The Physiological and Neural Mechanisms of Learning through PS-I

The Neural Basis of Learning through Productive Failure

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Abstract: Productive Failure (PF) is a learning design wherein learners generate solutions for novel problems prior to formal instruction. Research has demonstrated the effectiveness of PF, indicating cognitive mechanisms for why students learn better after encountering difficulties. However, neurophysiological mechanisms underpinning "learning from failure" have yet to be explored, despite robust evidence connecting neural activity, heartbeats, and cognitive processes. The present study explores neural and physiological mechanisms underlying PF, employing neural signature and heartrate variability measurements.

Background of the project

Problem-solving followed by instruction (PS-I), as entailed in learning through Productive Failure (Kapur, 2014), is a powerful design shown to advance students' conceptual understanding and transfer compared to instruction followed by problem-solving (I-PS; Sinha & Kapur, 2021). Within research on PS-I, various cognitive mechanisms have been explored; however, the physiological and neural basis of this design have not yet been studied. The present study-in-progress investigates underlying neural and physiological mechanisms of PS-I compared to I-PS, using electroencephalography (EEG) to measure brain activity and electrocardiography (ECG) to measure heartbeat activity during learning in a naturalistic environment.

EEG research in the past years shows that various neural oscillations or waves are related to cognitive processes. For example, while problem-solving and having an insight, gamma oscillations are enhanced in right prefrontal regions (Rosen & Reiner, 2017), in right anterior superior temporal gyrus (Jung-Beeman et al., 2004), and fronto-central regions (Sheth et al., 2008). Moreover, alpha oscillations are associated with semantic information processing, in particular with searching, accessing, and retrieving information from long-term memory (Klimesch et al. 1997). Since most cognitive tasks draw on these processes, alpha event-related activity can be observed in a wide range of task demands (Klimesch et al. 1997). Theta activity has been related to episodic and working memory as theta event-related synchronization increases parametrically with working memory load and is sustained during the retention period (Jensen and Tesche 2002; Kahana et al. 2001). Since these are all cognitive processes relevant to a learning situation, we measure delta, theta, alpha, beta, and gamma in the present study.

Recent findings have begun to disentangle how different heartbeat measurements are associated with both top-down and bottom-up cognitive processing of emotional stimuli and lower-order cognitive skills (Park & Thayer, 2014; Mather & Thayer, 2018), including for example recalling or memorizing basic knowledge. Specificall, higher resting heartrate variability is associated with more adaptive and functional top-down and bottom-up cognitive modulation of emotional stimuli (Park & Thayer, 2014). We use ECG to investigate different heartbeat measurements, including heart rate variability (HRV), along with differences in EEG activity related to the type of learning situation (i.e., PS-I versus I-PS).

Research goals

With this project I set out to study the physiological and neural mechanisms involved in the Productive Failure learning design. I will investigate the HRV and change of oscillatory brain activity during a learning situation including several simultaneous cognitive processes like attention, working memory, memory retrieval, creativity/search of novel ideas. To do so, I conducted a neuro-physiological study to investigate whether there are differences in brain oscillations between the phases of the conditions (problem solving vs. instruction), between the conditions in the same phases, and how heart rate variability (HRV) is influencing post-test performance. The results will help us understand why the productive failure design is so powerful and what the difference is in terms of cognitive activity in the condition PS-I versus I-PS. By understanding the brain processes, we will have a more thorough understanding on why this learning design works better than the usual direct instruction. This study can bring valuable insights from the neuroscientific point of view into an effective learning design.

Methodology

Participants: We followed previously confirmed methodologies in high-density EEG (e.g. Rosen & Rainer, 2017). A total of 60 healthy right-handed participants (age: 18 – 25 years old), randomly assigned to one of the conditions I-PS or PS-I (30 participants in each condition) were tested using EEG and ECG for all participants.

Design and Tasks: We set up a naturalistic EEG/ECG study in a learning setting. A computerized (Python w/ EEG trigger) version of a validated PF design (Kapur, 2014) was used. The experiment consisted of 3 parts: problem-solving, instruction, and posttest. During the problem-solving phase of the experiment, participants were exposed to problems of standard deviation. During instruction, participants received instructions and tasks with solutions, working through them on their own pace. The last part of the experiment, the post-test, consisted of 13 multiple choice questions on standard deviation. Participants were asked to use the keys 1 to 5 to answer the questions on the computer screen in front of them.

