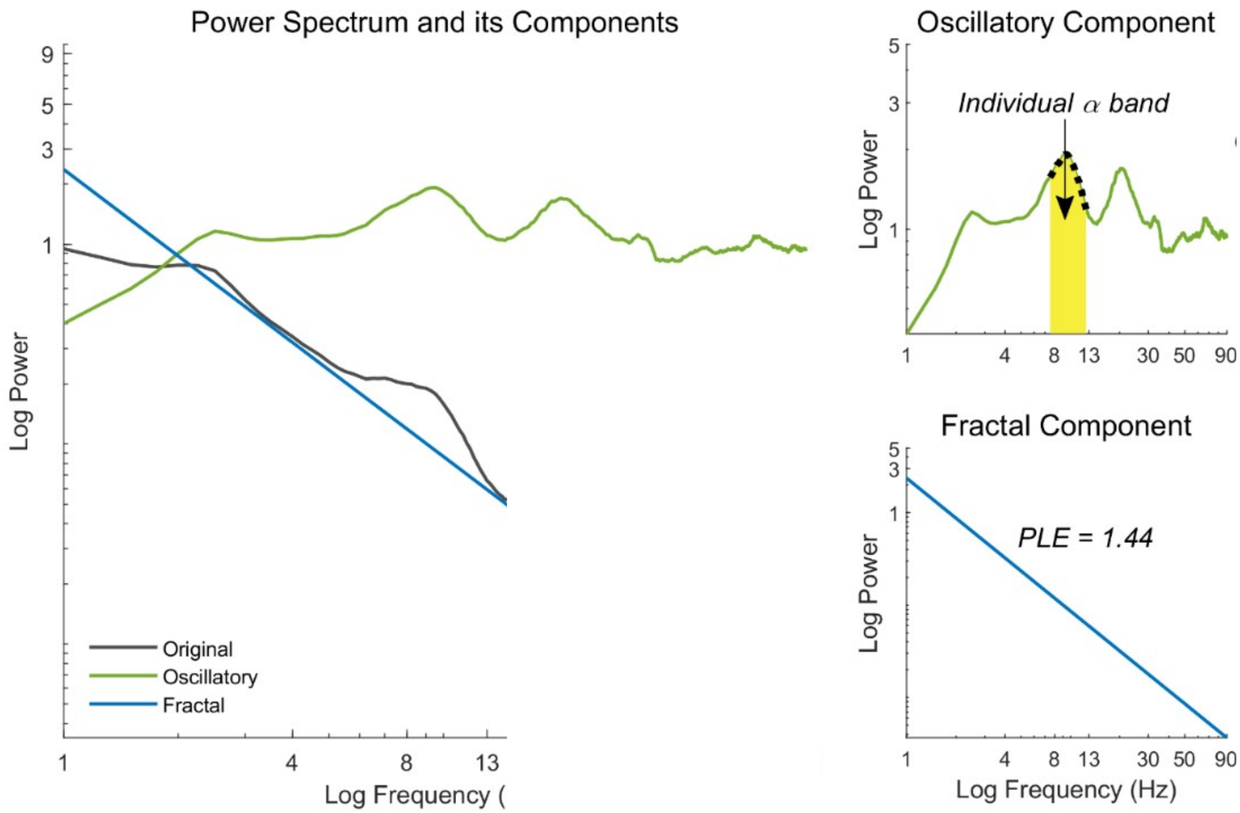

Figure 1. Power spectrum and its components and individual alpha frequency bands. **Large left**: The power spectrum of the original signal (black) contains oscillatory (green, upper right plot) and fractal (blue, lower right plot) components. Using fooof (Gerster et al, 2022), the components of the power spectrum were isolated and analyzed. **Upper right**: The power in the alpha band was computed from the area under the oscillatory component (yellow) at the specific frequencies.

v2023a.[32] Data was first imported to EEGLAB using the Brain Vision plugin. The EEG data was resampled to 500Hz using EEGLAB's anti-aliasing filter. The data was then high- and low-pass FIR filtered at 1 and 90Hz, after which Zapline[33] was used to remove electrical line noise at 60Hz. Noisy electrodes were then spherically interpolated if their mean values were ± 3 standard deviations away from the mean of all electrodes, and the data was re-referenced to the average. Ocular (blinks, saccades) and other artifacts were isolated using independent components analysis (ICA) with the infomax algorithm. Finally, artifacts were rejected using the Multiple Artifact Rejection Algorithm (MARA)[34,35] if the probability of being an artifact was greater than 85%.

