

A Data-Driven Mapping of Five ACT-R Modules on the Brain

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Abstract

In this paper we present a new, data-driven mapping of five ACT-R modules on the brain. In the last decade, many studies have been published that evaluated ACT-R models based on their ability to predict fMRI data in certain predefined brain regions. However, these predefined regions were based on a reading of the literature, and might not be optimal. Currently, we used the results of a model-based fMRI analysis of five datasets to define a new brain mapping for the problem state, declarative memory, manual, visual, and aural modules. Both the original and the new mapping were applied to data of an experiment that elicited differential activity in these five modules; the results were compared to model predictions. The new mapping performed slightly better for the problem state, declarative memory, aural, and manual modules, but not for the visual module. In addition, it provides a more principled way of validating ACT-R models. Although the mapping is ACT-R specific, the methodology can be used to map any cognitive architecture or model to the brain.

Keywords: ACT-R; model-based fMRI; Region-of-Interest.

Introduction

Computational cognitive models often have an internal complexity that cannot be adequately assessed using only behavioral measures (Anderson, 2007; Myung, 2000; Pitt & Myung, 2002; Roberts & Pashler, 2000). Computational models typically provide a moment-by-moment account of cognition with a millisecond time resolution. In contrast, reaction times and accuracy are cumulative measures that give some indication of what happened during a task, but do not provide a moment-by-moment account. This situation is problematic, because the cognitive steps that lead up to a response can often be arranged in different ways (see e.g., Borst et al., 2010, Figure 2; Marewski & Mehlhorn, 2011). In the last decade, researchers have turned to eye movements (e.g., Salvucci, 2006) and neuroimaging data (e.g., Anderson, 2007; Just & Varma, 2007) for additional constraints and guidance in developing cognitive models.

To constrain and validate models developed in the ACT-R cognitive architecture a methodology was developed to predict fMRI data (for introductions, see Anderson et al., 2008; Borst & Anderson, 2013a). ACT-R simulates cognition as a set of independent modules that function around a central procedural module. There are modules for perception (visual, aural) and action (manual, vocal), and several central cognitive modules. These modules have been mapped onto small regions-of-interest (ROIs) in the brain, which are assumed to be active when the corresponding

module is active. By convolving model activity with a hemodynamic response function, one can predict the Blood-Oxygen-Level-Dependent (BOLD) response in these regions – which can subsequently be compared to fMRI data to evaluate the model.

Although this approach has been very successful in the last decade – <http://act-r.psy.cmu.edu/mri/> lists over 50 publications that apply this methodology – the predefined mapping of modules on brain regions was based on a reading of the literature, and might therefore not be optimal. In this paper we will derive a new, data-driven mapping for five ACT-R modules from results presented in Borst and Anderson (2013b). To test the new mapping, we applied both the original and the new mapping to data of a multitasking experiment that was designed to elicit differential activity in the five ACT-R modules of interest (Nijboer et al., 2013).

In the next section we will discuss the Borst and Anderson study on which we based the new mapping. Afterwards we will describe the new ROI definitions and the experiment, followed by the results. We finish with a discussion.

Meta-model-based fMRI

To find the neural correlates of five ACT-R modules, Borst and Anderson (2013b) applied model-based fMRI to five existing datasets with associated ACT-R models. Model-based fMRI is a relatively recent method for analyzing fMRI data (e.g., Gläscher & O’Doherty, 2010). Instead of regressing the condition-structure of the experiment against the fMRI data, as is conventionally done, predictions derived from a computational model are regressed against the data. Thus, instead of showing where a certain experimental condition elicits activity in the brain, the method reveals which brain regions correspond to certain model constructs. Model-based fMRI has been successfully applied to locate regions involved in reinforcement learning (e.g., Daw et al., 2006) and decision making (e.g., Gluth, Rieskamp, & Büchel, 2012; van Maanen et al., 2011). Although the method is typically used with parameter values of mathematical models, we have previously shown that it also can be used with computational models, such as ACT-R (Borst, Taatgen, & Van Rijn, 2011).

Borst and Anderson (2013b) used model-based fMRI to locate the neural correlates of five ACT-R modules: the problem state (also referred to as the imaginal module), declarative memory, aural and visual perception, and right-

