MIS Quarterly

RESEARCH ARTICLE

AN FMRI EXPLORATION OF INFORMATION PROCESSING IN ELECTRONIC NETWORKS OF PRACTICE

Thomas O. Meservy
Information Systems Department, Marriott School of Business, Brigham Young University,
Provo, UT 84602 U.S.A. {tmeservy@byu.edu}

Kelly J. Fadel
Department of Management Information Systems, Utah State University,
Logan, UT 84322 U.S.A. {Kelly.Fadel@usu.edu}

C. Brock Kirwan
Department of Psychology and Neuroscience Center, Brigham Young University,
Provo, UT 84602 U.S.A. {kirwan@byu.edu}

Rayman D. Meservy
Information Systems Department, Marriott School of Business, Brigham Young University,
Provo, UT 84602 U.S.A. {meservy@byu.edu}

Appendix A

Prior IS Research on Electronic Network of Practice Forums

Recent IS research has begun to explore behavioral filtering patterns associated with content and contextual cues on a network forum. Using eye-tracking technology, this work has shed light on the cues attended to during filtering (Meservy et al. 2014) and how the attentional switching patterns between these cues (e.g., evaluating all cues of a single solution versus comparing a single cue across multiple solutions) affects filtering accuracy (Fadel et al. 2015). In the present study, we extend this prior work while making note of two important observations. First, although these studies have shed light on the role of different types of cues in forum information filtering, they are limited with respect to their ability to elucidate the actual cognitive processes that underlie this filtering. Gaze data from an eye-tracker can prompt inferences about the types of information attended to during the filtering process, but it is silent on the neurocognitive processes that occur. This leaves several important questions for ongoing theory development. For example, are different types of cues (e.g., content versus contextual) processed by different cognitive centers in the brain, which, depending on their relative activation levels, could produce more or less accurate filtering decisions? Or do similar neural mechanisms underlie both content and context-based processing, and any difference lies only in the type of information evaluated? Moreover, which types of cues are most important when filtering solutions, and how do combinations of cues affect this filtering process on both a behavioral and a cognitive level?

Second, prior studies have relied on dual process theories of cognition (Chaiken 1987; Petty and Cacioppo 1986) as a theoretical frame for examining information filtering on a network forum. Originating in the domain of persuasion psychology, dual process theories posit that persuasion can occur via two primary cognitive routes: the central (systematic) route, in which the arguments of the message itself are carefully evaluated, and the peripheral (heuristic) route, in which judgments are made primarily based on surrounding peripheral cues (Chaiken 1980; Petty et al. 2005; Petty and Cacioppo 1986). Applying this framing to the context of solutions on a network forum, central route processing would entail evaluation of solution content, and peripheral route processing would rely on evaluation of surrounding contextual cues such as source expertise and validation (Fadel et al. 2015; Meservy et al. 2014). We believe this conceptualization offers a useful lens for characterizing different types of information filtering behaviors; however, dual process theorists have noted that cues themselves are not categorically central or peripheral, but instead can play a dualistic role, influencing judgments either centrally or peripherally depending on their context and relevance to the information content being evaluated (Chaiken and Trope 1999). As observed by Petty et al. (2005, p. 110), "certain variables have a chameleon quality in that they induce different processes in different situations. Therefore, any given variable should not be thought of as exclusively fulfilling any one role." In this paper, our objective is not to label specific cues as strictly central or peripheral per se, but rather to explore the cognitive differences between filtering based on these cues. We therefore employ the terms *content* and *context* to refer, respectively, to solution content and surrounding contextual cues such as expert and community validation.

Appendix B

Experimental Instrument

Table B1. Problem Descriptions

Phase	Problem	Description
Training	Split a string on spaces	Write a block of code that splits a string into separate strings everywhere there is a space.
Experiment	Concatenate two lists	Write a block of code that takes two lists or arrays of integers and concatenates them together into a single new list or array.
Experiment	Calculate the factorial of a number	Write a block of code that calculates the factorial of an integer (the product of the integer and all the integers below it).
Experiment	Identify the greatest element in an array	Write a block of code that determines the largest value in an array of integers.
Experiment	Sum the values of an array	Write a block of code that computes the sum of all the values in an integer array.
Experiment	Split array	Write a block of code that splits an array of integers into two separate arrays or lists at a predetermined point.
Experiment	Check for palindrome	Write a block of code that determines whether a string is a palindrome (a word is spelled the same forward or backward).

