

UC Merced

Proceedings of the Annual Meeting of the Cognitive Science Society

Title

Snapshots of Working Memory: Using Early Eye Movements to Capture Temporal Dynamics

Permalink

<https://escholarship.org/uc/item/2t04c54n>

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 35(35)

ISSN

1069-7977

Authors

Lange, Nicholas
Thomas, Rick
Buttaccio, Daniel
et al.

Publication Date

2013

Peer reviewed

Snapshots of Working Memory: Using Early Eye Movements to Capture Temporal Dynamics

Nicholas D. Lange (ndlange@gmail.com) †‡

Rick P. Thomas (Rickey.P.Thomas-1@ou.edu) ‡

Daniel R. Buttaccio (buttacciodr@ou.edu) ‡

Eddy J. Davelaar (e.davelaar@bbk.ac.uk) †

†Birkbeck, University of London, Department of Psychological Sciences,
Malet Street, London, UK, WC1E 7HX

‡University of Oklahoma, Department of Psychology
Lindsey Street, Norman, OK, USA 73019

Abstract

Research investigating top-down attentional capture has demonstrated a tight coupling of working memory content with attention and eye movements. By capitalizing on this relationship, we have developed a novel methodology called the Memory Activation Capture (MAC) procedure for measuring the dynamics of working memory content supporting complex cognitive tasks (e.g., decision making, problem solving). By observing which items are preferentially fixated in *task irrelevant arrays* containing *task relevant information*, we gain a measure of working memory content as the task evolves through time. The efficacy of the MAC procedure is demonstrated in a hypothesis generation task. Results suggest a two-stage process following hypothesis retrieval whereby it undergoes a brief period of heightened activation before entering a lower activation state while being maintained for output. The present effects are of additional general interest as they represent the first demonstrations of top-down attentional capture driven by participant-established WM content retrieved from long-term memory.

Keywords: attention, memory, decision making, eye tracking, process tracing, hypothesis generation

Introduction

The considerable interest in understanding the cognitive dynamics of information use over time is underscored by the proliferation of process-tracing methodologies within several domains. Think-aloud procedures, in which a participant provides concurrent verbalization of their cognitive states while performing a task, were among the first of these techniques to be developed (Ericsson & Simon, 1993; Ford, Schmitt, Schechtman, Hults, & Doherty, 1989; Montgomery & Svenson, 1976; Svenson, 1979) and still enjoy widespread use today (Schulte-Mecklenbeck, Kühberger & Ranyard, 2011). The usage of eye movements as a window to dynamic cognitive processing has flourished as of late with application in several fields including decision making (Franco-Watkins & Johnson, 2011; Glaholt, Wu, & Reingold, 2009; Glaholt & Reingold, 2011; Sutterlin, Brunner, & Opwis, 2008), problem solving (Ellis, Glaholt, & Reingold, 2011), categorization (Rehder & Hoffman, 2005a, 2005b), language comprehension (Cooper, 1974; Tanenhaus, 1995), and diagnostic reasoning (Renkewitz & Jahn, 2012).

The methodology forwarded here shares the same goal as process-tracing techniques, namely to gain better understanding of cognitive dynamics by measuring information use as the task naturally unfolds. Our method, however, takes a novel approach towards revealing the content of working memory by relying on the recent literature addressing attentional “top-down capture” effects demonstrating a tight coupling between the content of WM and the deployment of attention and eye movements. For instance, Soto, Heinke, Humphreys, and Blanco (2005) and Soto & Humphreys (2007) provide evidence that attention is automatically captured by the contents of WM (although for contrasting evidence see Woodman & Luck, 2007). As the presently forwarded methodology relies on eye movement data it is of particular importance that Soto et al. (2005) found eye movements to be sensitive to the spatial congruency of target and WM-matching items. Moreover, Moores, Laiti, and Chelazzi (2003) found that first saccades were biased towards WM-matching items as well as semantic associates of items maintained in WM.