As the analysis of the EEG data would look at topographical differences between electrodes, the spatial localization of the cortical activity was important. For this reason, the data was re-referenced to the surface Laplacian reference.[36,37]

EEG data analysis

Power spectral analysis of the EEG data was done via the 'fitting oscillations and one over *f*' (FOOOF) method[38] implemented in FieldTrip v20240504[39] with MATLAB v2023a.[32]

To measure the power in individual alpha frequency bands, the bounds of the individual frequency bands were first determined using the methods of Cohen from the Journal of Neuroscience Methods.[40] This data-driven method called 'GED Bounds' uses covariance during resting state and cluster analysis to identify the bounds of frequency bands for each individual. Using the four-minute resting state data recorded before any task was completed, the frequency bounds for alpha were determined for each individual(Figure 1). It was these specific bands that were used to compute the alpha power, which was the area under the oscillatory component for each individual alpha frequency band. Using the oscillatory component only allowed us to isolate the alpha oscillatory power while omitting the fractal component which would not be the case in the original power spectral density (Figure 1).

From the fractal component of the power spectrum, the slope of the line, otherwise known as the power-law exponent (PLE) was calculated.[38] This measure indexes the scale-freeness of the neural activity, measuring the relationship between the lower and higher frequencies.

These two measures, alpha power and PLE, were measured during each video segment for all participants. As stated above, participants in both groups watched the same video segments.

Eye-tracking data acquisition and preprocessing

The eye-tracking data was acquired on a 24-inch screen with a 1920x1080 pixel resolution using the software Tobii Pro Lab. Participants sat approximately 60cm away from the screen with speakers on the left and right side of the screen for the auditory element of the video segments. Participants' eye movements were recorded using a Tobii Pro Spectrum (300 Hz sampling rate) which was calibrated using 9-point calibration and subsequent validation. The calibration accuracy was below 0.5° for all participants.

The eye-tracking data was exported from Tobii Pro Lab with the Tobii I-VT Fixation Filter applied (threshold of 30°/s). To preprocess the eye-tracking data, the PuPl Toolbox[41] with MATLAB v 2023a was used. After importing the Tobii data to the PuPl toolbox, extreme pupil sizes (mean ± 3 standard deviations) and extreme pupil dilation speeds (median + 5 median absolute deviations) were trimmed from the data. Islands of data points were also trimmed from the data (max length = 100ms, maximum separation = 40ms).

Eye blinks were then identified via gaps in the data, with gap boundaries of 100ms and 400ms. A buffer of 15% was added at each end. Blink data samples were then removed, with a 50ms buffer on either side of the blink to remove transient increases/decreases around the blink. The pupil foreshortening error was then corrected via multivariate linear regression.[42] Missing data points were then linearly interpolated, and all data was smoothed with a 150ms moving mean with a Hanning window.

Eye-tracking data analysis

To measure Shannon entropy, preprocessed pupil diameter data was used. Only the data from the nondominant eye was used, according to a previous study.[15] The identity of the dominant eye was according to the self-reported handedness of each individual at the beginning of the experiment; therefore, the nondominant eye was the opposite of what the participant stated as their dominant hand (i.e., right-handed, so nondominant eye was left eye).

The continuous pupil diameter data was isolated for each lecture video segment, and Shannon entropy was calculated according to the following equation:

where H is the measure of entropy, p is the probability of observing the i^{th} value of the bin series data x, and n is the number of bins.[43] The number of bins was calculated according to the Freedman-Diaconis rule[44] and the following equation:

where Q is the interquartile range of distribution X, n is the total number of data points, and the numerator is the maximum and minimum values in distribution X.[43] Because the data is binned in this measure of entropy and the probability is used, differences in task duration between groups was not relevant to this measure.

Statistical analysis

Statistical analysis for the behavioral and eye-tracking results was done in SPSS v29.0.2.0.[45] For these results, analyses of covariance (ANCOVA) were done to find the differences between the between subjects' factor (condition) and the within subjects' factor (task), while accounting for one covariate. As the dependent variables were not normally distributed, each level of the dependent variable and the covariates were transformed to ranks prior to the ANCOVA. For these statistical tests, the significance level was 0.05.

For the relative alpha power and the PLE results, permutation tests (1,000 iterations) were done to look at differences across electrodes. Because of the number of permutation statistical tests, the significance level was reduced to 0.01.

