Brain and Behavior in Engineering Design: An Exploratory Study on Using Concept Mapping

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To explore the connection between brain and behavior in engineering design, this study measured the change in neurocognition of engineering students while they developed concept maps. Concept maps help designers organize complex ideas by illustrating components and relationships. Student concept maps were graded using a pre-established scoring method and compared to their neurocognitive activation. Results show significant correlations between performance and neurocognition. Concept map scores were positively correlated with activation in students' prefrontal cortex. A prominent sub-region was the right dorsolateral prefrontal cortex (DLPFC), which is generally associated with divergent thinking and cognitive flexibility. Student scores were negatively correlated with measures of brain network density. The findings suggest a possible neurocognitive mechanism for better performance. More research is needed to connect brain activation to the cognitive activities that occur when designing but these results provide new evidence for the brain functions that support the development of complex ideas during design.

Introduction

A holistic design approach requires designers to develop a systems point of view [1, 2]. This means understanding the complex and dynamic relationships between components of the problem [2, 3]. Too often, engineers tend to isolate elements of a complex problem and design to optimize these individual elements [4, 5]. Design

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methods and tools that help open designers to see the entire system, rather than the individual pieces, holds the potential to improve their design outcomes.

Concept mapping is one approach to help designers think holistically about components of systems and their relationships. It can improve the engineering design process by helping designers connect new concepts with existing information [6]. Concept mapping works by organizing and graphically representing components and their relationships [7]. Concept maps begin with a main idea and then branch out to show how that main idea is related to other ideas, drawing connections between concepts at various hierarchical levels and from different categories.

Concept maps are also used as an educational tool because they help students learn complex systems [8]. For example, when teaching students about sustainability [9, 10]. Concept mapping coincides with constructivist learning processes. Learners can attain new knowledge by integrating new ideas or concepts with existing ideas that are illustrated within a concept map [6]. However, how connections between ideas are formed in the brain through concept mapping is not well understood. The amount of cognitive effort used for concept mapping certainly plays a role but where this effort occurs in the brain and how brain regions work together to create new concepts and connections is not well known. Better understanding designers' neurocognition when they are constructing concept maps and how this correlates with their performance can provide new indicators for design.

The study presented in this paper measured designers' neurocognition when they developed concept maps, their concept map scores, and the correlation between these two measures. Multiple methods for scoring concept maps are often used to assess designers' ability to think in systems [10, 11]. The most common is counting the number of concepts, cross-links, and the level of hierarchies represented on the maps [1]. Using this technique provides three measures to compare with designers' brain activation. A neuroimaging technique called functional near-infrared spectroscopy was used to capture brain activation when students were drawing a concept map for an engineering design problem. This study provides the correlations between these components of concept maps and their brain activation.

Background

Concept mapping provides an approach to visualize complexities and the interactions between concepts early in the design process [12]. The current understanding of how concept mapping improves design is it creates multiple retrieval paths in the brain for accessing new concepts and information [13]. However, this understanding is based predominantly on observational studies measuring design cognition through think aloud protocols, interviews, and the evaluation of products to infer changes in designers' brains [14, 15]. A limitation of these traditional approaches is the lack of objective measurements of the underlying mechanism of neurocognition.

Methods from neuroscience offer an approach to measure neurocognitive activity during engineering design [16]. This additional layer of information can help explain how tools and techniques, like concept mapping, create novel connections in designers' brains and how these connections correspond with designers generating new concepts. The neurocognitive function that supports a designers' ability to recognize complex relationships and how they use this to create new knowledge is under explored.

Prior literature suggests that concept mapping elicits greater activation in the prefrontal cortex, the region of the brain generally associated with cognitive functions that are involved with designing [11]. What is less understood is how this activation is related to performance. How does ability to recognize complex relationships correlate with cognitive effort? If concept mapping opens new retrieval paths in the brain, is this expressed as more connected brain regions? Establishing a connection between designers' brains and their minds can provide the foundation for future tools and new measures of design effectiveness. The research presented in this paper contributes to this aim by characterizing the neurocognition of designers while concept mapping and how changes in their brain are related to outcomes. The following section outlines the multiple techniques that are often used to observe designers' brain behavior.