As eye movements are biased by the content of WM, it may be possible to capitalize on this bias to develop a measure of WM content deployable in complex cognitive tasks. Specifically, by presenting brief visual arrays containing task related information at various points in time, differences in the oculomotor guidance towards the items contained in such “WM probe arrays” could be taken as evidence regarding the active content of WM at the time of the array presentations. In this way our methodology can be thought of as an effort to capture *snapshots* of WM across time. We refer to our methodology as the Memory Activation Capture (MAC) procedure. Although the logic of this procedure (as well as its specific advantages) have been treated elsewhere (Lange, Thomas, Buttaccio, & Davelaar, 2012), the present experiment represents the first deployment of this procedure in a complex cognitive task.

In the present paper, we deploy this procedure in the context of a memory retrieval task to investigate the temporal dynamics of hypothesis generation. We define hypothesis generation as a general case of cued recall in which the observation of one or multiple cues can lead to the retrieval of one or multiple hypotheses (Dougherty, Thomas, & Lange, 2010; Thomas, Dougherty, Sprenger, & Harbison, 2008). In our day-to-day lives, we utilize this

process to better understand the occurrences we witness in our environment. For instance, if a friend is acting differently than usual you may generate various explanations for their behavior. A professional example comes to us through medical diagnosis in which a physician observes various symptoms from a patient and retrieves associated diagnoses from long term memory (LTM).

Recently, we have investigated the influences of time and sequence on hypothesis generation by formulating a model addressing the influence of WM dynamics during information acquisition on the retrieval (i.e., generation) of hypotheses and confirmed model predictions (Lange, Thomas, and Davelaar, 2012; Lange, Thomas, Buttaccio, Illingworth, & Davelaar, 2012; Lange, Davelaar, & Thomas, In Press). This model assumes that the memory activation associated with each piece of acquired information (i.e., data) undergoes a dynamic rise and fall over time in accordance with 1) competition from other acquired items, 2) bottom-up activation, and 3) its self-recurrent excitation (see Davelaar, Goshen-Gottstein, Ashkenazi, Haarmann, & Usher (2005) for a fuller treatment and computational details). We hypothesize that the memory activations of acquired data and retrieved hypotheses are subject to the same competitive WM dynamics. We now provide a hypothetical example of how the memory activations of data and hypotheses may trade off in a simplified medical diagnosis task and use this example to illustrate a hypothetical deployment of the MAC procedure.

Figure 1 provides a hypothetical example of the deployment of our procedure in the context of a simplified medical diagnosis task (e.g., hypothesis generation, diagnostic reasoning). The task is initiated with the presentation of a patient symptom (e.g., fever). As this information is acquired, its associated memory representation becomes activated and rises. Shortly after this data has been acquired, the memory activation associated with an associated diagnosis begins to rise and is generated when its memory activation crosses a threshold distinguishing the content of WM. The memory activation of the diagnosis continues to rise while at the same time the activation associated with the symptom decreases due to competitive WM processes. The points labeled T1-T4 represent points at which the WM Probe Array could be presented. In this example, we assume that the probe array (represented visually) contains four items: the diagnosis and three distractor items. At T1, the diagnosis would not be fixated more than the distractors in the probe array. However, at T2, the diagnosis has been retrieved and resides in WM. At this point, we would expect to see the diagnosis being fixated more often than the distractor items, indicating that it is active in WM. Moreover, at time points T3 and T4 we might see a rise and fall in the fixation rate of the diagnosis due to the rise and fall of its associated memory activation. An important aspect regarding our use of top-down oculomotor capture as a measure of WM content is that, unlike any visual search task, the WM Probe Arrays used in the present experiments are completely task

irrelevant. That is, the participant does not have a task to perform on the array and is not instructed for any response to the arrays.