Measures: EEG data were collected with the Ant Neuro EEGO MyLab 128-channel EEG system at the ETHZ Decision Sciences Lab. At the same time, ECG data was collected with an electrode attached to the limb extremities and chest. The computerized version of the PF tasks had integrated markers sent to the EEG systems accordingly in order to form blocks of baselines, and different parts of the experiment. Additionally, participants' answers to multiple choice formed questions in the posttest were recorded and scored by the computerized task.

Procedure: An electrode cap was placed on the head of the participant, on which electrodes were attached using an electroconductive gel. We attached electrodes to the limb extremities and chest wall to allow detection of the voltage changes generated by the myocardium during each cardiac cycle of contraction and relaxation of the heart. The procedure followed classical and well-established ECG/EEG protocols. When all electrodes showed an acceptable to good signal, a laptop was placed in front of the participants, on which they solved the tasks in the order of the condition they were on (PS-I or I-PS). Both conditions consisted of 3 parts: Problem Solving, Instruction, and Posttest. In addition, they received short questionnaires about math anxiety and general questions about feelings in learning situations, cognitive load, and metacognition.

Data Analysis: ECG data processing: The ECG data is being processed using MATLAB based custom scripts for the analysis of heart rate variability (HRV) according to the recommended standards for HRV measurement (Electrophysiology, Circulation 93, 1043-1065 (1996)).

EEG data processing: The EEG data is being processed and analyzed using MATLAB custom scripts and the following toolboxes: EEGLAB for data preprocessing, including Independent Component Analysis (ICA) and artefact correction. Independent Component Analysis (ICA) is being used to identify and remove the eye-blink artifacts. Subsequently, the data will be visually inspected for other large artifact removal. Current source density (CSD) transformation (surface Laplacian) will be subsequently applied to the data in order to attenuate the low-spatial frequency features from the data, especially the cardiac-field artifact (CFA). The power spectral density (PSD) will be calculated using Welch's method. The power values at each electrode for each condition will be averaged over standard EEG frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), gamma (30–70 Hz) and subsequently log-transformed to normalize their distributions.

Statistical analysis: Repeated measures ANOVA and false discovery rate will be used to calculate differences between the conditions.

Expected Findings

Because of the underlying interdependent mechanisms proposed by Kapur (2016) and based on previous electroencephalography research, we expect enhanced gamma oscillations in the PS-I condition (compared to the I-PS condition) in the right prefrontal regions (Rosen & Reiner, 2017), in right anterior superior temporal gyrus (Jung-Beeman et al., 2004), and/or fronto-central regions (Sheth et al., 2008) during the problem-solving phase. Furthermore, we expect enhanced alpha oscillations during the problem-solving phase in the PS-I condition compared to the I-PS condition (Klimesch et al. 1997). We also expect that in the I-PS condition there will be a parametrical increase in theta activity during the instruction phase and a retention thereof in the Problem-Solving phase (Jensen and Tesche 2002; Kahana et al. 2001). As higher HRV is related to a better inhibition, we therefore expect that a higher HRV shows advantages in the PS-I condition (Park & Thayer, 2014). The results will help understand the heart and brain processes involved in productive failure and show how these processes reflect the differences in PS-I versus I-PS. By investigating the brain processes, we will have a more thorough understanding at the neural level on why this learning design works better than the usual direct instruction. This study can bring valuable insights from the neuroscientific point of view.

References

Afonso, V. X., Tompkins, W. J., Nguyen, T. Q., & Luo, S. (1999). ECG beat detection using filter banks. IEEE transactions on biomedical engineering, 46(2), 192-202.

Cranford, K. N., Tiettmeyer, J. M., Chuprinko, B. C., Jordan, S., & Grove, N. P. (2014). Measuring load on working memory: the use of heart rate as a means of measuring chemistry students' cognitive load. Journal of Chemical Education, 91(5), 641-647.

Darnell, D. K., & Krieg, P. A. (2019). Student engagement, assessed using heart rate, shows no reset following active learning sessions in lectures. PloS one, 14(12), e0225709.