Using fNIRS to Explore Neurocognitive Activation and Brain Network

Multiple techniques are available to measure neurocognition, such as functional magnetic resonance imaging (fMRI) [17], electro-encephalography (EEG) [18], and functional near-infrared spectroscopy (fNIRS) [19]. Each technique has its pros and cons. fMRI provides excellent spatial resolution through whole head scanning, but requires participants to lie down in a closed environment without much mobility [20]. EEG has the best temporal resolution, but it is harder to pinpoint the brain region where electrical activity occurs [21]. fNIRS offers relatively good resolution in both space and time, but it is usually limited to measuring activations in the human cortex rather than the whole brain [22].

Considering the nature of engineering design and concept mapping, fNIRS was used in this study because it provided participants a more realistic design environment than fMRI with relatively good spatial resolution of participants' prefrontal cortex. fNIRS measures the change of oxygenated (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb), also called blood oxygenation level dependent (BOLD) response. BOLD response is a proxy for brain activity [23]. An increase in oxy-Hb typically mirrors more neuronal activity and implies the allocation of resources and nutrients by the cerebrovascular system [24].

The prefrontal cortex (PFC) was the brain region of interest in this study. The PFC is the neural basis of working memory and higher-order cognitive processing, such as sustained attention, reasoning, and evaluations [25]. Based on anatomy and function, the PFC is divided into several sub-regions, including the dorsolateral PFC (DLPFC), ventrolateral PFC (VLPFC), medial PFC (mPFC) and orbitofrontal cortex (OFC),

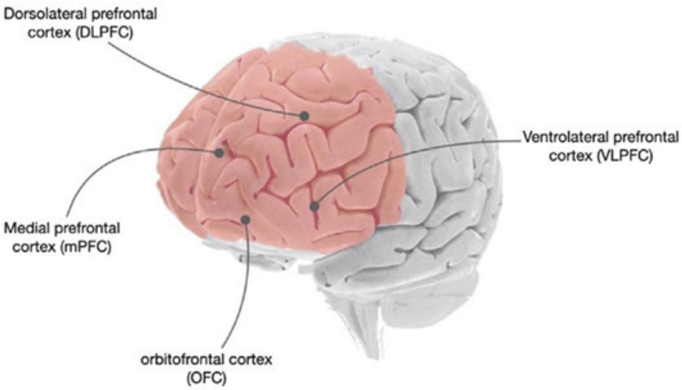


Fig. 1 Prefrontal cortex and its sub-regions [28]

shown in Fig. 1. These sub-regions contribute to different aspects of the cognitive processing in the PFC, and asymmetric cognitive functions are usually identified in the two brain hemispheres [26, 27].

There are several types of analysis used to understand neurocognitive data in neuroimaging studies [29], such as activation analysis (change of activation level) [30], network analysis (functional connectivity among different regions) [28], and interpersonal analysis (activation synchronization between two collaborating subjects) [31]. Activation analysis and network analysis have been used in prior design neurocognitive studies to describe changes in the brain of individual designers [28, 29]. Activation analysis usually compares the activation variables extracted from the BOLD response, such as mean, the area under the curve, kurtosis, time to peak, slope, or the beta coefficients from the general linear models between different subjects or under different conditions [29]. Network analysis calculates the functional correlation and develops the network among the brain regions of interest [29]. Numerous network features, such as network density, clustering coefficient, and efficiency, can be calculated using graph theory to characterize the neural coordination between different brain regions [32].

Brain networks provide an approach to explore functional connectivity and information processing in the brain [33]. Central regions, or nodes, in the brain may facilitate functional interaction and act as a control for information flow as it interacts with many other brain regions [34]. Specific regions or nodes maybe be important, what is not known is whether the size of the functionally connected regions in the brain (i.e., density, clustering coefficient) is correlated to performance.

Brain networks have been used to explore underlying neural correlates of creativity [35]. Yet, little is known about brain functional connectivity during concept generation. Design neurocognition has focused primarily on brain activation [36, 37] more than functional connectivity. The aim in this study was to observe both brain activation and functional connectivity and measure how these are correlated with designers' performance when creating concept maps.

Research Questions

The aim of the research presented in this paper was to understand how neurocognition is related to performance when concept mapping. The specific research questions are:

(1) What is the relationship between concept mapping performance and neurocognition?
(2) What is the relationship between concept mapping performance and neuro-network coordination?

