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The impact of semantic feedback on functional connectivity during design ideation: a preliminary study

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ABSTRACT: This study aims to examine the influence of semantic feedback on the functional connectivity of students' brains in design education. We evaluated functional connectivity using EEG. After the instructor provided feedback, we observed a significant reduction in students' alpha-band activity across 16 channel pairs. It suggests that, after receiving feedback, participants relied more on localized neural circuits rather than on broad, diffuse connections. Semantic feedback potentially facilitates participation in more efficient cognitive processes, thereby assisting design ideation.

KEYWORDS: design cognition, design education, electroencephalography (EEG), semantic feedback, functional connectivity

1. Introduction

Creativity in designers is vital in design because it helps to improve their outcomes (Sarkar & Chakrabarti, 2011). Design creativity differs from general creativity in that it requires evaluating several aspects, including novelty, usefulness, and the surprise of design outcomes (Lazar, 2018; Sarkar & Chakrabarti, 2015). One of the aims in design education is to foster innovations in engineering design, enhance productivity, elevate quality, minimize errors, increase the acceptance of new products, and decrease development costs, therefore cultivating more creative designers (Zoltowski et al., 2012). In real design education scenarios, instructors often use feedback to convey important information to students, helping them refine their ideas and deepen their involvement in the creative process (Georgiev & Georgiev, 2024) (Figure 1). Consequently, design education could significantly benefit from effective methodology and the strategic utilization of feedback.

In contrast to traditional feedback, semantic feedback is a method that integrates semantic attributes of the speech relevant to design tasks to augment design creativity (Casakin & Georgiev, 2021). Semantic features can be calculated from semantic analysis, a methodology that scrutinizes words by computing semantic metrics, including polysemy, abstraction, information content (IC), and semantic similarity. This approach is regarded as a valuable way to quantify and compare various design processes and their relations to outcomes (Georgiev & Casakin, 2019). Researchers have also attempted to understand whether semantic measures can successfully predict idea generation (Casakin & Georgiev, 2021). The semantic analysis approach has been applied to understand the semantic content of conversations in design contexts (Casakin & Georgiev, 2021). Semantic feedback provided to the designer emphasizes the importance of the semantic features of the design to the design processes. Previous research has shown the influence of semantic measures on design education (Casakin & Georgiev, 2021). Recent research has also demonstrated that the semantic features of semantic stimuli could influence design thinking (Wang, et al., 2024a) and that receiving semantic feedback enhances engagement and attention during design ideation (Wang et al., 2024c). Therefore, incorporating semantic feedback into design education

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may be a promising approach to fostering more creative ideas during design ideation and cultivating more creative designers.

The use of non-invasive brain imaging techniques, such as functional magnetic resonance imaging (fMRI), functional near-infrared spectroscopy (fNIRS), and electroencephalography (EEG), enables the exploration of neural activity. These methods have enabled the emergence of a new research domain known as design neurocognition, which focuses on the neuroscientific investigation of design cognition (Balters et al., 2023; Gero & Milovanovic, 2020). Among these tools, electroencephalography (EEG) is a high-temporal resolution technique for monitoring cerebral activity that has been effectively applied in the study of design creativity (Jia, 2021; Vieira et al., 2022; Zangeneh Soroush & Zeng, 2024). The EEG band refers to a specific region of the oscillatory spectrum, with the alpha frequency band typically defined as 8–13 Hz, recognized as significant for creativity (Martindale et al., 1984; Stevens & Zabelina, 2019). Power-spectral-based analysis is a method that measures the strength of different brain wave frequencies captured by EEG, allowing researchers to identify which frequencies are most active during specific mental tasks. Many studies have employed power-spectral-based analyses to investigate design neurocognition (Vieira et al., 2019, 2020), with the alpha frequency band emerging as one of the most commonly examined (Wang 2024b).