Eight solutions for each problem written in C#, Java, or C++ were gathered from programming forums, standardized to C#, and validated for use in the experiment. These languages were selected because they are syntactically similar to each other and are among the most popular modern programming languages (Cass 2016; TIOBE 2016). The figures below show examples of these solutions in the experimental instrument.

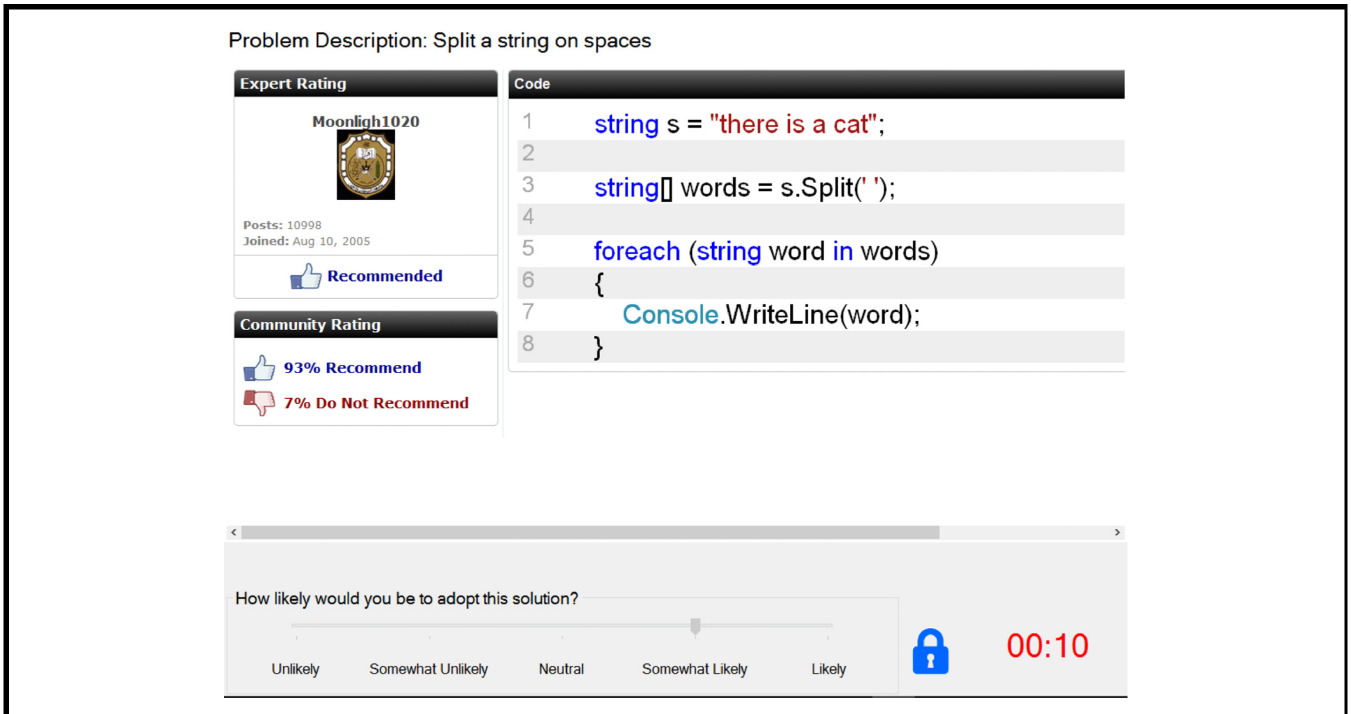


Figure B1. Sample Stimulus

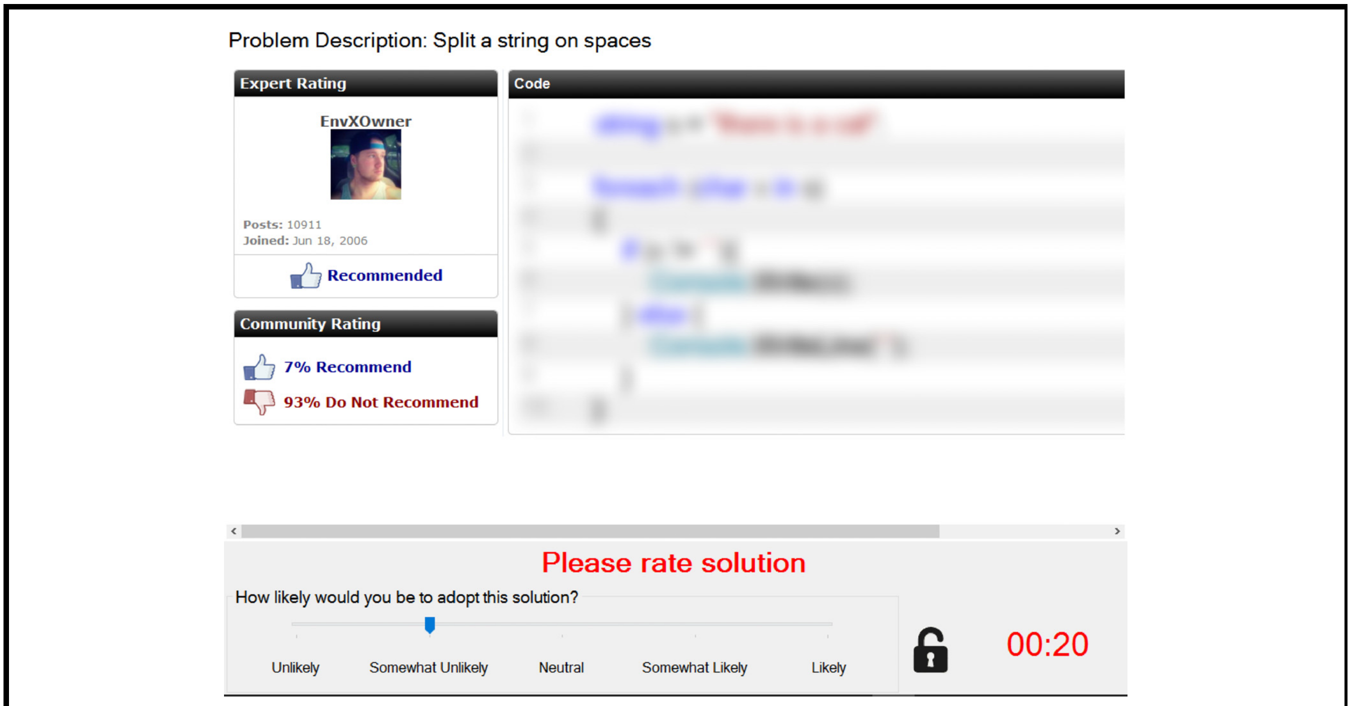


Figure B2. Sample Blurred Stimulus (Context Phase)

Appendix C

Experimental Procedure

A high-level overview of the experimental procedure is shown in Figure C1. When participants arrived at the MRI facility, they were presented with a consent form and again completed an MRI screening form to ensure their safety inside the scanner. Participants were then shown an introductory video to acclimate them to the scanner and to explain the experimental instrument and associated task. The video explained that each participant would be shown solutions to several programming problems and would be asked to rate each solution using a hand-held controller that operated the custom experimental instrument while in the scanner. After the video, the researchers answered any questions related to the task, the experimental instrument, the programming solutions, or any safety concerns associated with the scanner.