Methods

Experiment Design

The study was part of a larger project that explored the effects of concept mapping on engineering concept generation. Here we report on the correlation between the concept map scores and neurocognition when developing their concept maps. The Institutional Review Board at Virginia Tech approved the project. Participants were recruited from engineering courses at Virginia Tech. A total of 33 engineering graduate and undergraduate students completed the concept mapping experiment.

Prior to the experiment, engineering students were briefed and trained to use concept maps. This pre-experiment training included a 4-min video introducing concept maps and drawing a concept map to learn and practice how to do it. Engineering students were then outfitted with the fNIRS cap, as shown in Fig. 2a (Shimadzu LIGHTNIRS model). Change in oxygenated hemoglobin (oxy-Hb), a proxy for neurocognitive activity [23], was measured using this fNIRS cap. Figure 2b illustrates the placement of light sensors and channels according to the international 10–20 placement system. The 22 channels captured the change in oxy-Hb in the prefrontal cortex (PFC), covering multiple sub-regions in the PFC.

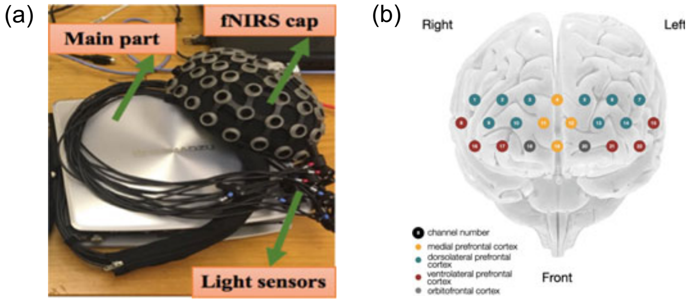


Fig. 2 **a** fNIRS equipment, and **b** prefrontal cortex channel placement

Once the fNIRS instrument began recording change in oxy-Hb, students were instructed to complete a word tracing task prior to concept mapping. The change in oxy-Hb while word tracing was later used as a baseline for activation in their PFC and subtracted from the change in oxy-Hb when developing their concept maps. Participants were then instructed to create a concept map. The instructions were to *Create a concept map illustrating all of the mobility systems on campus. The average time spent on this task is 10 min, but you have as much time as you need to do it. Hit the space bar when you are done reading this prompt and are ready to begin developing your concept map.*

Participants were given as much time as they needed to create their concept maps. PsycoPy was used in the experiment to provide engineering students with timed instructions [38]. The average time length for concept mapping lasted 8.48 min (SD = 4.38 min).

Data Analysis

Each hand-drawn concept map was digitized and all concepts and relationships were coded using the tool CMAP-PARSE [39]. This is a frequently used and previously developed method for scoring concept maps. A limitation of this approach is its quantitative focus. It works by counting the number of concepts (NC), the level of highest hierarchies (HH), and the number of crosslinks (NCL) between different categories [10]. A concept map score (CMS) was determined using Eq. (1). More details about the scoring method can be found in [10]. Each of the variables (NC, HH, NCL, and CMS) were used as an indicator of concept mapping performance. The higher the CMS score the better the performance.

$$\mathrm{CMS} = \mathrm{NC} + 5 * \mathrm{HH} + 10 * \mathrm{NCL} \tag{1}$$

To eliminate noise and motion artifacts, fNIRS's raw data were processed using a bandpass filter (0.01–0.1 Hz, third-order Butterworth filter) and independent component analysis with a coefficient of spatial uniformity of 0.5. The parameters in these steps were selected based on prior research [40, 41]. Filtering was conducted using Shimadzu's fNIRS software. Two out of 33 participants were removed due to bad signals. Baseline correction and z transformation were applied to normalize the data between subjects.

Neurocognitive data were analyzed using two approaches: activation analysis and network analysis. Both are standard approaches to understanding design neurocognition [28, 29]. The activation analysis focused on the change of oxy-Hb in different brain regions when concept mapping. The positive area under the oxy-Hb curve (AUC) when concept mapping (illustrated as the colored area in Fig. 3) was used as a proxy for cognitive load since AUC takes both activation level and time into account. Prior research has also demonstrated that AUC provides a high level of accuracy when classifying the level of cognitive load [42, 43]. The AUC was calculated for each subject when they were developing their concept maps.