Dweck, C. S. (1992). Article commentary: The study of goals in psychology. Psychological Science, 3(3), 165-167.

Electrophysiology, T. F. O. T. E. S. O. C. T. N. A. S. O. P. (1996). Heart rate variability: standards of measurement, physiological interpretation, and clinical use. Circulation, 93(5), 1043- 1065.

Forte, G., & Casagrande, M. (2019). Heart rate variability and cognitive function: a systematic review. Frontiers in neuroscience, 13, 710.

Hopko, D. R., Mahadevan, R., Bare, R. L., & Hunt, M. K. (2003). The abbreviated math anxiety scale (AMAS) construction, validity, and reliability. Assessment, 10(2), 178-182.

Jensen, O., & Tesche, C. D. (2002). Frontal theta activity in humans increases with memory load in a working memory task. European journal of Neuroscience, 15(8), 1395-1399.

Jung-Beeman, M., Bowden, E. M., Haberman, J., Frymiare, J. L., Arambel-Liu, S., Greenblatt, R., ... & Kounios, J. (2004). Neural activity when people solve verbal problems with insight. PLoS Biol, 2(4), e97.

Kahana, M. J., Seelig, D., & Madsen, J. R. (2001). Theta returns. Current opinion in neurobiology, 11(6), 739-744.

Kapur, M. (2014). Productive failure in learning math. Cognitive science, 38(5), 1008-1022.

Klimesch, W., Doppelmayr, M., Schimke, H., & Ripper, B. (1997). Theta synchronization and alpha desynchronization in a memory task. Psychophysiology, 34(2), 169-176.

Klimesch, W., Doppelmayr, M., Pachinger, T., & Ripper, B. (1997). Brain oscillations and human memory: EEG correlates in the upper alpha and theta band. Neuroscience letters, 238(1-2), 9-12.

Klimesch, W., Doppelmayr, M., Pachinger, T., & Russegger, H. (1997). Event-related desynchronization in the alpha band and the processing of semantic information. Cognitive Brain Research, 6(2), 83-94.

Leighton, J. P., Tang, W., & Guo, Q. (2015). Developing and validating the attitudes towards mistakes inventory (atmi): A self-report measure. In annual meeting of the National Council on Measurement in Education (NCME), Chicago, Illinois.

Mather, M., & Thayer, J. F. (2018). How heart rate variability affects emotion regulation brain networks. Current opinion in behavioral sciences, 19, 98-104.

McGowan, A., Hanna, P., Greer, D., & Busch, J. (2018, November). Lecturing to Your Students: Is Their Heart In It?. In Proceedings of the Future Technologies Conference (pp. 1005-1016). Springer, Cham.

Minkley, N., Xu, K. M., & Krell, M. (2021, April). Analyzing relationships between causal and assessment factors of cognitive load: associations between objective and subjective measures of cognitive load, stress, interest, and self-concept. In Frontiers in Education (Vol. 6, p. 53). Frontiers.

Park, G., & Thayer, J. F. (2014). From the heart to the mind: cardiac vagal tone modulates top-down and bottom-up visual perception and attention to emotional stimuli. Frontiers in psychology, 5, 278.

Rosen, A., & Reiner, M. (2017). Right frontal gamma and beta band enhancement while solving a spatial puzzle with insight. International Journal of Psychophysiology, 122, 50-55.

Seth, A. K., Dienes, Z., Cleeremans, A., Overgaard, M., & Pessoa, L. (2008). Measuring consciousness: relating behavioural and neurophysiological approaches. Trends in cognitive sciences, 12(8), 314-321.

Sinha, T., & Kapur, M. (2021). When Problem Solving Followed by Instruction Works: Evidence for Productive Failure. Review of Educational Research, 00346543211019105.

Sinha, T., Kapur, M., West, R., Catasta, M., Hauswirth, M., & Trninic, D. (2021). Differential benefits of explicit failure-driven and success-driven scaffolding in problem-solving prior to instruction. Journal of Educational Psychology, 113(3), 530.

Thayer, J. F., Åhs, F., Fredrikson, M., Sollers III, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews, 36(2), 747-756.

Thayer, J. F., & Sternberg, E. (2006). Beyond heart rate variability: vagal regulation of allostatic systems. Annals of the New York Academy of Sciences, 1088(1), 361-372.