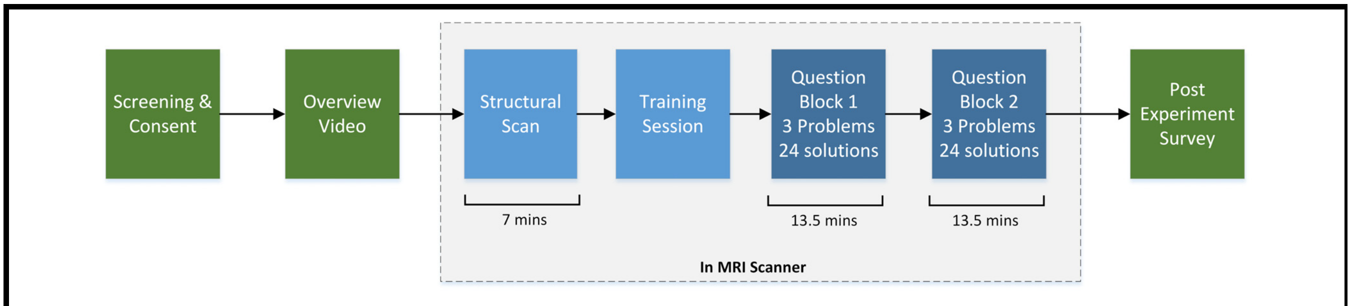


Figure C1. High-Level Overview of Experiment

After the introductory/consent process, each participant was taken to the scanner room and prepared for the experiment. The participant was first outfitted with headphones and a microphone to enable periodic communication with the researchers during the experiment. This ensured the participant's safety and ongoing comprehension of what s/he was asked to do. The participant was then situated in the scanner, and an initial standard-resolution localization and structural scan (approximately 7 minutes) was conducted to capture the participant's brain structure so that it could be co-registered with the functional MRI data. Following the structural scan, a training run was conducted to familiarize the participant with the experimental instrument. In this run, the participant was presented with four different solutions to a single programming problem. Each solution was presented for a total of 30 seconds, comprising both the context and content phases described above. Between each presented solution, there was a short,two-second break during which the participant was shown a baseline block (a gray screen with a black cross in the middle), as is common in fMRI experiments (Huettel et al. 2003; Jenkins et al. 2016). At the conclusion of the training run, researchers answered any remaining participant questions before proceeding to the experimental task. Figure C2 shows the timings for each block presented.

During the primary experimental task (27 minutes), the participant was shown each of the 48 programming solutions in sequence. Participants viewed the experimental stimuli on a large MR-compatible monitor at the opening of the MRI scanner by means of a mirror attached to the head coil. The participant used a four-button handheld controller to interact with the instrument and provide ratings of the likelihood of adopting the presented solutions. Each solution was presented for a total of 30 seconds, comprising both the context and content phase described above, followed by a two-second break during which the participant was shown the baseline block. As each context and content phase was self-terminated when the participant locked in a rating (see Figure C2), each of these events had a variable duration. Consequently, in our fMRI individual-level (first-level) regression analyses described below, we modeled the context phase and content phase as variable-length events. The time remaining in each 30-second block after participants had locked in their content rating was included with the 2-second inter-trial interval in the model's baseline, thus accomplishing a random temporal jitter between trials in the model. This represents a mixed blocked/event-related design (Petersen and Dubis 2012) where the task occurred in extended periods (as in a block design) but were of a variable duration and had a variable delay between them (as in an event-related design). This design more closely mimics what a participant might do when seeking information from an online forum.

To minimize cognitive burden and participant fatigue, solutions were grouped by problem, and the six problems were randomly grouped into two 3-problem blocks so that the participant could rest between blocks. To avoid any confounding effects due to ordering, all other aspects of stimulus presentation were randomized, including problem order, solution order within each problem, expert and community validation levels, and information about the expert who validated the solution. After concluding the primary experimental task, the participants were escorted out of the scanner to an adjoining room, where they completed a short survey that captured demographic information and perceptions about the experimental task.