Network analysis was used to calculate brain functional connectivity. Pairwise activation (i.e., oxy-Hb) synchronization among the 22 channels for each participant was calculated and represented in a Pearson correlation matrix. A threshold (0.75 was used in this study) was applied to transform the correlation matrix into a binary matrix. Channel pairs with the value "1" in the matrix suggest the high functional connectivity between the two brain regions. The connectivity is represented as an edge linking the two channels in the network figure. Figure 4 presents the process of developing a brain network from the oxy-Hb response. More details on brain network calculations can be found in [28, 32]. Then network features including density, clustering coefficient, and efficiency, were calculated for each participant.

To address Research Question (1), Pearson correlation analysis was performed using the 31 participants that had adequate signal data comparing their concept map performance scores (including each of the concept map variables NC, HH, NCL, CMS) and their neurocognitive activation (AUC) in their prefrontal cortex. To

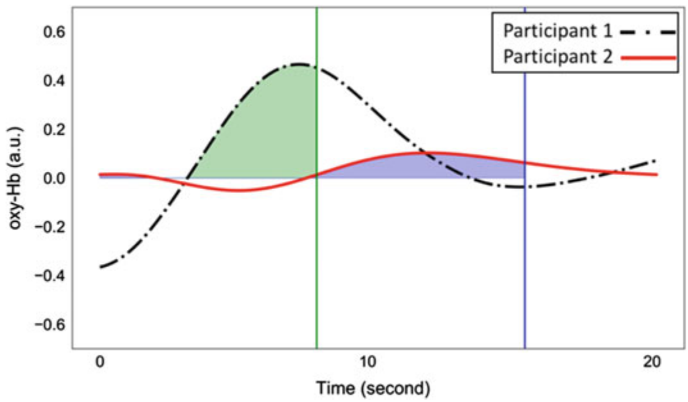


Fig. 3 An example of the positive area under the curve (AUC), where the first vertical lines represent a change in stimuli and the second vertical line represents the end of the task

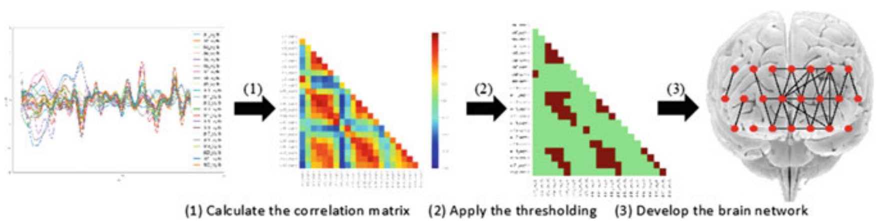


Fig. 4 The process of creating brain network graphs, which is a proxy for functional coordination in the prefrontal cortex

address Research Question (2), Pearson correlation analysis was performed using the 31 participants' concept map performance scores (including the concept map variables NC, HH, NCL, CMS) and network features (density, clustering coefficient, efficiency).

Results

The mean and standard deviation of the number of concepts (NC), highest hierarchy (HH), number of crosslinks (NCL), and concept map scores (CMS) averaged from participants are shown in Table 1. Here, the average concept map score is 89 with 21 concepts, 4 hierarchies, and 4 crosslinks.

Examples from two participants are used to visualize the concept map, activation, and brain network coordination. One of the example participants had a relatively lower CMS (39) and the other had a relatively higher CMS (131) compared to the mean of 89. These participants' concept maps are illustrated in Fig. 5.

Average activation area under the curve (AUC) in the prefrontal cortex (PFC) and the heat map illustrating AUC for both participants is illustrated in Fig. 6. Their brain network features, and brain network graphs are included in Table 4.

The participants with higher performance in concept mapping (i.e., a higher CMS) showed higher cognitive activation (i.e., a higher AUC value). The example participant, who had the high CMS of 131, elicited an AUC value of 2.33. The example participant, who had the low CMS of 39, elicited an AUC value of 1.88. These results were common across participants and suggest a potential relationship between concept mapping performance and neurocognitive activation represented by AUC.