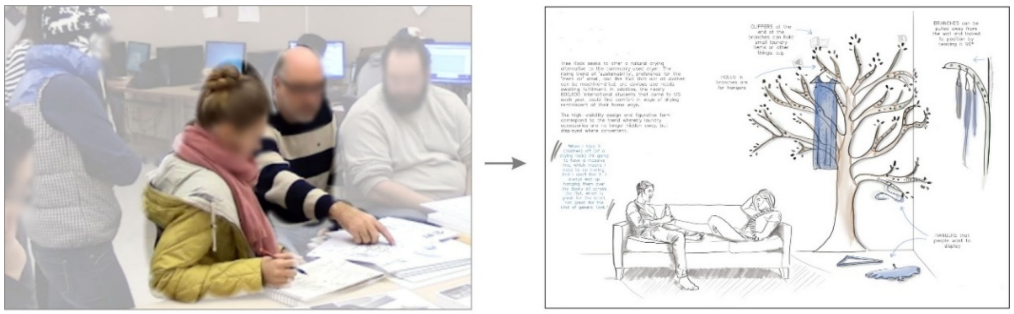


Figure 1. Real-world design education setting with design concept as outcome (modified from Georgiev & Georgiev, 2024)

Beyond power-spectral-based analysis, functional connectivity analysis has been employed to represent how different brain regions communicate with each other during a task by measuring the synchronization of brain wave patterns between EEG channels, revealing coordinated neural activity across the brain that wouldn't be visible by looking at individual brain regions alone. This is particularly relevant for design ideation, which involves multiple mental processes happening simultaneously, such as internal attention, working memory, and deliberately recalling relevant knowledge, all of which are supported by interactions among spatially separated brain regions (Beaty et al., 2016). The Phase Lag Index (PLI) is a measurement tool that determines how strongly different brain regions are communicating by examining the timing patterns of their electrical signals. As a phase-based index that discounts instantaneous, zero-lag correlations, the PLI is well-suited for this purpose because it filters out false connections such as electrical signals spreading across the scalp or passing through brain tissue (Stam et al., 2007), allowing it to better identify genuine communication between brain regions. The PLI produces a value from 0 to 1. A value of 0 indicates either no connection exists (coupling) or coupling with a phase difference centered at 0 mod π. Whereas a value closer to 1 indicates strong communication between brain regions, where the electrical signals show timing patterns that are slightly out of sync (ideal phase locking at a phase difference distinct from 0 mod π). In summary, the higher the PLI value, the more confidently researchers can say that two brain regions are actively working together (Stam & Van Straaten, 2012).

This preliminary study aims to investigate whether semantic feedback from instructors influences students' design ideation and, if so, how it affects their functional connectivity in the alpha frequency band. The semantic feedback provided in this study is customized for each participant based on the design outcomes of their design ideation, aiming to improve design creativity. The alpha frequency band PLI was adopted as a neural index to reflect the status of functional connectivity. The focus on the alpha band during ideation is motivated by prior evidence linking alpha activity to internally oriented cognition

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and creative processing (Vieira et al., 2021). Accordingly, examining alpha-band functional connectivity with PLI provides a network-level insight into how information is coordinated during idea generation, rather than just how strongly localized oscillations increase or decrease.

2. Method

2.1. Participants

Nine healthy, right-handed participants (four women and five men) with normal or corrected-to-normal vision were recruited at the University of Oulu. Before the experiment began, all participants were asked to complete a screening questionnaire to exclude those who did not meet the requirements for an EEG study, such as those with neurological disorders or illnesses. Because two participants were unable to sketch their ideas on paper and the design outcome could not be clearly identified, they were excluded from the final analysis, leaving seven (three women and four men) for formal evaluation. All participants were novices in design. The University of Oulu Ethics Committee of Human Sciences approved the study. Before participation, all participants were informed about the experimental procedures and gave their written consent.

2.2. Experimental design

To investigate the effect of semantic feedback on design ideation, an EEG experiment was conducted in three separate sessions. Figure 2 shows the experimental procedure.