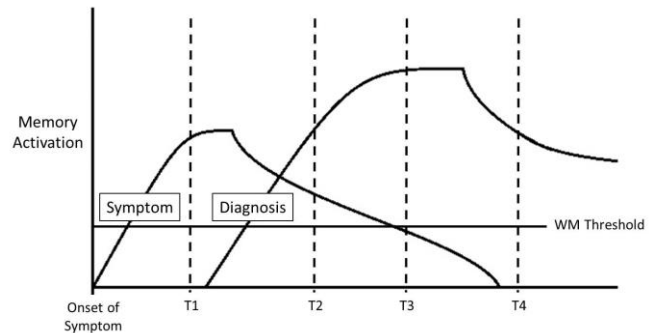


Figure 1: Hypothetical deployment of the MAC procedure in the context of a simplified medical diagnosis task. Time points T1-T4 represent the presentations of the WM Probe Arrays where eye movements are measured.

We now present an experiment deploying the MAC procedure to investigate the time course of memory retrieval in the context of a hypothesis generation task. The task is explained to the participants as a “Cause and Effect learning task” in which they are to learn associations between colors, some representing Causes and some representing Effects emanating from those Causes. Thus, the present task contains the essential structure for a hypothesis generation task in which one reasons from events (Effects) to explanations (Causes).

Deploying the MAC Procedure

In this experiment we test the efficacy of the MAC procedure to detect the retrieval of a likely hypothesis into working memory and its sensitivity to retrieval timing.

Participants Twenty-three participants from the University of Oklahoma participated for course credit.

Apparatus, Stimuli, and Procedure Eye movements were recorded monocularly (dominant eye) via an Eye Link 1000 (SR Research) at a sampling rate of 1000 Hz and a distance of 60 cm from a 17” monitor. Stimulus presentation and data recording were controlled via Experiment Builder. A ResponsePixx box was used to collect manual responses during the experiment. Eight colors were used during the experiment (blue, green, orange, purple, red, salmon, white, and yellow). Gray was used as the background color throughout the experiment and the fixations were black. Prior to the start of the experiment, the colors were randomly assigned as causes, effects, or distractors.

The experiment consisted of two main phases, a training phase in which the participants learned probabilistic relationships between the Causes and Effects followed by an elicitation phase in which the MAC procedure was deployed. Training consisted of two parts, passive exemplar training and active exemplar training in what could be considered as a “probabilistic paired-associates category

learning task”. Participants first went through the passive training portion which was followed by active training and the entirety of the training phase constituted four repeated pairings of passive and active blocks. In passive training, the participant was presented with many individual exemplars in which a single “Cause” and “Effect” pairing with an arrow going from the Cause towards the Effect. Each exemplar appeared for 1,500 ms after which point the participant pressed the response box to view a new Cause and Effect exemplar. There were four screen configurations in which the pairing could appear and these were randomly selected on each trial to ensure that the Causes and Effects were balanced across spatial locations.

During active training, the participant was presented with an exemplar in which the Cause was absent and the participant had to select the likely Cause with a manual button press. The participant then received feedback (correct/incorrect) for each trial and was shown the correct Cause on incorrect trials. For the first block of active training, participants had 3,000 ms to respond with the related Cause and this decreased to 1,500 ms for the second, third, and fourth blocks.

The statistical associations between the Causes and Effects were dictated by the values in Table 1. Note, Effect 1 was highly diagnostic of Cause 1 and Effect 2 was highly diagnostic of Cause 2 (while Effects 3 and 4 were non-diagnostic). For example, there is a 90% chance that Effect 1 will be present given Cause 1 as described in Table 1, therefore when Effect 1 is observed it is highly likely that Cause 1 is responsible. Additionally, it is important to note that Effect 1 and Effect 2 were complementary with one another as were Effects 3 & 4. For instance, in medical diagnosis context Effect 1 could represent “fever” and Effect 2 would represent “no fever”.