While participants with higher performance in concept mapping (i.e., a higher CMS) showed higher cognitive activation (i.e., a higher AUC value), they also showed a sparser brain network with fewer complexities (i.e., lower values in network features) compared to participants with lower performance in concept mapping. The two example participants are shown in Table 2 and their results are similar to the remaining participants. These results suggest another potential relationship between concept mapping performance and brain network features. The better the concept map performance, the higher the AUC, but sparser the brain network.

Table 1 Students' average concept mapping performance scores

	NC	HH	NCL	CMS
Mean	21.3	4.6	4.5	89.0
Standard deviation	8.72	2.93	5.44	63.40

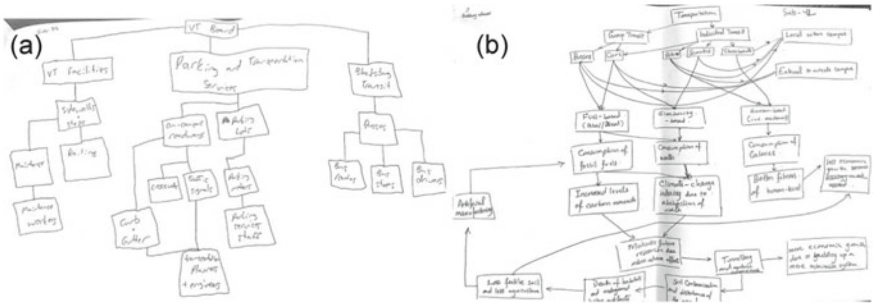


Fig. 5 Examples of concept maps with **a** a low Concept Map Score (CMS) of 39 and **b** a high Concept Map Score (CMS) of 131

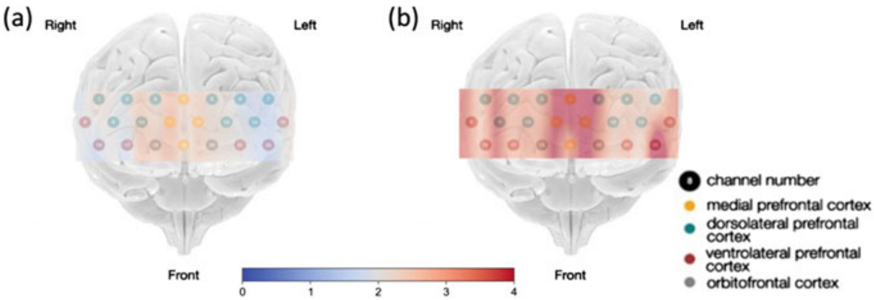


Fig. 6 Example of participants change in AUC: **a** An AUC score of 1.88 for a participant with a low CMS and **b** an AUC of 2.33 for a participant with a high CMS

Table 2 Network features for two participants when developing concept maps

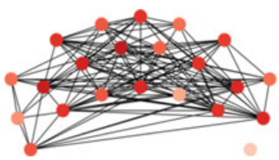
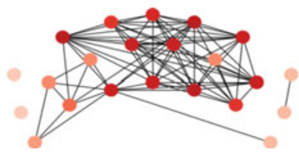
Network	Participant with a lower CMS	Participant with a higher CMS
Density	0.75	0.29
Clust. Coef.	0.87	0.64
Efficiency	0.88	0.55
Graph		

Table 3 Pearson correlation coefficients between brain activation and concept mapping performance (NC is the number of concepts, HH is the highest hierarchy, NCL is the number of crosslinks, and CMS is the concept maps score; *Note* * denotes $p < 0.05$, ** denotes $p < 0.001$)

Brain regions	NC	HH	NCL	CMS
PFC	0.391*	0.035	0.685**	0.650**
Right PFC	0.427*	0.085	0.738**	0.712**
Left PFC	0.353	0.024	0.630**	0.595**
Right DLPFC	0.392*	0.087	0.756**	0.723**
Left DLPFC	0.339	0.077	0.651**	0.624**
Right OFC	0.565**	0.130	0.463*	0.506*
Left OFC	0.453*	−0.011	0.520*	0.507*
Medial PFC	0.348	0.121	0.561*	0.558*
Right VLPFC	0.433*	0.089	0.695**	0.677**
Left VLPFC	0.237	0.036	0.468**	0.443*

Students' Neurocognitive Activation Is Positively Correlated with Their Concept Mapping Performance