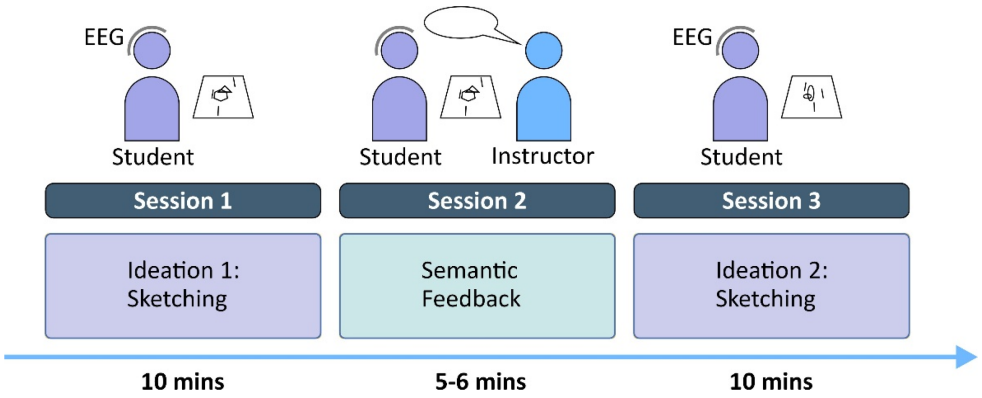


Figure 2. Experimental procedure

In the first session, participants engaged in a design task for ten minutes. Afterward, they were given a brief break before explaining their design ideas to an instructor. In the second session, which lasted about five to six minutes, during this session, an instructor provided personalized semantic feedback based on each participant's design results, similarly to design education settings (see Figure 1). After that, participants did the same ideation task for another ten minutes. During this session, they could either refine their initial design or create an entirely new concept based on the feedback received. After the final session, they were asked to explain their ideas to the instructor once more.

2.3. Design task

The design task adopted in this study is "You are a designer. You are invited to design an amphibious bike. You can sketch and annotate as many ideas as you want. The vehicle can be any type of bike, including a bicycle or a motorcycle. Amphibious vehicles are designed for use on both land and water. You can design several options for the product features and functions, such as the propulsion system and the number of allowed passengers" (Li et al., 2021). This open-ended design task was selected due to its relevance in everyday life and its moderate difficulty for non-designers. Furthermore, in this experiment, all participants were instructed to generate a single idea based on the task, not only to simplify the process for non-designers but also to enhance the novelty and utility of their ideas in relation to design creativity.

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2.4. Semantic feedback

The semantic feedback was based on a preliminary draft of 430 words and was customized for each participant by the instructor according to their designs. The feedback contains information relevant to solutions of this design task, including the general topic of the design task, followed by feedback on movement, propulsion, construction, and context. The general structure of the draft was maintained, with a small part of the feedback being customized to the particular solution. For participants focused on concrete features of the solution, the instructor offered feedback using more abstract words. On the contrary, if the participants focused on more general features, the instructor offered feedback with more concrete words. For example, 'vehicle' and 'thing' are abstract nouns, and 'bike' and 'car' are concrete nouns used in the feedback.

2.5. EEG recordings

During the experiment, participants were fitted with EEG devices that continuously monitored their brain activity. Brain Products, Germany (Sauer, 2025) supplied a 32-channel active electrode system for capturing EEG signals. This system used sintered Ag/AgCl sensors embedded in the cap and ran at a sampling rate of 1000Hz. To ensure signal quality, all channels' impedance was kept below 10 kΩ. The reference and ground electrodes (GND) were carefully placed at the FPz and FCz sites, respectively (Figure 3). To reduce potential noise during design ideation and feedback sessions, participants were told to maintain a neutral facial expression and limit movement. The entire experiment occurred in a specially designed EEG chamber optimized to reduce external electromagnetic signal and noise interference.