Table 1: The Cause-Effect contingency table governing the associations between the Causes and Effects.

| | Effect 1 | Effect 2 | Effect 3 | Effect 4 |
|---------|----------|----------|----------|----------|
| Cause 1 | 0.9 | 0.1 | 0.9 | 0.1 |
| Cause 2 | 0.1 | 0.9 | 0.9 | 0.1 |

The elicitation phase, in which we deployed the MAC procedure (and recorded eye movements), commenced following the fourth round of active training. In this phase, participants were instructed that on each trial they would be presented with an Effect and would have to respond (manually with left/right button press) to select the most likely Cause given the effect. On 2/3 of trials a WM Probe Array was briefly presented for 396 ms containing four colored disks (top to center = 15 mm and right to center = 14). Two of the colors were those of the Causes and the two other colors were those assigned as distracter colors at the beginning of the experiment (which had not appeared at any point prior in the experiment). These four colored disks were positioned around a circle (unseen) with a radius of 86 mm. Relative to a clock face one disk appeared at 1 or 2 o’clock, another at 4 or 5 o’clock, another at 7 or 8 o’clock, and the last at 10 or 11 o’clock. Each of the four items

(Causes & Distractors) were randomly assigned to these four positions in the WM probe array.

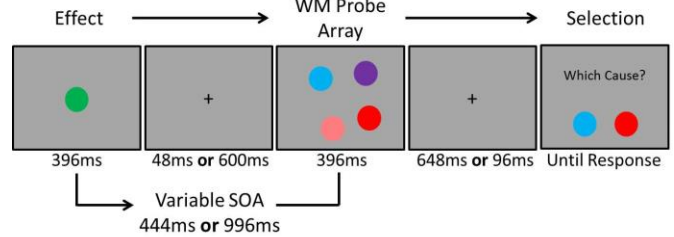


Figure 2: Trial schematic demonstrating the sequence of events for trials on which the WM Probe Array appeared.

The focal independent variable was the timing of the WM Probe Array on the trials in which an array appeared. The WM Probe Arrays were manipulated to appear at a variable SOA following the onset of the Effect. For the Short SOA condition, the ISI with a fixation cross was presented for a brief duration (48 ms) and for the Long SOA condition the fixation was presented for a longer duration (600 ms). The relative duration of the second fixation cross was inverted from the duration of the first fixation (600 ms for Short SOA trials and 48 ms for Long SOA trials). On the remaining third of trials, no WM Probe Array appeared. These trials were included to limit the expectation of the WM Probe Array’s appearance throughout elicitation. On these “no-probe trials”, the Effect was followed by a fixation for 1092 ms prior to the selection screen. Thus, total trial time was equal across all trials. Participants completed 36 trials (12 Short SOA, 12 Long SOA, and 12 No-Probe trials). Within each of these conditions, three trials occurred with each Effect. Participants were not informed of WM probe array’s appearance nor were they provided instruction for any response when it appeared.

Although Effects 3 and 4 were presented in the elicitation phase, we were not concerned with these trials as these Effects were non-diagnostic. Effects 1 and 2, on the other hand, were highly diagnostic and, accordingly, it is on these trials where our interest and predictions fall. On these trials, the likely hypothesis should be retrieved into WM and bias eye movements towards its matching representation in the WM probe array through top-down capture. Thus, we hypothesized that participants would fixate the likely hypothesis first more often than the unlikely hypothesis and distractors. Additionally, we hypothesized that a difference in the time course of the generation process might emerge between the two SOA conditions as a result of the time pressure applied in the active training.

Results

For eye movement analyses, regions of interest (ROIs) were centered on each colored disk appearing in the WM Probe Arrays measuring 34.5 mm top to center and 32 mm right to center. A disk was considered fixated when a fixation landed in its corresponding ROI. For analysis we took our primary DV as the first WM Probe Array disk fixated. Only trials in which participants were presented with a diagnostic

Effect (i.e., Effect 1 or 2) were analyzed. Trials on which the participant selected the less likely Cause at the end of the trial were considered as incorrect trials and discarded prior to analysis (24 %)¹. Two additional criteria were applied to each trial for inclusion in the analysis 1) the participant must have been fixating within an ROI at the center of the screen at the beginning of the trial (32 mm tall x 34 mm wide) and 2) an item in the array must have been fixated. An additional 8% of the total trials were discarded for central fixation criterion and an additional 37% of the total trials were discarded for the array item fixation criterion.

