2023 Annual Conference & Exposition
Baltimore Convention Center, MD | June 25 - 28, 2023
The Harbor of Engineering
Education for 130 Years
ASEE
Paper ID #39290

Board 337: Measuring the ”Thinking” in Systems Thinking: Correlations between Cognitive and Neurocognitive Measures of Engineering Students

Dr. Tripp Shealy, Virginia Tech

Tripp Shealy is an Associate Professor in the Civil and Environmental Engineering Department at Virginia Tech. He is also the director of the interdisciplinary Sustainable Land Development Graduate Program. His research is focused on helping improve engineering design. He teaches classes about sustainable engineering design, human behavior and infrastructure systems, and adaptive reuse.

Dr. John S. Gero, University of North Carolina, Charlotte

John Gero is Research Professor in Computer Science and Architecture at UNCC He was formerly Research Professor in Krasnow Institute for Advanced Study, and Research Professor in Computational Social Science at George Mason University and Professor of Des

Paulo Ignacio Jr.

Measuring the “thinking” in systems thinking: Correlations between cognitive and neurocognitive measures of engineering students

Introduction and background

Systems thinking is a critical skill for engineering students to solve complex and ill-structured design problems [1]. Concept mapping is a tool for systems thinking [2]. It involves connecting disparate pieces of information and using these connections to generate new ideas and relationships to frame and solve problems [3]. Concept mapping is a thinking tool that works by beginning with a main idea and then branching out to show how the main idea is related to other ideas. Students draw connections between concepts at various hierarchical levels and from different categories. For example, a mechanical engineering student could draw components that make up a manufacturing process, such as the raw materials, the machines, how workers interact in the process, quality control measures, and the relationships between these concepts and ideas.

Concept mapping is often used to evaluate student learning. For example, to assess students’ understanding of sustainable design [4], [5]. Methods have been developed to score the content and structure of students’ concept maps to provide instructors with insights into the depth and breadth of students' understanding of a topic [6]. In addition to being used for assessment, concept mapping is often used as a learning tool [7], [8]. Concept maps force students to engage with the relationships between ideas and organize information in a way that makes sense to them. The premise is that creating concept maps facilitates knowledge transfer to new situations [9]. For example, an engineer who has experience designing buildings with steel and asked to use concrete could facilitate their learning by creating a concept map that starts with their knowledge of “loads and forces,” “design principles,” and “material properties” and as they learn more about concrete add new nodes for concepts such as “concrete mix design,” “strength and durability,” and “reinforcing materials” and link these new nodes to related nodes in the steel structure branch to show how the concepts are related and how they can be applied new ways.

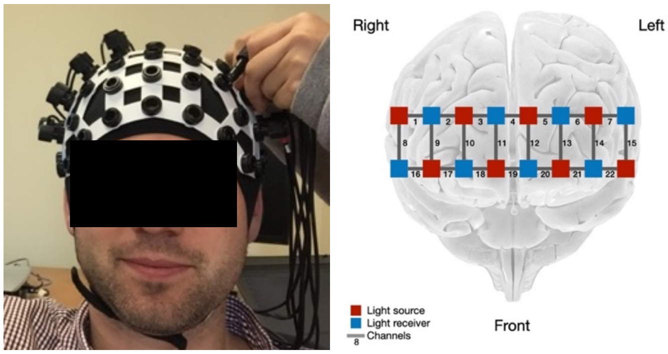
Despite the usefulness of concept mapping in assessment and learning, a gap exists in understanding how it translates to changes in students’ engineering designs. How concept mapping, as a tool for systems thinking, shapes subsequent design thinking is under-explored. Neuroscience provides an approach to measure the underlying neural processes involved in concept mapping and its effect on students’ designs. For instance, concept mapping may enhance students’ ability to efficiently organize and integrate information, making designing less cognitively demanding. Concept mapping was previously observed to increase oxygenated blood flow in brain regions involved in semantic processing, working memory, and attentional control [10]. The priming of these regions through concept mapping may lead to changes in the recruitment of brain regions during subsequent design tasks.