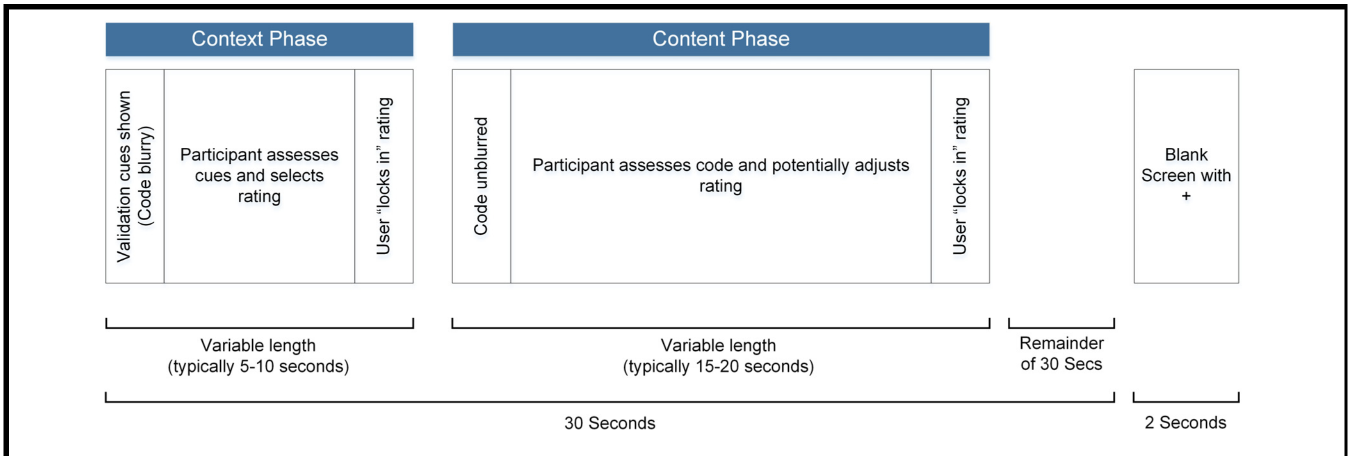


Figure C2. Overview of Each Block

Appendix D

Ordinal Mixed Effects Regression Models Suitability

Before employing ordinal mixed effects regression models with both fixed and random effects, we estimated a series of preliminary models to determine whether multilevel analysis was appropriate for our data (i.e., whether the higher-order variables of solution, problem, and participant exerted discernable random effects on the dependent variable). We began by estimating a single intercept-only baseline model with final rating as the dependent variable. We then estimated a random-effects-only model with final rating as the dependent variable and random intercept effects for solution, problem, and participant. A log likelihood comparison test revealed that the fit of the random-effects-only model improved significantly over that of the baseline (χ^2 = 434.32, p < .001), indicating some explanatory power of the grouping variables. To ascertain the magnitude of the individual random effects, we calculated an intraclass correlation (ICC) for each higher-order variable (Snijders and Bosker 2012), which indicates the proportion of total variance in the final rating explained by each higher-order variable. Solution had the largest ICC (.34), followed by participant (.04) and problem (.00). We tested the significance of these effects by comparing the fit of models that included each random effect independently against the fit of the baseline model. Results showed no significant improvement in fit for problem, indicating that the problems into which the solutions were grouped did not affect the final ratings. Effects for both solution (χ^2 = 404.11, p < .001) and participant (χ^2 = 13.989, p < .001) were significant, indicating that average final rating did vary somewhat by both participant and solution. However, although participant effects were entirely random in our design, solutions were experimentally manipulated by altering their code quality, which could account for at least some of the between-solution variance in final ratings. We therefore estimated an additional mixed-effects model that included code quality as a fixed-effect covariate. As expected, the ICC of solution (.09) dropped substantially under this model; however, a log likelihood comparison still showed a significant random effect for solution (χ^2 = 56.741, p < .001), indicating that final ratings may have been higher (or lower) for some solutions than for others due to experimentally exogenous factors. Therefore, although the ICC values indicate relatively modest random effect sizes, we retained both participant and solution as higher-order random effects variables in our analyses to account for their potential explained variance in the solution ratings.

Appendix E

fMRI Analysis

Two individual-level regression analyses were conducted to fit the ideal hemodynamic response to the brain data. Both used six motion regressors (for roll, pitch, yaw, and translations in the X, Y, and Z directions) and seven polynomial regressors per run to account for scanner drift in addition to behavioral regressors coding for task conditions. All behavioral regressors were modeled as a boxcar function with variable duration according to the participants' latency to respond convolved with the canonical hemodynamic response.

The first regression analysis separately modeled the four factorial combinations of high/low community and high/low expert validation levels in the context phase of each trial in order to test the effect of context cues on the preliminary ratings in the context phase. To test the effect of the consistency between context cues and final subjective rating, the regression model also contained two regressors coding for whether the final subjective rating of the solution was consistent with both the expert and community validation (i.e., all high levels or all low levels). Two more regressors coded for final ratings that were high or low but where the expert and community validation levels were mixed (one high and the other low).

The second regression analysis modeled four regressors according to whether the subjective participant rating was high or low in either the context phase (preliminary rating) or the content phase (final rating), regardless of the community or expert validation or the objective code quality. These models, which were used to test processing in the content phase, were included under the rationale that participants' neural activation patterns would correspond more closely with their perceptions of the information being presented (i.e., a solution believed by the participant to be high quality) than with the actual treatment condition.[1] For these models, subjective ratings of 4 or 5 were collapsed as "high" and ratings of 1 or 2 were collapsed as "low."