As displayed in Figure 3 the likely Cause was more often fixated first than the unlikely Cause and distractors in the Short SOA condition, $z = 4.3$, $p < 0.001$, and $z = 4.96$, $p < 0.001$, as well as in the Long SOA condition, $z = 1.91$, $p < 0.056$, and $z = 3.45$, $p < 0.001$ (although this difference was marginal between the likely and unlikely Cause). More importantly, logistic regression revealed that the likely Cause was more often fixated first in the Short SOA condition than in the Long SOA condition, $\chi^2(1) = 5.92$, $p < .05$. No such differences were found for the unlikely Cause, $\chi^2(1) = 1.36$, $p = .24$, or distractors, $\chi^2(1) = 2.9$, $p = .08$.

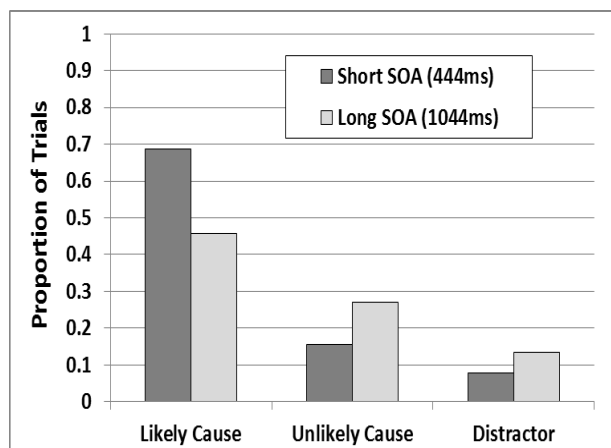


Figure 3: Proportion of trials on which each item type was the first array item fixated. Results demonstrate increased fixation of the Likely Cause at the Short SOA relative to the Long SOA and greater fixation rates for the Likely Cause relative to the Unlikely Cause and Distractors.

Discussion

We have developed a novel methodology to non-intrusively measure the content of WM in complex cognitive tasks as they unfold over time. Here we deployed the MAC procedure in the context of a hypothesis generation task in which participants retrieved a hypothesis from LTM based on the presentation of an associated cue. Our procedure shares the aims of the multitude of process tracing approaches that have been developed over the last thirty years – to assess moment by moment cognitive dynamics

¹ The plotted numerical values change very little with the inclusion of incorrect trials and the pattern of statistical results remains identical.

and changes in the representations utilized en route to final task output. By capitalizing on the tight connection between WM content and attentional allocation via top-down capture (Soto, Heinke, Humphreys, & Blanco, 2005; Soto & Humphreys, 2007), we have developed a new method of such assessment. Moreover, by designing our procedure to assess WM content briefly and on task-irrelevant arrays, we have aimed to develop a procedure that will be less interfering to the processes under investigation than traditional processing measures which essentially constrain the participant with a dual-task (see Russo, 1978; Russo, Johnson, & Stevens, 1989).

Two important effects manifest in the present experiment: 1) The Likely Cause was most often fixated first relative to the other items in the WM probe arrays, and 2) There was an effect of SOA such that the likely Cause was more likely to be fixated at the shorter SOA. It has previously been suggested (Makovski & Jiang, 2008) that biases towards WM matching content, as revealed through RTs, are sensitive to the representational strength of the WM content. Additionally, Lange, Thomas, Buttaccio, & Davelaar (2012) provide preliminary evidence that eye movements are sensitive to WM activation. We interpret the present effect of SOA for the likely hypothesis as demonstrating differences in the memory activation (i.e., representational strength) possessed by the likely hypothesis between the short and long SOAs. The present results suggest that shortly after a hypothesis is retrieved into WM, it undergoes a brief period of heightened activation before moving into a decreased state of activation as it is maintained for output.