Pearson correlation analysis was conducted to better test the relationship between concept mapping performance, cognitive activation, and network features. Concept map performance was measured by the number of concepts (NC), highest hierarchy (HH), number of crosslinks (NCL), and concept maps score (CMS). Each of the variables was compared to sub-regions within the PFC. NC had a significant positive relationship with brain activation across the PFC, specifically, the right PFC, the right dorsolateral PFC (DLPFC), the right orbitofrontal cortex (OFC), the left OFC, and the right ventrolateral PFC (VLPFC). NCL was positively correlated with brain activation in the PFC and all sub-regions. Considering NC weighs most in the CMS, CMS shows a similar positive correlation with brain activation in the PFC and other significant sub-regions. The HH shows no significant correlation with brain activation. The Pearson correlation coefficients are included in Table 3. The most significant correlation between CMS and AUC was in the right DLPFC. These results are also illustrated in Fig. 7a.

Students' Brain Network Features Are Negatively Correlated with Their Concept Mapping Performance

Significant negative correlations were identified between concept mapping performance and the multiple network features among the 31 participants. As Table 4 suggests, correlations between clustering coefficients with HH, NCL, and CMS are significant but negative. Other correlations between network features and concept

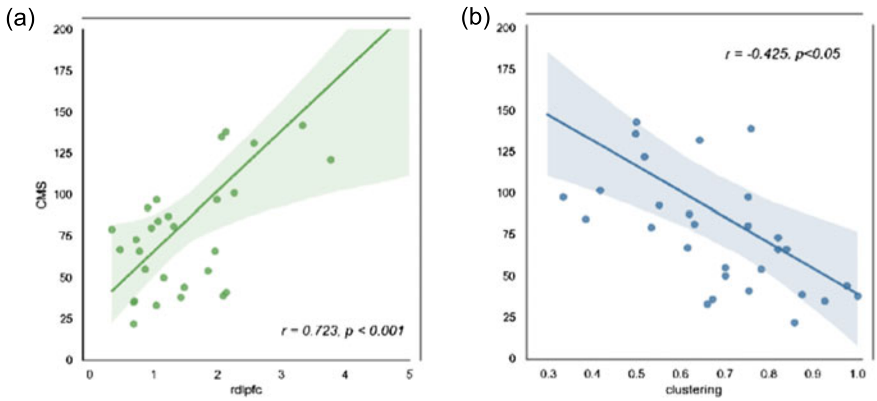


Fig. 7 Significant positive correlation between **a** CMS and brain activation and **b** significant negative correlation between CMS and clustering coefficient

Table 4 Pearson correlation coefficients between network features and concept mapping performance

Network features	NC	HH	NCL	CMS
Density	−0.231	−0.320	−0.289	−0.354
Clustering coefficient	−0.128	−0.404*	−0.370*	−0.425*
Efficiency	−0.218	−0.327	−0.235	−0.307

Note * $p < 0.05$; $p^{**} < 0.001$

mapping performance are also negative but not statistically significant. The most significant correlation between the clustering coefficient and CMS is visualized in Fig. 7b.

Discussion

Neurocognitive activation and the functional network of students' prefrontal cortex (PFC) were different for students with higher and lower concept map scores. Students with higher concept map scores elicited significantly higher overall cognitive effort (i.e., brain activation measured as the positive area under the oxy-Hb curve, or AUC) in their PFC. The PFC plays a critical role in sustaining focused attention and performing executive functions [25]. Higher AUC in the PFC among high concept map achievers is consistent with prior studies from other fields that also measured behavioral performance or task completion [44]. However, activation in the PFC may not always be synonymous with performance. Rather, it may be a better proxy for mental effort [44]. Novices, for example, tend to exert more mental effort for a similar level of task completion as an expert [45].

Designing is more complex than just task completion and this may have an effect on patterns of neurocognitive activation. For instance, novice versus expert designers tend to approach design problems differently [46] and this may also be reflected in brain activation. For example, when brainstorming, first-year engineering students elicited higher brain activation in a region generally associated with divergent thinking whereas senior engineering students, with more experience brainstorming, recruited higher activation in their brains in a region generally associated with uncertainty processing and self-reflection [30].