Structural data were first co-registered to the functional scans and then normalized to MNI template space using ANTs. The results of the single-subject regression analyses (known as beta maps or parameter estimates) were blurred using an 8mm FWHM Gaussian and then normalized to MNI space using the transformation calculated from the structural scan alignment. All group-level analyses described below were performed in MNI space and were masked for regions where we had spatial coverage in the functional scan for all participants in the sample, resulting in the exclusion of the more inferior aspect of the cerebellum since coverage of the cortex was prioritized.

We corrected for multiple comparisons using the AFNI 3dClustSim program, which uses Monte Carlo simulations to calculate the appropriate clusters of voxels that are large enough to be statistically significant (Forman et al. 1995; Xiong et al. 1995). Spatial smoothness was estimated for each subject using AFNI program 3dFWHMx based on the residuals resulting from the individual-level regression analyses described above (see Cox et al. 2017). The mean smoothness parameters for the group were used in the 3dClustSim program as the estimate of overall spatial smoothness when simulating the noise distribution. Based on the Monte Carlo simulations, we used a voxel-wise threshold $p < .001$ and minimum cluster threshold of 58 voxels.

[1]As noted in the paper, a Pearson chi-squared test of independence showed that final ratings were closely associated with the high and low experimental conditions for expert rating ($\chi^2 = 166.48$, $p < 0.001$) and community rating ($\chi^2 = 886.66$, $p < 0.001$) in the context phase and code quality ($\chi^2 = 401.52$, $p < 0.001$) in the content phase.

Appendix F

fMRI Results

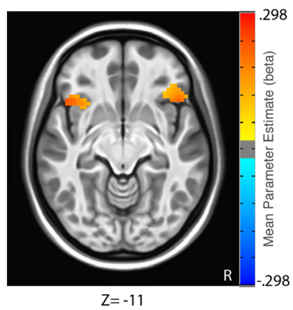
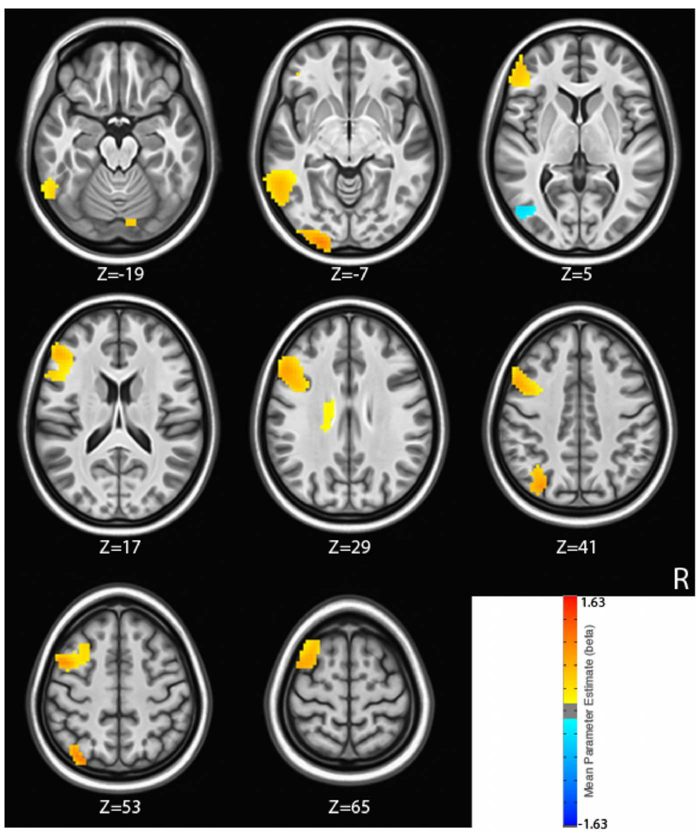


Figure F1. Clusters of Significant Activation in the Contrast of High Final Rating > Low Final Rating Included in the Bilateral Anterior Insula. R = right



As this contrast resulted in large activation differences, all results are presented with voxel-wise *p* < .0001 and a spatial extent threshold of k > 58 contiguous voxels.