Results

Longer consideration of instructions and shorter durations in generate condition during lecture tasks

To determine if there was greater learning or skill development in the generate condition during the lecture tasks, we first looked at some of the behavioral data.

As the data at each level of the dependent variable was not normally distributed, we transformed the data, along with the covariate, to ranked data. A repeated measures analysis of covariance (ANCOVA) was then done to determine if there was an effect of condition (copy, generate) and task (1-4) on the duration of the instructions (Figure 2A, right boxplot). The duration of the resting state instructions served as the covariate (Figure 2A, left boxplot). We found a significant effect of condition ($F(1,18) = 82.653$, $p < .001$, $\eta2 = .821$), but not of task ($F(3,54) = 2.032$, $p = .120$, $\eta2 = .101$), with those in the generate condition having longer instruction durations than those in the copy condition.

Next, we looked at the duration of the lecture tasks. An ANCOVA was done to determine if there was an effect of condition (copy, generate) and task (1-4) on the duration of the tasks (Figure 2B, right boxplot), with the median duration of control drawing tasks of molecules as the covariate (Figure 2B, left plot). We found a significant effect of condition ($F(1,19) = 8.184$, $p = .010$, $\eta^2 = .301$), but not of task ($F(3,57) = 1.131$, $p = .344$, $\eta^2 = .056$), with those in the copy condition having longer task durations. There was, however, a significant interaction between condition and task ($F(3,57) = 21.224$, $p < .001$, $\eta^2 = .528$). Therefore, participants in the generate condition took longer to read the task instructions but were faster to complete the tasks.

Lower entropy in eye pupil diameter in the generate condition during lecture tasks

We then looked at the eye-tracking data. Similarly to a recent study on task performance,[15] we measured Shannon entropy in the pupil diameter of the nondominant eye during the lecture tasks.