The specific question this study attempted to answer was what is the relationship between brain activation during concept mapping and subsequent design problem framing? Design problem framing is the aspect of designing that was explored because of its early and substantial influence on engineering design [11].

Methods

Engineering students (n=28) were recruited through engineering courses and department bulletin boards and listservs. The average age of students was 22.13 (SD = 2.93 years). The students were given a $30 gift card for their participation in the study. The experiment procedure was approved by the university's Institutional Review Board. None of the students who participated were familiar with concept mapping. So, the first step was to provide them with a four-minute video about the elements and relationships in a concept map and how to construct a concept map. They were then asked to develop a concept map about their educational experience. While developing this initial concept map, they were encouraged to ask questions. They were told this was just for practice and meant to help them understand what would be asked of them later.

Students were then outfitted with functional near-infrared spectroscopy (fNIRS). fNIRS was chosen as the neuroimaging instrument because it offers relatively good resolution in both time and space compared to functional magnetic resonance imaging (fMRI) and electroencephalography (EEG). fNIRS measures the change of oxygenated (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb). An increase in oxy-Hb is a proxy for neural activity in the brain [12]. An increase in oxy-Hb implies the allocation of resources and nutrients by the cerebrovascular system [13]. The cortical region of interest was the prefrontal cortex (PFC) because of its involvement with working memory and higher-order cognitive processing, such as sustained attention, reasoning, and evaluations [14]. Figure 1 illustrates the fNIRS device and the placement of sensors and detectors that make up channels along the prefrontal cortex.



(a)

Figure 1: (a) fNIRS cap on the participant, (b) prefrontal cortex channel placement

Design task

While wearing the fNIRS cap, students were asked to complete a word-tracing task to record baseline activation in their brains. This type of baseline recording is typical among neurocognitive studies [15], [16]. After the word tracing, participants were asked to rest for thirty seconds by staring at a crosshair. Students were then prompted to construct a concept map using paper and pencil. The prompt read, "Create a concept map illustrating all the mobility systems on campus. The average time spent on this task is 10 minutes, but you have as much time as you need to do it." Students were given as much time as needed to create their concept maps. The average time length for concept mapping lasted 8.48 minutes (SD = 4.38 minutes).

Neuroimaging data

The fNIRS raw data for the students were processed using a bandpass filter (frequency ranging between 0.01 and 0.1 Hz, third order Butterworth filter) which was done to eliminate low-frequency physiological and high-frequency instrumental noises. Additionally, an independent component analysis (ICA) with a coefficient of spatial uniformity of 0.5 was applied to remove motion artifacts. This elimination step was critical in processing the raw fNIRS data to avoid false discovery in the fNIRS analysis [17]. The parameters in data processing are based on prior research [18]. Shimadzu fNIRS software was used to filter and pre-process the fNIRS data. After preprocessing, fNIRS data were analyzed using a locally developed Python script. A baseline correction and z-transformation were applied to make fNIRS data comparable between subjects.

The positive area under the Oxy-Hb curve (AUC) was calculated when concept mapping and developing design problem statements. AUC was used as a proxy for the cognitive load in students' PFC 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 effort [19], [20]. An example of the AUC is provided in Figure 2.