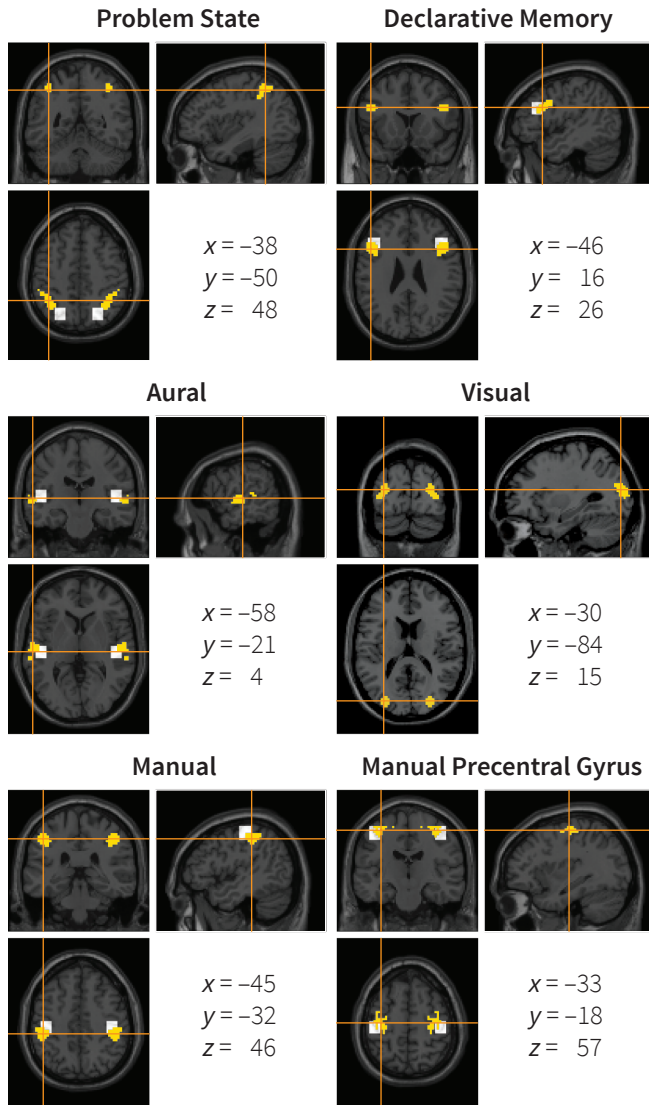


Figure 1. The new ROI-definitions. Yellow indicates the new ROIs, the white squares indicate the old, predefined mapping.

manual actions. These modules were localized in five existing datasets with associated ACT-R models, which ranged from paired-associate learning to multitasking. The results of these five sets of analyses were combined in a meta-analysis to obtain a mapping that was independent of idiosyncrasies of the tasks and models.

As expected, ACT-R's right-manual model was localized in the left motor cortex, extending from the precentral gyrus, through the postcentral gyrus, into the parietal lobe. The aural module mapped onto a region around the superior temporal gyrus in both hemispheres. The visual module correlated significantly with activity in the left and right middle occipital gyri, extending into the inferior parietal lobules. Both the problem state and declarative memory modules correlated significantly with activity around the inferior frontal gyrus and the anterior cingulate. In addition,

the problem state module mapped onto an extensive region around the intraparietal sulcus.

To further dissociate the neural correlates of the problem state module and declarative memory, Borst and Anderson investigated for which regions the declarative memory predictions explained significantly more variance than the problem state predictions and vice versa. This revealed a region in the inferior frontal gyrus for declarative memory, and, not surprisingly, the region around the intraparietal sulcus for the problem state module.

In the next section we will use these results to develop new ROIs for these five modules.

Methods

ROI definition

To create new ROIs we used the meta-analysis of Borst and Anderson (2013b). We thresholded their results on $p < 10^{-7}$ and at least 250 voxels per cluster. For the manual, visual, and aural modules, we then took the most significant voxel as a seed, and repeatedly selected the most significant voxel bordering the currently selected region, until we reached 100 voxels.¹

For the problem state and declarative memory modules we followed the same procedure, except that we took the most significant voxels of the dissociation analysis as a seed. That is, for the problem state module we used a voxel close to the intraparietal sulcus as a seed, and for declarative memory a voxel close to the inferior frontal gyrus. These voxels were best in dissociating between problem state and declarative memory contributions to the BOLD signal, and will consequently lead to ROIs that can be used most successfully to distinguish between those modules.

For reasons that will become clear below, we also defined a second manual ROI. Instead of using all results from the meta-analysis, we restricted ourselves to voxels in the precentral gyrus (as defined in the aal atlas; Tzourio-Mazoyer et al., 2002; inspired by Gluth et al., 2012). It is well known that the primary motor cortex is located in this region, which might improve the results.² Because only 80 significant voxels remained, this ROI is slightly smaller than the others.

As described above, we took the most significant voxel for each module as a seed. For all modules this voxel was located in the left hemisphere, yielding left-hemisphere ROIs. We mirrored those ROIs to additionally create right-hemisphere ROIs.

The resulting ROIs are shown in Figure 1, in yellow. The white squares indicate the original mapping of ACT-R on the brain. For most modules the original and the new

¹ 100 voxels is a somewhat arbitrary size. However, it results in ROIs that are small enough to yield a precise signal, while being large enough to account for anatomical and functional brain differences between subjects.

² We only used this approach for the motor region, because we know from the literature exactly where it should be located. For the other modules this is less clear; even for the aural and visual modules one could choose several different regions.