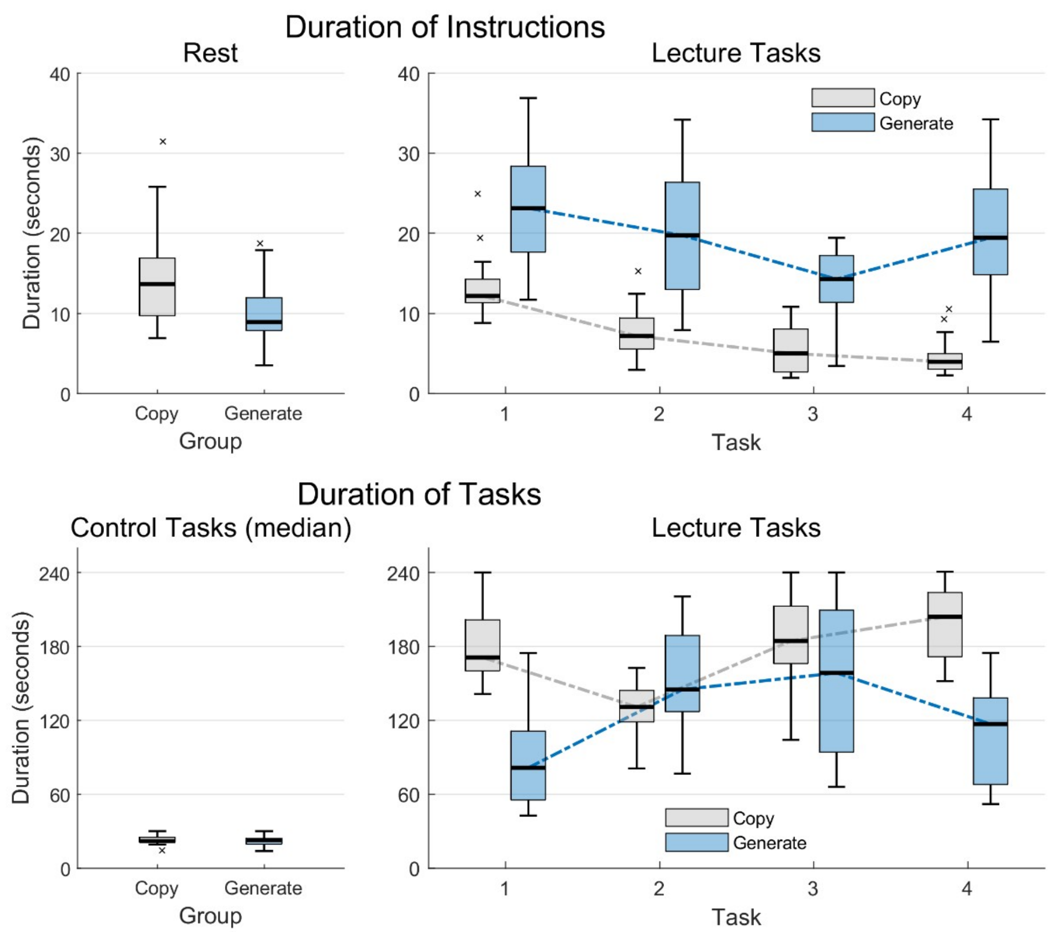

Figure 2. Behavior results during the lecture tasks. **A**: Duration of instructions for the lecture tasks, with duration of resting state instructions as a covariate. An ANCOVA found a significant effect of condition but not of task, showing longer instruction durations in the generate group. **B**: Duration of lecture tasks, with median duration of control drawing tasks (6) of chemical molecules as covariate. An ANCOVA found a significant effect of condition but not of task, with a significant interaction between the

An ANCOVA was done to determine if there was an effect of condition (copy, generate) and task (1-4) on the entropy of the pupil diameter of the nondominant eye (Figure 3, right plot), with the entropy of the pupil diameter of the nondominant eye during the control tasks (median) (Figure 3, left plot). We found a significant effect of condition ($F(1,17) = 8.957$, $p = .008$, $\eta^2 = .345$), but not of task ($F(2.168, 36.856) = 0.942$, $p = .406$, $\eta^2 = .052$), showing that those in the generate condition had lower entropy across tasks than those in the copy condition. There was, however, a significant interaction between condition and task ($F(2.168, 36.856) = 8.876$, $p < .001$, $\eta^2 = .343$). In sum, our analysis of the eye-tracking data found a lower Shannon entropy in the generate condition during lecture tasks.

Higher alpha power in the fourth lecture video segment in the generate condition

Our second research question asked about engagement during the lecture video segments after the first task was completed. To answer this question, we analyzed the EEG data according to previously used measures.[15,38] We focused on features of the power spectrum, specifically the power in the alpha band and the relationship between the different frequencies which is indexed by the power-law exponent.[18,46]

We first looked at the alpha power in the oscillatory component of the power spectrum during the lecture video segments (Figure 4). Permutation tests (1,000 iterations) were done between conditions for each video segment. The black dots indicate electrodes that were found to have significant differences between conditions for each lecture video segment. In lecture video segment 4, electrodes in the left temporal cortex were found to be significantly higher in the generate condition.

These findings show greater increase of alpha power, relative to the first video segment, in the last lecture video segment in the generate condition.

Increases in scale-free activity in lecture video segments in the generate condition

Continuing with the EEG data, we finally computed the power-law exponent (PLE) which indexes the scale-free activity in the signal (Figure 5). As with the alpha power results above, we calculate the percent change of the PLE relative to lecture video segment 1, before the first prompt was given and the first task was completed.

Using permutation tests (1,000 iterations), relative to lecture video segment 1 we found a significantly higher PLE in occipital and frontal (video 2), frontal and temporal (video 3), and temporal and central electrodes (video 4). This higher PLE shows greater power in the lower frequencies relative to the higher frequencies in the generate condition at these electrodes.

In sum, our findings show a greater increase in the $1/f$ slope of the power spectrum in the generate condition over lecture video segments.

Discussion

Exploring note-taking by students during lectures can provide valuable insight into the learning processes and challenges faced by today's undergraduate