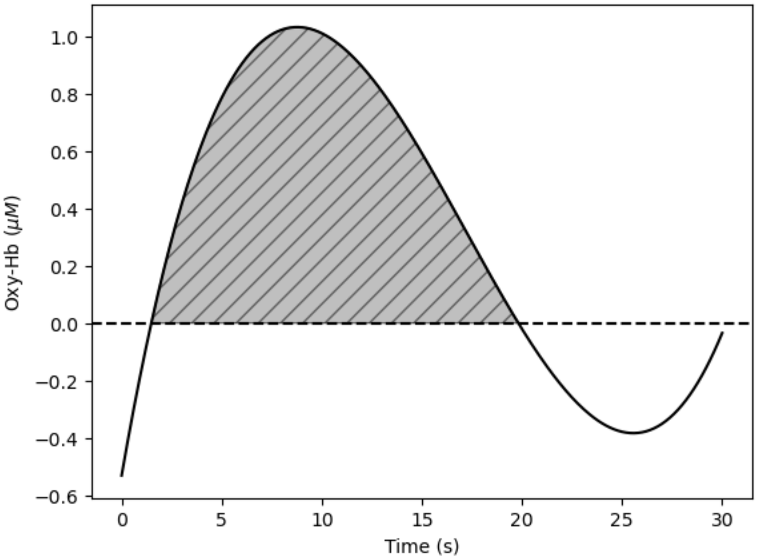


Figure 2: Example of the positive area under the Oxy-Hb curve

Design problem statements

In addition to calculating the AUC in the PFC among students when developing their concept map and design problem statements, the number of words in their design problem statements was used to measure their design products. While imperfect, the number of words in a student's design problem statement indicates some level of detail and complexity of their design. A longer description may suggest that the student put more thought and effort into their design problem statement. A longer statement provides more details and explanations about their design choices. Common "stop words" were removed from the text data, using the Natural Language Tool Kit package for Python [21]. The length of the problem statements only included descriptive words about their design problem.

Data analysis

The AUC across the PFC when concept mapping was compared using ordinary least squares regression to the number of words students included in their design problem statements. Next, the average AUC across the prefrontal cortex (PFC) when concept mapping was analyzed for each student and compared using ordinary least squares regression to the AUC across students' PFC when they were developing their design problem statements. Finally, the AUC across the prefrontal cortex (PFC) when concept mapping was compared using ordinary least squares regression to both the AUC across students' PFC when they were developing their design problem statements and the number of words in students' design problem statements.

Results

The amount of neuro-cognitive activation in the prefrontal cortex while concept mapping was positively correlated to the number of words students included in their design problem statements (R-squared was 0.425, adjusted R-squared was 0.405). As the neuro-cognitive effort, measured by the Oxy-Hb AUC, increased, so did the number of words students included in their problem statements. This is illustrated in Figure 3.

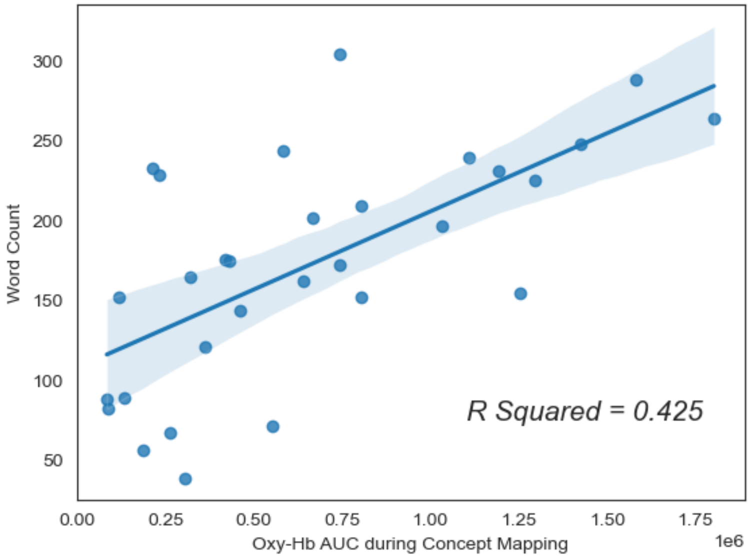


Figure 3: Ordinary least square regression between the Oxy-Hb AUC while concept mapping and the number of words students subsequently included in their design problem statements.