We refer to this initial heightened stage as a “retrieval input” stage as it is the act of retrieval from LTM that endows the hypothesis with this heightened activation state. We refer to the following stage of decreased activation as a “maintenance” stage as the hypothesis is being maintained in WM for eventual overt output. This account is readily captured by the context-activation model (Davelaar et al., 2005) which we have recently incorporated into a temporally dynamic model of hypothesis generation (Lange, Thomas, & Davelaar, 2012). In the context-activation model, the memory activation of an item at each time step is determined by the item’s activation on the previous time step, self-recurrent excitation that it recycles onto itself, inhibition from the other active items, external input, and noise². Besides external input, the model can also be excited by information retrieved from LTM and the model readily produces the trend we see in the fixation data at the short and long SOAs. As demonstrated in Figure 4, when the model is provided “retrieval input” for 500 iterations, which is then removed for the final 500 iterations, the trend evidenced in the data is produced. Although the focus of this paper is not in modeling the empirical data, it is encouraging to see that a crucial component of our theoretical framework accounts for the data with such ease.

² Please see Davelaar et al. (2005) for computational details.

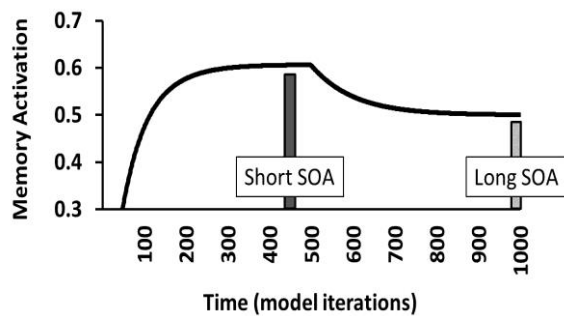


Figure 4: Context-Activation Model account of the SOA difference observed in Experiment 2 for the likely hypothesis. Shortly after retrieval, the hypothesis enjoys a brief period of heightened activation in WM (measured at the short SOA) before moving into a less activated maintenance state (measured at the long SOA) prior to output.

Two related and recently developed methodological approaches deserve further consideration. Mehlhorn, Taatgen, Lebiere, and Krams (2011) used a lexical decision task to measure memory activation of candidate hypotheses in a diagnostic reasoning task. By interspersing the lexical decision task (yes/no response to indicate “hypothesis or not”) at different time points in a diagnostic reasoning task they were able to draw conclusions regarding memory activation by assessing the relative speed with which the lexical decision was made for the various hypotheses of interest. This procedure and the MAC procedure share an emphasis on quickly assessing the content of memory with a brief “probe” presented to the participant. However, as with traditional process tracing, this modified lexical decision procedure requires a secondary (albeit not entirely concurrent) task in addition to the primary task of interest. Despite this difference, we believe the procedure of Mehlhorn et al. (2011) to be highly complementary to ours.

Also of note is the “memory indexing” technique of Renkewitz and Jahn (2012) capitalizing on the phenomenon of looking-at-nothing (Ferreira, Apel, & Henderson, 2008). By holding the spatial locations of the task relevant information constant throughout the experiment, they were able to use eye movements relating to the spatial locations of this information in the testing phase as an index of what was actively being considered across time in the task (despite the fact that the screen was mostly blank as this data was collected and the participants were *looking at nothing*). This procedure has been successfully utilized to investigate multi-attribute choice (Renkewitz & Jahn, 2012) as well as diagnostic reasoning (Jahn & Braatz, 2012). Each of these three procedures (memory activation capture, modified lexical decision, and memory indexing) has their own strengths and weaknesses. By coordinating their utilization within the domain of hypothesis generation and diagnostic reasoning we may be well poised to gain a much deeper understanding of the dynamic memorial underpinnings of these tasks.

Lastly, although we have focused primarily on the domain of hypothesis generation and diagnostic reasoning here, it is important to note that the MAC procedure itself is entirely domain general. Although specific procedural details would need to be tailored for deployment in additional tasks (e.g., specific array stimuli), there is nothing in the logic or mechanics of the procedure that exclude it from use in other domains. We are hopeful that the application of the MAC procedure in domains such as problem solving, multi-attribute choice, probability judgment, and hypothesis testing will foster additional insights concerning the cognitive dynamics operating in these domains as well.