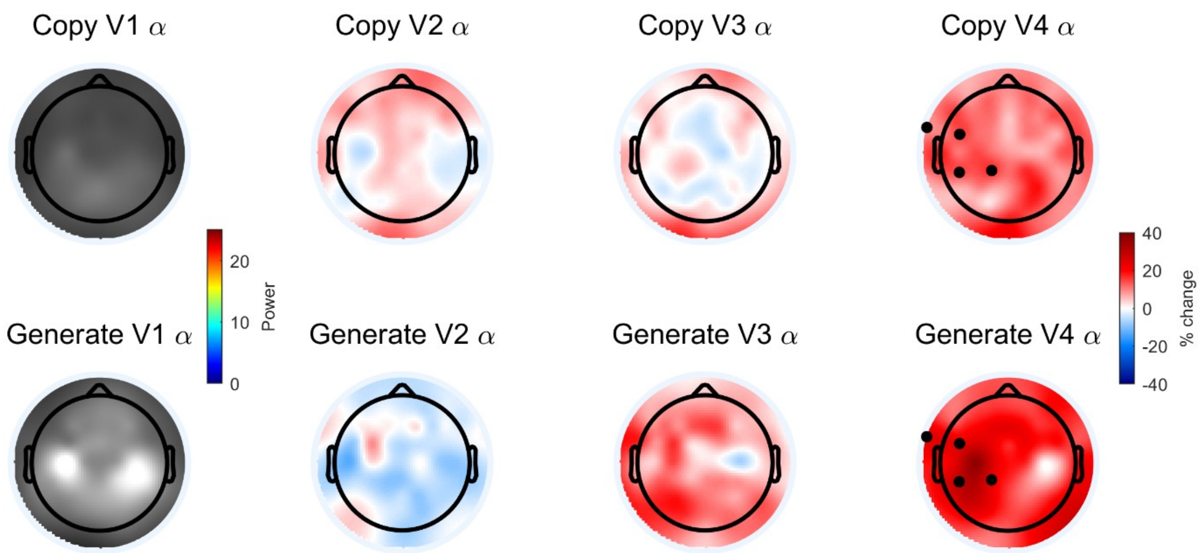

Figure 4. Alpha power of the oscillatory component of the power spectrum during the lecture video segments. **Far Left**: mean alpha power over all participants during lecture video segment 1. **Column 2-4**: The relative alpha power in the remaining 2-4 lecture video segments was computed according to segment 1 as percent change. Therefore, the data in columns 2-4 (red, white, and blue) show relative differences from the first video segment on the far left (in black and white). Red = relative increase in alpha power; blue = relative decrease in alpha power. Black dots:

science students. We therefore developed technology to prompt on-screen note-taking during organic chemistry video lectures. Using eye-tracking and EEG throughout the lecture segments and the tasks, in this exploratory study we analyzed the effects of note-taking on learning and task performance as the lecture proceeds.

Task duration differences and lower entropy of pupil diameter in generate condition

Our study revealed interesting behavioral and eye-tracking differences between the generate and copy conditions, providing a glimpse into the cognitive processes underlying generative learning.

Behaviorally, we observed that participants in the generate condition spent more time reading and examining the mechanism before starting the task, but then completed the task itself more quickly compared to those in the copy condition. This pattern suggests a fundamental difference in approach between the two groups. The longer duration spent on instructions in the generate condition likely reflects the increased cognitive effort required for processing generative learning tasks.[9,10,12] Participants may have recognized the need for a deeper understanding of the instructions to successfully complete the more cognitively demanding generative task.