A stronger correlation was observed between the Oxy-Hb AUC in students' PFC when concept mapping and the Oxy-Hb in students' PFC when developing their design problem statements (R-squared was 0.683, adjusted R-squared was 0.672). The more neuro-cognitive effort students recruited for the concept mapping, the more cognitive effort they recruited for their design problem statement. This is illustrated in Figure 4.

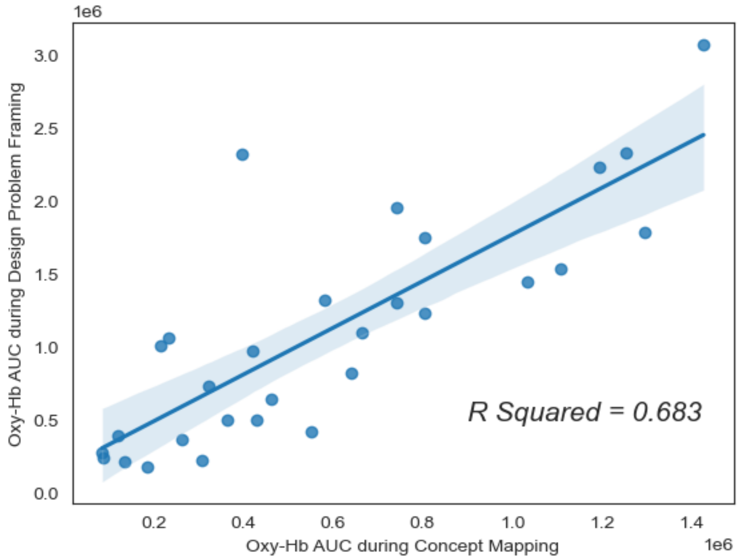


Figure 4: Ordinary least square regression between the Area Under the Curve for Oxy-Hb when concept mapping and the Area Under the Curve for Oxy-Hb while developing design problem statements.

The strongest correlation was using both the number of words and the cognitive effort when developing design problem statements compared to the cognitive effort when concept mapping. The R-squared was 0.775, and the adjusted R-squared was 0.758. In other words, the neuro-cognitive effort when concept mapping was strongly related to both the number of words students generated and the neuro-cognitive effort students recruited when developing their design problem statements. The regression model is illustrated in Figure 5.

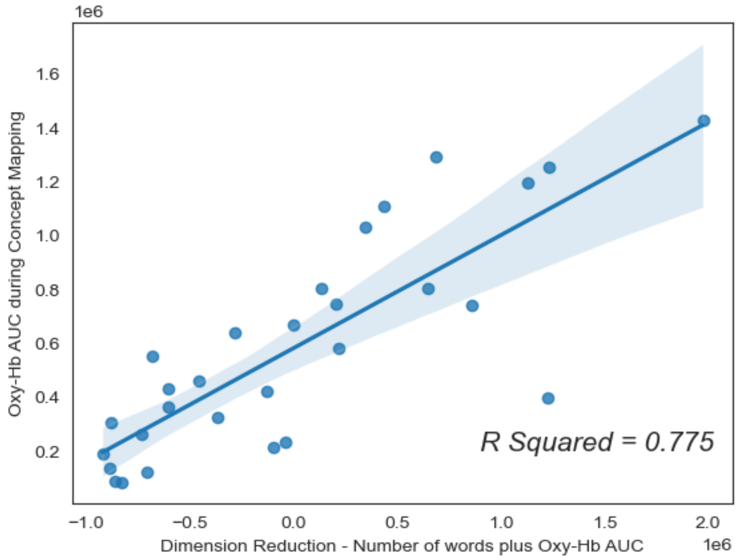


Figure 5: Ordinary least square regression between the Area Under the Curve for Oxy-Hb during concept mapping and the combined through dimension reduction Area Under the Curve for Oxy-Hb while developing design problem statements and the number of words students produced.