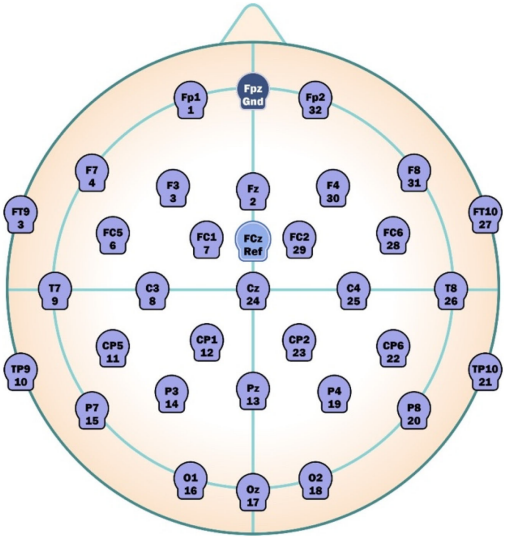


Figure 3. EEG channels' distribution

2.6. EEG data preprocessing

All EEG data collected during the study were processed and analyzed with MATLAB (MATLAB 2022b) (MATLAB, 2025). EEG data was preprocessed using the EEGLAB toolbox (EEGLAB v. 2023.0) (Delorme & Makeig, 2004), which was supplemented with custom scripts. During preprocessing, the continuous EEG recordings were filtered with a 1-40 Hz bandpass filter to improve signal clarity by removing unwanted frequencies. The filtered data was then divided into 2-second epochs for further analysis. To ensure data quality, head motion artifacts were manually detected and removed. Independent Component Analysis (ICA) was used to remove electrooculogram (EOG) artifacts caused by eye movements and blinks, preventing them from interfering with EEG signals. An automatic detection method was used to identify and remove EEG segments with wavelet amplitudes greater than 100 μV, indicating abnormal electrical activity. Finally, the data were re-adjusted to reflect the average of all brain electrodes, excluding the FT9, FT10, and TP9/TP10 channels.

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2.7. Functional connectivity analysis

After preprocessing, 12 channels (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, O1, Oz, O2) were chosen for further analysis of functional connectivity because they represented different scalp areas and hemispheres. To illustrate the communication between different channel locations, customized scripts calculated the PLI for each channel pair of 12 interested channels described above. To explore how the functional connectivity difference between Session 1 (Ideation 1) and Session 3 (Ideation 2) on each channel pair for the alpha frequency band, the network-based statistic (NBS) was used. The NBS is a non-parametric statistical method that helps avoid multiple comparison problems when there is mass univariate statistical testing in functional networks (Zalesky et al., 2010). The statistical tests were implemented using the MATLAB toolbox NBS v1.2 (NITRC: Network-Based Statistic (NBS): Tool/Resource Info, 2024). The pipeline of functional connectivity analysis is shown in Figure 4.

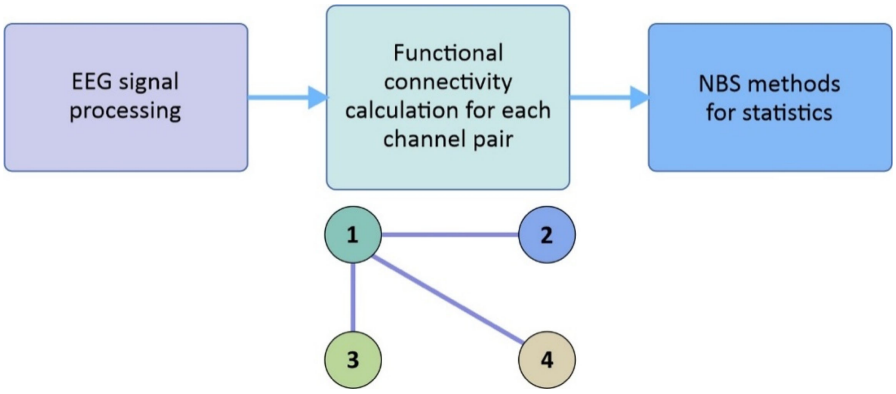


Figure 4. Pipeline of functional connectivity analysis. The circles represent four channels, and the red lines are the channel pairs related to channel 1, which represent the connections from channel 1 to all the other channels

3. Results

Figure 5 illustrates the PLI values of each channel pair and the statistical results for channel pairs exhibiting considerably greater PLI values in Session 1 (Ideation 1) compared to Session 3 (Ideation 2) in the alpha frequency band (corrected p =.0238).