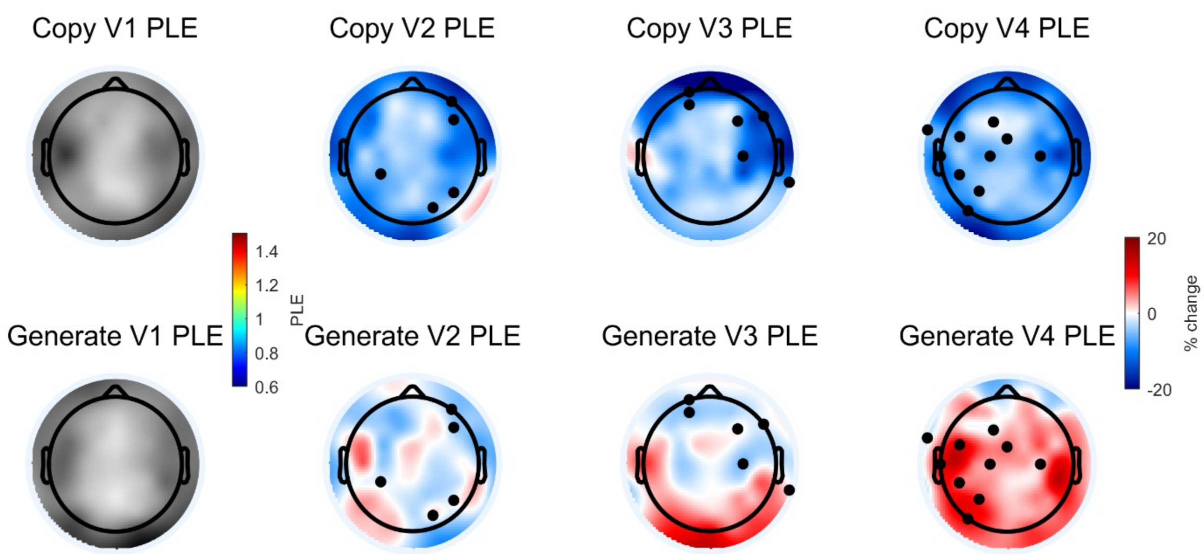

Figure 5. Power law exponent (PLE) of the fractal component of the power spectrum during the lecture video segments. **Far Left**: Mean PLE over all participants in each group for lecture video segment 1 (black and white). **Column 2-4**: Differences in PLE per group, relative to lecture video 1, measured in percent change. A gradual increase in PLE was seen in the generate condition (bottom row) at electrodes specified (black dots). In the copy condition (top row), a decrease in the PLE was seen across videos relative to video 1. Red = relative increase in PLE; blue = relative decrease in PLE. Black dots:

Conversely, the shorter task duration in the generate condition, coupled with the longer time spent on copying in the copy condition, indicates a potential difference in focus and strategy. Participants in the copy condition may have prioritized accuracy and detail in their reproduction, leading to a more meticulous and time-consuming approach. This focus on perfect replication might have come at the expense of grasping the overall concept, which was more readily achievable by those in the generate condition.

While previous research has shown a relationship between time-on-task and learning outcomes, the strength and direction of this relationship have been inconsistent.[14] Given this variability, we cannot draw definitive conclusions about learning outcomes based solely on task duration. However, the observed differences in time allocation between condition indicate distinct cognitive approaches to the task.

Our eye-tracking data provide additional evidence supporting enhanced performance in the generate condition. Specifically, we found lower entropy of nondominant pupil diameter in the generate condition during task completion. This finding aligns with previous studies that have associated lower pupil diameter entropy with successful task completion[16] and better overall task performance.[15]

Entropy of pupil diameter has been interpreted as a measure of visual scanning efficiency.[47] Lower entropy suggests that more cognitive resources are available to the participant, leading to improved task performance due to a reduced cost of retrieving information from the visual system.[15,48] In our study, the lower entropy observed in the generate condition implies that these participants had more cognitive resources at their disposal during the task, potentially facilitating better performance.

Conversely, the higher entropy of pupil diameter in the copy condition suggests that these participants had fewer available cognitive resources, which could result in decreased performance. This interpretation is consistent with the literature on pupil diameter entropy during task performance[15,48] and supports the notion of enhanced learning in the generate condition.

When we consider our behavioral and eye-tracking results together, a consistent story emerges. The longer time spent on instructions in the generate condition, coupled with the lower pupil diameter entropy during task execution, suggests a more effective allocation of cognitive resources. Participants in the generate condition appear to have invested more effort in understanding the task requirements upfront, leading to more efficient task execution with greater available cognitive resources.

In summary, our findings provide compelling evidence for the benefits of generative learning strategies. The behavioral data reveal distinct approaches to task engagement, with generate condition participants demonstrating a more concept-focused strategy. The eye-tracking results further support this interpretation, indicating more efficient visual processing and greater availability of cognitive resources in the generate condition. Together, these results suggest that generative learning tasks promote deeper engagement with the material, more efficient cognitive processing, and potentially enhanced learning outcomes. Future studies could build on these findings to further explore the relationship between cognitive resource allocation, task performance, and long-term learning outcomes in generative learning contexts.

Increased alpha power and scale-free activity during lectures in generate condition

In the generate condition, we found a relative increase in alpha power in lecture video segment 4. This finding aligns with previous research on complex language learning and creative thinking processes and can be interpreted through the lens of functional inhibition, a key mechanism associated with alpha band activity.

Recent studies have consistently shown a relationship between increased alpha power and several aspects of learning and cognitive performance. A comprehensive review[49] found an association between increased in alpha power and learning,[49] while task-specific studies have linked higher alpha power to improved task performance, such as shorter reaction times[50] and enhanced performance during complex language learning.[20] Moreover, increased alpha power has been observed in non-task related cortical areas when participants exert greater effort, particularly during tasks that demand complex information processing.[27,28]

The creative thinking process, which involves complex information processing, has also been associated with increases in alpha power. Multiple studies have documented alpha power increases at several stages of creativity and idea generation.[51–55] Specifically, one study found increased alpha power during later stages of alternative idea generation,[17] attributing this to the engagement of top-down executive processes, including the active inhibition of known associations to facilitate novel idea combinations.[17,52,54,56,57] This aligns with other research showing alpha power increases during idea elaboration[57] and later stages of creative thinking.[53,54]

To understand the functional significance of these findings, including our own, it's crucial to consider the role of alpha band activity in cognitive processes. Alpha oscillations are thought to reflect active inhibitory control[58] and regulate information access in the brain.[50] The functional inhibition hypothesis posits that increased alpha power in specific cortical areas suppresses task-irrelevant neural activity,[58,59] thus enhancing the processing of task-relevant information in other areas.