Figure F2. Clusters of Significant Activation in the Contrast of Content Phase > Context Phase. R = right

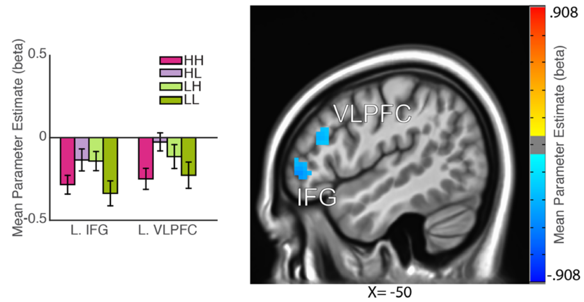


Figure F3. Clusters of Significant Activation for Congruent (Top) Versus Incongruent (Bottom) Contextual Cues

References

Cass, S. 2016. "The 2016 Top Programming Languages," IEEE Spectrum (http://spectrum.ieee.org/computing/software/the-2016-top-programming-languages).

Chaiken, S. 1980. "Heuristic Versus Systematic Information Processing and the Use of Source Versus Message Cues in Persuasion," *Journal of Personality and Social Psychology* (39:5), pp. 752-766.

Chaiken, S. 1987. "The Heuristic Model of Persuasion," in *Social Influence: The Ontario Symposium*, M. P. Zanna, J. M. Olson, and C. P. Herman (eds.), Hillsdale, NJ: Erlbaum, pp. 3-39.

Chaiken, S., and Trope, Y. 1999. *Dual-Process Theories in Social Psychology*, New York: Guilford Press.

Cox, R. W., Chen, G., Glen, D. R., Reynolds, R.C., and Taylor, P. A. 2017. "FMRI Clustering in AFNI: False-Positive Rates Redux," *Brain Connectivity* (7:3), pp. 152-171.

Fadel, K. J., Meservy, T. O., and Jensen, M. L. 2015. "Exploring Knowledge Filtering Processes in Electronic Networks of Practice," *Journal of Management Information Systems* (31:4), pp. 158-181.

Forman, S. D., Cohen, J. D., Fitzgerald, M., Eddy, W. F., Mintun, M. A., and Noll, D. C. 1995. "Improved Assessment of Significant Activation in Functional Magnetic Resonance Imaging (FMRI): Use of a Cluster-Size Threshold," *Magnetic Resonance in Medicine* (33:5), pp. 636-647.

Huettel, S. A., Song, A. W., and McCarthy, G. 2003. *Functional Magnetic Resonance Imaging.*, Sunderland, MA: Sinauer Associates, Inc.

Jenkins, J. L., Anderson, B. B., Vance, A., Kirwan, C. B., and Eargle, D. 2016. "More Harm Than Good? How Messages That Interrupt Can Make Us Vulnerable," *Information Systems Research* (27:4), pp. 880-896.

Meservy, T. O., Jensen, M. L., and Fadel, K. J. 2014. "Evaluation of Competing Candidate Solutions in Electronic Networks of Practice," *Information Systems Research* (25:1), pp. 15-34.

Petersen, S. E., and Dubis, J. W. 2012. "The Mixed Block/Event-Related Design," *NeuroImage* (62:2), pp. 1177-84.

Petty, R. E., and Cacioppo, J. T. 1986. "The Elaboration Likelihood Model of Persuasion," *Advances in Experimental Social Psychology* (19), pp. 123-205.

Petty, R. E., Cacioppo, J. T., Strathman, A. J., and Priester, J. R. 2005. "To Think or Not to Think: Exploring Two Routes to Persuasion," in *Persuasion: Psychological Insights and Perspectives*, T. C. Brock and M. C. Green (eds.), Thousand Oaks, CA: SAGE Publications, pp. 81-116.

Snijders, T. A. B., and Bosker, R. J. 2012. *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling* (2nd ed.), Los Angeles: SAGE Publications.

TIOBE. 2016. "TIOBE Index for October 2016" (http://www.tiobe.com/tiobe-index/).

Xiong, J., Gao, J. H., Lancaster, J. L., and Fox, P. T. 1995. "Clustered Pixels Analysis for Functional MRI Activation Studies of the Human Brain," *Human Brain Mapping* (3:4), pp. 287-301.