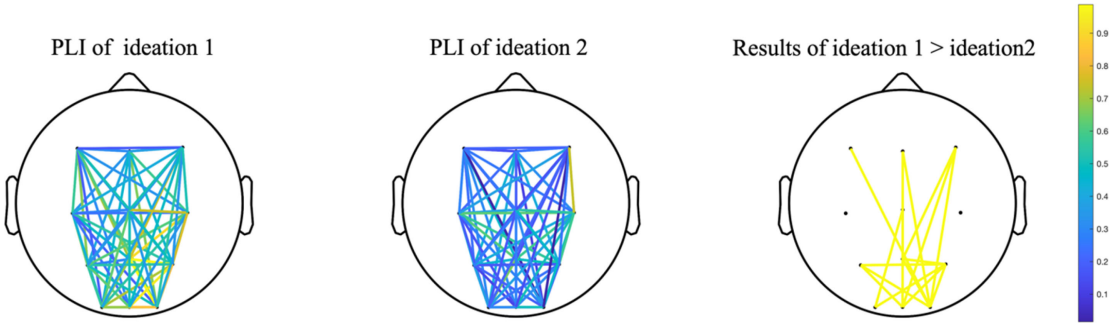


Figure 5. Functional connectivity results. The left figure displays the PLI values before receiving semantic feedback, the middle figure illustrates the PLI values after to receiving semantic feedback, and the right figure reflects the significant statistical results based on NBS $p < .05$

Specifically, a total of 16 significant channel pairs were identified. The channel pairs could be further separated into five categories (Figure 6):

1. Frontal-Parietal connections (2 channel pairs): Fz-Pz and F4-P4.
2. Frontal-Occipital connections (5 channel pairs): F3-O2, Fz-Oz, Fz-O2, F4-Oz, and F4-O2.
3. Central-Occipital connections (1 channel pair): Cz-O1 channel pair.
4. Parietal-Parietal connections (2 channel pairs): P3-P4 and Pz-P4.
5. Parietal-Occipital connections (6 channel pairs): P3-Oz, P3-O2, PZ-O2, P4-O1, P4-Oz, and P4-O2.

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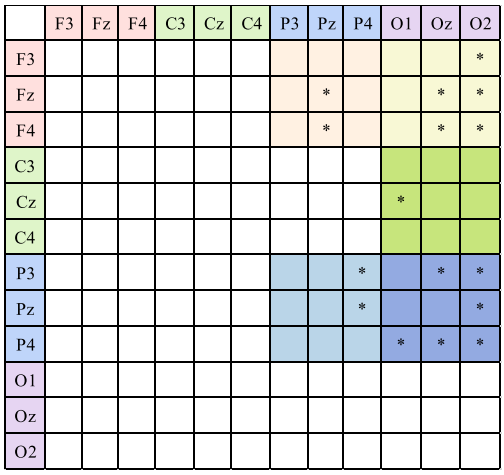


Figure 6. Results of different brain regions' connections. Indicates significant channel pairs based on NBS $p < .05$. The channel pairs in the table, along with their names and different colors, represent different scalp areas

4. Discussion

4.1. Functional connectivity influenced by semantic feedback

The present study offers neurophysiological evidence regarding the impact of semantic feedback on functional connectivity during design ideation. Previous studies indicate that semantic feedback enhances overall brain activity across frequency bands, correlating with heightened engagement and attentional focus (Wang, Soomro, Gong, Wang, et al., 2024). Our findings add an important layer to the picture.