Discussion and conclusion

The results of this study suggest that there is a positive relationship between the neuro-cognitive effort involved in concept mapping and the subsequent number of words generated by students when developing their design problem statements. This finding highlights the potential benefits of using concept mapping as a tool to support engineering students when designing. This relationship suggests that concept mapping may help students to organize their thoughts and enable them to generate more detailed and comprehensive design problem statements. By visually organizing and connecting disparate pieces of information, students may be better equipped to develop a complete understanding of the problem and thus generate more ideas.

The relationship between neuro-cognitive effort during concept mapping and subsequent neuro-cognitive effort when developing design problem statements may suggest these tasks are cognitively related. The ability to connect and integrate information is a critical component of both concept mapping and design problem framing [22]. The use of concept mapping may help prime neuro-cognitive activation that is relevant to design problem framing. However, further research is needed to support this claim. While correlations were observed between concept mapping and design problems, it may be more relevant to the attention students gave to both tasks. For instance, all the students were unfamiliar with concept mapping. So, students who tried harder during the concept mapping may have been more likely to try harder during the design problem statement regardless of the effect of concept mapping on their cognition. Future research could begin to explore how the neuro-cognitive relationship changes over time. As familiarity with concept mapping increases, and it becomes cognitively easier, how does this change neurocognition when developing their design problem statement? Further research is also needed to explore the relationship between concept mapping and other aspects of engineering design, such as developing detailed design solutions. In addition, more comparisons, and a deeper investigation into what is included in their design statements, not just the length of the statement, are also needed.

Acknowledgments

This material in this paper is based on research supported by the National Science Foundation under Grant Nos. 1929892 and 1929896. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] M. Nehdi and R. Rehan, “Raising the Bar for Civil Engineering Education: Systems Thinking Approach,” *Journal of Professional Issues in Engineering Education and Practice*, vol. 133, no. 2, pp. 116–125, 2007, doi: 10.1061/(ASCE)1052-3928(2007)133:2(116).

[2] M. Hu and T. Shealy, “Methods for Measuring Systems Thinking: Differences Between Student Self-assessment, Concept Map Scores, and Cortical Activation During Tasks About Sustainability,” presented at the ASEE, Salt Lake City, UT, Jun. 2018. Accessed: Jun. 04, 2018. [Online]. Available: https://www.asee.org/public/conferences/106/papers/22718/view

[3] R. Valdes-Vasquez and L. Klotz, “Using the Concept-Mapping Method for Empirical Studies in Construction Research,” *Journal of Construction Engineering and Managanagement*, vol. 139, no. 10, p. 04013002, 2013, doi: 10.1061/(ASCE)CO.1943-7862.0000720.

[4] M. Hu, T. Shealy, J. Grohs, and R. Panneton, “Empirical evidence that concept mapping reduces neurocognitive effort during concept generation for sustainability,” *J. Clean. Prod.*, vol. 238, p. 117815, Nov. 2019, doi: 10.1016/j.jclepro.2019.117815.

[5] J. Segalas, D. Ferrer-Balas, and K. F. Mulder, “Conceptual maps: measuring learning processes of engineering students concerning sustainable development,” *European Journal of Engineering Education*, vol. 33, no. 3, pp. 297–306, Jun. 2008.

[6] M. K. Watson, J. Pelkey, C. R. Noyes, and M. O. Rodgers, “Assessing Conceptual Knowledge Using Three Concept Map Scoring Methods,” *Journal of Engineering Education*, vol. 105, no. 1, pp. 118–146, Jan. 2016, doi: 10.1002/jee.20111.

[7] J. D. Novak, *Learning, Creating, and Using Knowledge: Concept Maps as Facilitative Tools in Schools and Corporations*, 2nd ed. New York: Routledge, 2009. doi: 10.4324/9780203862001.

[8] N. D. McWhirter and T. Shealy, “Teaching decision-making for sustainable infrastructure: a wind energy case study module,” *International Journal of Sustainability in Higher Education*, vol. 19, no. 5, pp. 893–911, Jun. 2018, doi: 10.1108/IJSHE-10-2017-0183.