The most significant differences between students with high and low concept map performance was in their right dorsolateral PFC (DLPFC) and medial PFC. A significant positive correlation was found between the AUC in these sub-regions and the number of concepts and crosslinks that the student designers developed. The right DLPFC is often associated with divergent thinking and cognitive flexibility [47]. This finding echoes those of a prior neurocognitive study that have also found concept mapping elicited higher brain activation in the DLPFC [11]. The medial PFC is often involved in making associations [48]. This cognitive function provides a possible explanation for the positive correlation between AUC in the medial PFC and the number of crosslinks, since crosslinks represent associations between different categories of concepts.

While the increased activation in the right DLPFC and medial PFC was positively correlated with concept map performance, network density, clustering coefficient, and efficiency was negatively correlated with concept mapping performance. This might suggest that new retrieval paths for accessing concepts and making associations between these concepts may not be reflected in the complexity of the brain network (i.e., density and clustering coefficient). Less global coordination across the PFC and greater localized activation within specific sub-regions like the DLPFC and medial PFC may lead to better design performance [11].

These results also present new questions about what happens in designers' brains and how this may affect their designs. For instance, how might these results differ with expert designers? The student designers in this study were not experts in systems thinking, which likely contributed to the positive correlation between cognitive activation and performance. More variability may occur among design experts who may have a higher degree of systems thinking ability than the students or more experience and knowledge to make associations between concepts. Another question is how these student designers' brains may change as their ability to create concept maps improves. A possible explanation is the activation in their right DLPFC, and medial PFC, increase more quickly as they become familiar with this type of design activity and train their brain to perform well on the task. Future research can begin to test this assumption and explore how other tools and techniques shape both brain and designer behavior.

There are several limitations that need mentioning. This study focused on previously established scoring methods to assign concept maps a score. A preliminary analysis of the contents and quality can be found in [49]. The study presented in this paper also only measured the neurocognitive activity in the PFC. This region of interest was selected because of its importance in engineering design and concept generation [28]. Other brain regions are required for this type of cognitive task and maybe equally important for engineering design (e.g., parietal cortex) [11, 50]. However, whole brain scans come with a trade-off in portability and realism in replicating engineering design in an experiment. The sample size of 31 subjects produced good statistical power and met the average sample size of 28 subjects suggested in a systematic review [29], but a future study may consider replicating the experiments with a larger sample size.

Conclusion

Significant brain-behavior correlations were observed when student designers were using concept maps during engineering design. Concept mapping performance, measured using the traditional scoring method, is positively correlated with cognitive activation in the prefrontal cortex (PFC), especially the right dorsolateral PFC. This region is generally associated with divergent thinking and cognitive flexibility. In contrast, concept mapping performance was negatively correlated with functional connectivity across the prefrontal cortex. These opposed relationships might suggest that concept mapping relies more on activation in a specific region, specifically the right DLPFC, rather than coordination between PFC sub-regions.

Understanding how concept mapping performance correlates with neurocognition can begin to help inform pedagogy and design practice for eliciting the underlying neurocognitive patterns that help promote performance. More qualitative-quantitative analysis is also needed to expand how performance of concept maps is being measured. The approach used in this study to measure performance relied on the concept map scores, which were derived using the number of concepts, the level of highest hierarchies, and the number of crosslinks between different categories. This approach did not adequately account for the novelty or quality of the ideas. Future research can consider these additional measures and how they may relate to patterns of neurocognition. In addition, these findings may differ among expert designers compared to novices.

The research reported here presents one aspect of the development of the neural underpinnings of design activity. It forms part of the triangulation for measuring design output (the design), design cognition (the mind) and design neurocognition (the brain). The findings from this research open new questions about how brain behavior and design behavior are related, how this may vary across designers, and what this means for design education. Evaluating a design remains fraught with subjectivity, where the criteria for measurement are not yet fully agreed upon, let alone how to measure those criteria. Measuring design cognition is better developed with several approaches whose results potentially map onto each other. It still contains a mixture of subjective and objective measurements but measuring brain activations during design activities provides an objective result that is independent of the measurer. There is still considerable research needed to connect brain activations and their resultant networks to the cognitive activities that occur during designing. Methods for analyzing brain activity measurements themselves require further development if they are to capture the higher order cognition involved in designing.

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