We observed a decrease in alpha band functional connectivity, as measured by the PLI, after students received semantic feedback by instructor. A decrease in PLI indicates a change in how various brain regions interact, and a lower PLI does not always indicate that students were less active or engaged. In contrast, neural networks became less synchronized throughout the brain. They may, however, have specialized and improved their communication skills. In other words, the participants' brains demonstrated more focused activity in specific areas rather than a variety of areas working together. This implies that, following feedback, the ideation process relied on localized neural circuits rather than broad, diffused connections. The channel pairs predominantly identified were Frontal-Occipital and Parietal-Occipital connections, indicating that disconnection from the occipital region in the alpha frequency band is crucial for design ideation, corroborating the finding that increased occipital alpha is associated with distraction (Zumer et al., 2014). Taken together, the current findings support the interpretation that semantic feedback might help students eliminate irrelevant perceptual interference and put resources toward controlled retrieval, restructuring, and recombination of ideas. Thus, a decrease in alpha PLI could potentially be interpreted as indicating more efficient coordination rather than decreased effort.

4.2. The role of semantic feedback in design education

These findings are significant for design education because they demonstrate that the customized semantic feedback by instructor enables students to refine their creative thinking while reducing unnecessary cognitive load. This decrease suggests that students employed more efficient cognitive processes after receiving semantic feedback. It is most likely as a result of improved clarity, enhanced ideation techniques, as well as due to reduced ambiguity in their design thinking. These results highlight the importance of semantic feedback in supporting students' progressive learning and helping them better negotiate the challenges of design cognition.

Regarding the future application of semantic feedback in design education, this study tailored semantic feedback based on participants' design outcomes and provided feedback appropriately. Specifically, we strategically used the abstraction semantic feature, allowing the instructor to provide feedback in more abstract terms for participants who were more interested in concrete features. Conversely, if the participants appeared more generic, the instructor provided feedback using more specific terms. Future research should consider this viewpoint, as we did not investigate the potential effects of the various abstraction levels of the semantic feedback on design creativity.

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By incorporating semantic feedback mechanisms into design education, educators can create learning environments that enhance cognitive efficiency, foster collaboration, and promote student creativity. Investigating how semantic feedback affects neural efficiency and cognitive engagement may yield valuable insights for developing the next generation of adaptable and innovative designers.

5. Limitations and future work

This preliminary research has several limitations. First, the sample size is small, which limits the strength of the conclusions. Second, performing a functional connectivity analysis on a single frequency band narrows the findings in terms of other frequency bands.

Future research might advance this work in several directions. First, expanding the sample size beyond the current limited group of participants to a statistically significant cohort size and to include a broader range of design students that would enhance the reliability and generalizability of the findings, especially in larger educational contexts. Second, adding measures of design creativity in future studies would help researchers gain a better understanding of how semantic feedback contributes to the development of innovative thinking and problem-solving. Third, strengthening the feedback approach to include more comprehensive instructional strategies could improve its applicability in a variety of educational settings. Fourthly, incorporating semantic analysis into the feedback workflow would provide useful information about how specific linguistic and conceptual features promote creative thinking during design ideation. Finally, to better understand the difference between novice and expert thinking, future research involving designers and novices should be undertaken.

6. Conclusion

This study used EEG methodology to investigate the effects of semantic feedback on brain network activity during design ideation. We conducted a functional connectivity analysis and used PLI as a neural index to represent phase synchronization between channel pairs in the alpha frequency band. The results of the decreased connections suggest that receiving semantic feedback causes a shift from widespread coupling to more selective, task-relevant coordination during the design ideation process. The findings suggest that semantic feedback might contribute to facilitating more effective design thinking. This preliminary study shows that semantic feedback could influence brain connectivity during design ideation. Therefore, we highlight the potential of incorporating the semantic feedback of instructors as a valuable pedagogical strategy in design education.

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