[9] G. W. Ellis, A. Rudnitsky, and B. Silverstein, “Using concept maps to enhance understanding in engineering education,” *International Journal of Engineering Education*, vol. 20, no. 6, pp. 1012–1021, 2004.

[10] M. Hu, T. Shealy, J. Gero, J. Milovanovic, and P. Ignacio, “Brain and Behavior in Engineering Design: An Exploratory Study on Using Concept Mapping,” in *Design Computing and Cognition’22*, Cham, 2023, pp. 199–214. doi: 10.1007/978-3-031-20418-0_13.

[11] N. Kelly and J. S. Gero, “Reviewing the concept of design frames towards a cognitive model,” *Design Science*, vol. 8, p. e30, ed 2022, doi: 10.1017/dsj.2022.25.

[12] F. Herold, P. Wiegel, F. Scholkmann, and N. G. Müller, “Applications of Functional Near-Infrared Spectroscopy (fNIRS) Neuroimaging in Exercise–Cognition Science: A Systematic, Methodology-Focused Review,” *Journal of Clinical Medicine*, vol. 7, no. 12, Nov. 2018, doi: 10.3390/jcm7120466.

[13] T. Csipo, A. Lipecz, P. Mukli, D. Bahadli, O. Abdulhussein, C. D. Owens, S. Tarantini, R. A. Hand, V. Yabluchanska, J. Kellawan, F. A. Sorond, J. A. James, A. Csiszar, Z. I. Ungvari, & A. Yabluchanskiy, “Increased cognitive workload evokes greater neurovascular coupling responses in healthy young adults,” *PLOS ONE*, vol. 16, no. 5, p. e0250043, May 2021, doi: 10.1371/journal.pone.0250043.

[14] A. Dietrich, “The cognitive neuroscience of creativity,” *Psychon. Bull. Rev.*, vol. 11, no. 6, pp. 1011–1026, Dec. 2004, doi: 10.3758/BF03196731.

[15] M. Hu and T. Shealy, “Systems versus Linear Thinking: Measuring Cognitive Networks for Engineering Sustainability,” *Construction Research Congress*, Apr. 2018, doi: 10.1061/9780784481301.072.

[16] S. Tak and J. C. Ye, “Statistical analysis of fNIRS data: A comprehensive review,” *NeuroImage*, vol. 85, Part 1, pp. 72–91, Jan. 2014, doi: 10.1016/j.neuroimage.2013.06.016.

[17] H. Santosa, A. Aarabi, S. B. Perlman, and T. Huppert, “Characterization and correction of the false-discovery rates in resting state connectivity using functional near-infrared

spectroscopy," *Journal of Biomedical Optics*, vol. 22, no. 5, p. 055002, May 2017, doi: 10.1117/1.JBO.22.5.055002.

[18] N. Naseer and K.-S. Hong, "fNIRS-based brain-computer interfaces: a review," *Frontiers in Human Neuroscience*, vol. 9, 2015, doi: 10.3389/fnhum.2015.00003.

[19] Y. Gao, P. Yan, U. Kruger, L. Cavuoto, S. Schwaitzberg, S. De, X. Intes, "Functional brain imaging reliably predicts bimanual motor skill performance in a standardized surgical task," *IEEE Transactions on Biomedical Engineering*, pp. 1–1, 2020, doi: 10.1109/TBME.2020.3014299.

[20] A. Y. A. Oku and J. R. Sato, "Predicting Student Performance Using Machine Learning in fNIRS Data," *Frontiers in Human Neuroscience*, vol. 15, 2021, doi: 10.3389/fnhum.2021.622224.

[21] S. Bird, E. Klein, and E. Loper, *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*. O'Reilly Media, Inc., 2009.

[22] T. Shealy, J. Gero, and P. Ignacio Jr, "The neurocognition of engineering students designing: A preliminary study exploring problem framing and the use of concept mapping," in *2022 ASEE Annual Conference & Exposition*, 2022.