In our study, the relative increase in alpha power may indicate active inhibition of irrelevant sensory input or competing cognitive processes, allowing for more focused attention on the lecture content. The localization of this increase to roughly the left somatosensory cortical area (left central-temporal electrodes with a surface Laplacian reference) is consistent with previous findings of increased left alpha mu rhythm during effortful tasks.[27,28] This suggests that participants in the generate condition were exerting greater cognitive effort to process the lecture content in video segment 4, potentially indicating deeper engagement and more elaborate cognitive processing.

This functional inhibitory mechanism is particularly relevant to generative learning, where learners must connect new information to prior knowledge[8,9,12] while suppressing irrelevant associations and distractions. The observed increase in alpha power likely reflects this top-down control, facilitating the integration of new concepts with existing mental models.[60] This interpretation is supported by previous arguments that alpha band activity is more related to processes involving stored and meaningful information rather that the processing of new information.[50]

The relationship between alpha power, functional inhibition, and learning outcomes can also be viewed through the framework of Desirable Difficulty (DD).[61,62] DD posits that learning activities demanding more cognitive effort enhance learning outcomes.[63,64] The increased cognitive effort required for generative learning, as reflected in our alpha power increase and supported by a recent EEG study[28], may contribute to the creation of stronger and more durable memory traces by inducing more germane cognitive load.[65])

One of our study's novelties lies in the separation of oscillatory and fractal components of the EEG signal, allowing for more precise findings. To account for changes in the scale-free aspects of the EEG signal, we also investigated the power-law exponent (PLE), which reflects the relationship between frequencies. Our second EEG finding showed greater increases in scale-free ($1/f$ slope) neural activity in the generate condition. The $1/f$ slope is thought to reflect the excitation/inhibition balance (EIb) in the brain, which is the ratio of excitatory to inhibitory cell activity in a neural population, with an increase in slope indicating a decrease in EIb.[66] Recent research has directly associated EIb, $1/f$ slope, and learning,[67] supporting our findings on scale-free activity.

Literature across various modalities[68–70] and recent studies[19,20] have associated improved performance with a steeper $1/f$ slope*.* Additionally, a steeper $1/f$ slope has been linked to increased adaptability[71] and the capacity to learn more complex information.[20] In the context of organic chemistry, learning was associated with an increase in $1/f$ activity and was correlated with individual learning gains,[18] further supporting our hypothesis and findings.

In summary, our findings of increased alpha power in the left temporal region and changes in scale-free neural activity during generative learning tasks provide strong evidence for the neural mechanisms underlying effective learning processes. The observed increase in alpha power can be interpreted as a manifestation of functional inhibition, supporting the effortful cognitive processes involved in integrating new information with prior knowledge. This aligns with both Generative Learning Theory and the concept of Desirable Difficulty.

Furthermore, the changes in scale-free neural activity, as indicated by the steeper $1/f$ slope, suggest a shift in the brain's excitation/inhibition balance that is conducive to learning and adaptability. Together, these neural signatures represent key physiological correlated of deep, effective learning processes. Our study’s novel approach of separating oscillatory and fractal components of the EEG signal provides a more subtle understanding of the neural dynamics underlying generative learning, offering valuable insights for both neuroscience and educational research.