References

- Cooper, R. M. (1974). The control of eye fixation by the meaning of spoken language: A new methodology for the real-time investigation of speech perception, memory, and language processing. *Cognitive Psychology*, 6, 84–107.
- Davelaar, E. J., Goshen-Gottstein, Y., Ashkenazi, A., Haarmann, H. J., & Usher, M. (2005). The demise of short term memory revisited: Empirical and computational investigations of recency effects. *Psychological Review*, 112(1), 3-42. doi: 10.1037/0033-295X.112.1.3
- de Groot, A. D. (1965). *Thought and choice in chess* (1st ed.). The Hague: Mouton Publishers.
- Dougherty, M.R.P., & Hunter, J.E. (2003a). Probability judgment and subadditivity: The role of WMC and constraining retrieval. *Memory & Cognition*, 31(6), 968-982.
- Dougherty, M.R.P., & Hunter, J.E. (2003b). Hypothesis generation, probability judgment, and working memory capacity. *Acta Psychologica*, 113(3), 263-282.
- Dougherty, M.R.P. & Sprenger, A. (2006). The influence of improper sets of information on judgment: How irrelevant information can bias judged probability. *Journal of Experimental Psychology: General*, 135(2), 262-281.
- Dougherty, M., Thomas, R., & Lange, N. (2010). Toward an integrative theory of hypothesis generation, probability judgment, and hypothesis testing. In B. H. Ross, B. H. Ross (Eds.), *The psychology of learning and motivation: Advances in research and theory (Vol 52)* (pp. 299-342). San Diego, CA US: Elsevier Academic Press.
- Ellis, J. J., Glaholt, M. G., & Reingold, E. M. (2011). Eye movements reveal solution knowledge prior to insight. *Consciousness and Cognition*, 20, 768–776.
- Ericsson, K.A. & Simon, H.A. (1980). Verbal reports as data. *Psychological Review*, 87, 215- 251.
- Ericsson K. A. & Simon H. A. (1993). *Protocol Analysis: Verbal Reports as Data*. MIT Press, Cambridge, MA.
- Ferreira, F., Apel, J., & Henderson, J. M. (2008). Taking a new look at looking at nothing. *Trends in Cognitive Sciences*, 12, 405–410. doi: 10.1016/j.tics.2008.07.007
- Franco-Watkins, A.M. & Johnson, J.G. (2011) Applying the *decision moving window* to risky choice: Comparison of eye-tracking and mouse-tracing methods. *Judgment and Decision Making*, 6, 740-749.
- Ford, J. K., Schmitt, N., Schechtman, S. L., Hults, B. M., &