Limitations

Our study had several limitations. First, our small sample sizes in each group limited our analyses and potentially weakened the strength of our findings. While acceptable for an exploratory study testing the experimental design and the feasibility of the technology, the small sample size reduces the generalizability of our results. Next, our choice of a between-subjects experimental design magnified the impact of interindividual variability, particularly in neural activity measures such as alpha power, which is known to have a wide range of individual differences. A future replication or expanded study should opt for a within-subjects design which would minimize interindividual variability in the frequency bands of neural activity. Third, while our continuous and relatively naturalistic experimental design was more ecologically valid compared to event-related designs, it also presented challenges in data analysis. Traditional designs that average over multiple trials allow for a higher signal-to-noise ratio of effects and a relative decrease in interindividual variability. Our design, while more reflective of real-world learning scenarios, made it more difficult to isolate task-specific neural signatures. Fourth, our study did not include long-term follow-up assessments to evaluate the endurance of learning. This limitation prevents us from drawing conclusions about the long-term efficacy of generative learning compared to copying strategies. Finally, there are several potential technical limitations associated with EEG and eye-tracking measurements. They include spatial specificity of 64-electrodes with the surface Laplacian reference, and the reliability of eye-tracking measurements throughout a continuous study design. Acknowledging these technical constraints is important for accurate interpretation of the neurophysiological data. Despite these limitations, our study provides valuable preliminary evidence for the neural and behavioral correlates of generative learning.

Conclusion

We investigated the effects of integrated note-taking in two conditions on learning during a chemistry video lecture. Our findings show that participants tasked to generate notes, rather than copy visuals verbatim, took longer reading instructions, were faster to complete tasks, and had lower entropy in pupil diameter during tasks. During the lecture videos, participants who were generating notes had a higher relative increase in alpha (8-13Hz) band power during the latter part of the lecture, and greater increases in scale-free neural activity throughout the lectures, compared to participants who copied notes verbatim. Together, these findings suggest greater engagement and learning during the video lecture. Pausing and prompting generative notetaking during visual-heavy lectures is recommended to sustain learners' engagement with the lecture content.

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Supporting Information

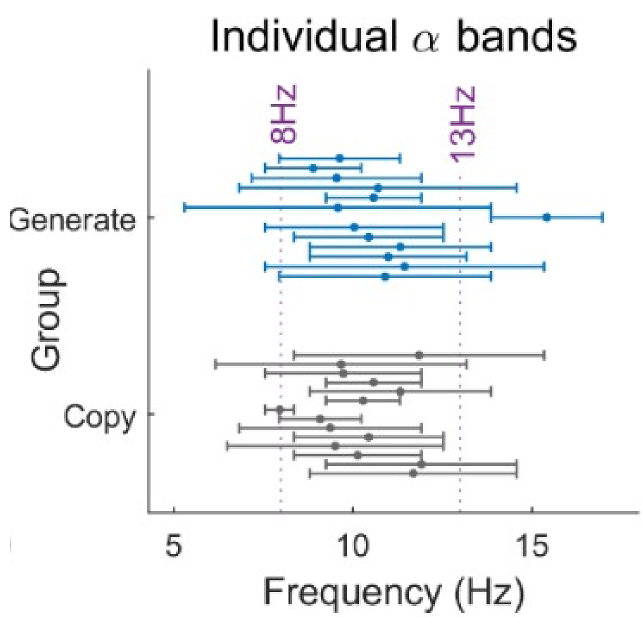

Figure S1. Individual alpha frequency bands for each participant determined according to the methods of (Cohen, 2021).[40] Standard alpha frequency bounds are shown in purple dotted lines at 8Hz and 13Hz. The circle in each band shows the mean of that specific band.

Supplementary Table 1: Task prompts for both conditions

Task	**Prompt for Copy**	**Prompt for Generate**	**Characters**
1	Now that the lecture has paused, copy down the lecture notes as they are written on the screen. Think of this exercise like copying notes down in a lecture. Take all the time you need, going at a comfortable pace.	1. t-Bu stands for tert-butyl. If you know the structure of tert-butyl, draw it. If not, write down anything you can remember about this term. 2. Draw the ketone shown above in its CHAIR structure (show template).	212, 213
2	Please copy down the lecture notes as they are written on the screen. Think of this exercise like copying notes down in a lecture.	Using words and pictures, propose an explanation for how axial or equatorial hydride attack gives either the CIS or TRANS product.	130
3	Now that the lecture has paused, copy down the lecture notes as they are written on the screen. Think of this exercise like copying notes down in a lecture. You can take whatever time you need, but please copy at a comfortable pace.	You just heard that energy differences from bond rotations will help explain this reactivity. Write down everything you can remember about energy differences between different conformations (e.g., eclipsed). Using Newman projections may help.	232, 242
4	Now that the lecture has paused, copy down the lecture notes as they are written on the screen. Think of this exercise like copying notes down in a lecture.	Draw the chemical transition state (i.e., as the reaction is happening) in the reaction for the equatorial hydride attack, to show the eclipsing interaction.	156, 157