- Doherty, M. L. (1989). Process tracing methods: Contributions, problems, and neglected research questions. *Organizational Behavior and Human Decision Processes*, 43, 75–117.
- Glaholt, M. G. & Reingold, E. M. (2011). Eye Movement Monitoring as a Process Tracing Methodology in Decision Making Research. *Journal of Neuroscience, Psychology, and Economics*, 4, 125-146.
- Glaholt, M. G., Wu, M., & Reingold, E. M. (2009). Predicting preference from fixations. *PsychNology Journal*, 7, 141–158.
- Jahn, G. & Braatz, J. (2012) Memory Indexing of Sequential Symptom Processing in Diagnostic Reasoning. In N. Miyake, D. Peebles, & R. P. Cooper (Eds.), *Proceedings of the 34th Annual Conference of the Cognitive Science Society* (pp. 497-502). Austin, TX: Cognitive Science Society.
- Lange, N.D., Davelaar, E.J., & Thomas, R.P. (In Press). Data Acquisition Dynamics and Hypothesis Generation. *Cognitive Systems Research*. Invited Submission for Special Issue: Best of International Conference on Cognitive Modeling. doi: 10.1016/j.cogsys.2012.12.006
- Lange, N.D, Thomas, R.P., & Davelaar, E.J. (2012) Temporal dynamics of hypothesis generation: Influences of data serial order, data consistency, and elicitation timing. *Frontiers in Psychology: Cognitive Science* 3:215.
- Lange, N.D., Thomas, R.P., Buttaccio, D.R. & Davelaar, E.J. (2012) Catching a glimpse of working memory: Top-down capture as a tool for measuring the content of the mind. *Attention, Perception, & Psychophysics*, 74(8):1562-7. doi: 10.3758/s13414-012-0378-9
- Makovski, T. & Jiang, Y. V. (2008). Indirect assessment of visual working memory for simple and complex objects. *Memory & Cognition*, (36)6, 1132-1143. doi: 10.3758/MC.36.6.1132
- Mehlhorn, K., Taatgen, N. A., Lebiere, C., & Krems, J. F. (2011). Memory activation and the availability of explanations in sequential diagnostic reasoning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 37(6), 1391-1411.
- Montgomery, H., & Svenson, O. (1976). On decision rules and information processing strategies in multiattribute decision making. *Scandinavian Journal of Psychology*, 17, 283-291.
- Moores, E., Laiti, L., & Chelazzi, L. (2003). Associative knowledge controls deployment of visual selective attention. *Nature Neuroscience*, 6(2), 182-189. doi: 10.1038/nn996
- Rehder, B., & Hoffman, A. B. (2005a). Eyetracking and selective attention in category learning. *Cognitive Psychology*, 51, 1–41.
- Rehder, B., & Hoffman, A. B. (2005b). Thirty something categorization results explained: Selective attention, eyetracking, and models of category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 31, 811–829.
- Renkewitz, F., & Jahn, G. (2012, April 30). Memory Indexing: A Novel Method for Tracing Memory Processes in Complex Cognitive Tasks. *Journal of Experimental Psychology: Learning, Memory, and Cognition*. Advance online publication. doi: 10.1037/a0028073
- Russo, J.E., Johnson, E.J., & Stephens, D.L. (1989). The validity of verbal protocols. *Memory & Cognition*, 17, 759-769.
- Russo, J.E. (1978) Eye Fixations Can Save the World: A Critical Evaluation and A Comparison Between Eye Fixations and Other Information Processing Methodologies. *Advances in Consumer Research*, 5, 561-570.
- Schulte-Mecklenbeck, M., Kühberger, A. & Ranyard, R. (Eds.). (2011). *A Handbook of Process Tracing Methods for Decision Research: A Critical Review and User's Guide*. New York: Taylor & Francis.
- Soto, D., Heinke, D., Humphreys, G.W., & Blanco, M. (2005). Early, involuntary top-down guidance of attention from working memory. *Journal of Experimental Psychology: Human Perception and Performance*, 31(2), 248-261. doi: 10.1037/0096-1523.31.2.248
- Soto, D. & D., Humphreys (2007). Automatic guidance of attention from verbal working memory. *Journal of Experimental Psychology: Human Perception and Performance*, 33(3), 730-757. doi: 10.1037/0096-1523.33.3.730
- Sprenger, A.M., Dougherty, M.R., Atkins, S.M., Franco-Watkins, A.M., Thomas, R.P., Lange, N., & Abbs, B. (2011) Implications of cognitive load for hypothesis generation and probability judgment. *Frontiers in Psychology: Cognitive Science*, 2:129. doi: 10.3389/fpsyg.2011.00129
- Sutterlin, B., Brunner, T. A., & Opwis, K. (2008). Eye-tracking the cancellation and focus model for preference judgments. *Journal of Experimental Social Psychology*, 44, 904–911.
- Svenson, O. (1979). Process descriptions of decision making. *Organizational Behavior and Human Performance*, 23, 86-112.
- Tanenhaus, M. K., Spivey-Knowlton, M. J., Eberhard, K. M., & Sedivy, J. C. (1995). Integration of visual and linguistic information in spoken language comprehension. *Science*, 268, 1632–1634.
- Thomas, R.P, Dougherty, M.R., Sprenger, A.M., and Harbison, J.I. (2008). Diagnostic hypothesis generation and human judgment. *Psychological Review*, 115, 155-185.
- Woodman, G.F. & Luck, S.J. (2007). Do the contents of working memory automatically influence attentional selection during visual search? *Journal of Experimental Psychology: Human Perception and Performance*, 3(22), 363-377. doi: 10.1037/0096-1523.33.2.363