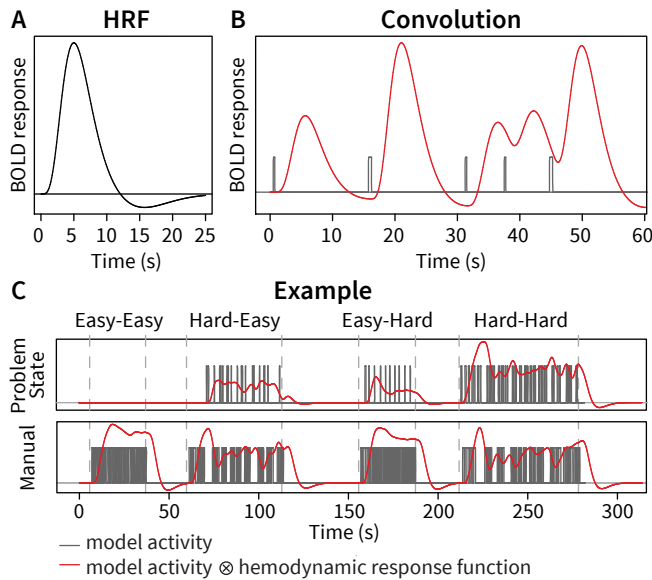


Figure 2. Predicting the BOLD response: A shows a hemodynamic response function, B demonstrates the convolution of model activity with the HRF, and C shows an example from one of the tasks in Borst & Anderson (2013b). Adapted with permission from Figure 3 in Borst, Taatgen, & Van Rijn, 2013, Validating models of complex, real-life tasks using fMRI. In A. Johnson & R. W. Proctor (Eds.), *Neuroergonomics*, Palgrave Macmillan.

mapping at least partly overlap. However, the new mapping follows brain structures, unlike the original mapping. In addition, the new ROI for the problem state is more anterior than in the original mapping, and the new visual ROI is in a different location than the original ROI (located in the fusiform gyrus; $x = -43$, $y = -60$, $z = -16$). The new ROIs can be downloaded from <http://www.jelmerborst.nl/models>, both as binary images and MarsBar ROI definitions for use with SPM (Brett et al., 2002).

Predicting the BOLD response

The reason for having a mapping between ACT-R and the brain is that it can be used to evaluate models. To this end, one can generate BOLD predictions for each ACT-R *module* by convolving the module's activity with the hemodynamic response function, and subsequently compare these predictions to the measured BOLD response in the ROIs.

Figure 2 demonstrates how one can predict the BOLD response. Panel A shows a hemodynamic response function (HRF; e.g., Friston et al., 2007), which simulates the BOLD response in reaction to neural activity at time 0. Panel B shows the effect of convolving module activity (in gray) with this HRF. The size of the predicted BOLD response depends on the duration and the number of module actions. Panel C gives an example of this procedure applied to the problem state and manual modules of an actual model

(Borst et al., 2010). For more details, equations, an example model, and Matlab code to generate BOLD predictions, please see Borst and Anderson (2013a).

Experiment

To compare the new mapping to the original mapping we applied them to an fMRI dataset of Nijboer et al. (2013). In their experiment, 16 subjects were asked to perform three different tasks: a visual tracking task, an n-back task, and a tone-counting task. The tasks had to be performed both in isolation as well as in combination (e.g., n-back and tone counting concurrently), resulting in six different conditions.

In the visual tracking task, subjects were asked to track a horizontally moving dot on the screen by pressing right and left keys with their right hand.

In the tone-counting task, 20 tones were presented at pseudo-random intervals in a 30 second period. Tones could either be high or low; subjects were instructed to only count high tones (10-17 per trial). During the tone-counting task a fixation cross was presented in the center of the screen, subjects were asked to give a response after the trial. In the single task and in the tone-counting & n-back condition this response was given with the right hand, in the tone-counting & tracking condition it was given with the left hand.

In the n-back task a stream of letters was presented on the screen. Each letter was displayed for 1000 ms, followed by a 1500 ms blank between letters. For each letter, subjects had to indicate whether it was the same or different as the letter 2-back, using their left hands.

In the dual-task conditions, both tasks were displayed on the screen at the same time. Trials lasted 30 seconds in all conditions, followed by a 10 second response period in the tone-counting conditions. This corresponds to a total of 20 2-second fMRI scans. For details on subjects, stimuli, and procedure, see Nijboer et al. (2013).

Results

We will discuss the results on a module-by-module basis. For each module, we will discuss model predictions and results in the original and in the new ROI. To generate model predictions we used the model of Nijboer et al. (2013). The model predictions were generated before the experiment was run; no attempt was made at fitting the predictions to the results. This makes it an unbiased – and therefore suitable – dataset for comparing the performance of the original and the new ROIs. Figure 3 shows the results for the problem state, declarative memory, aural, and visual modules; Figure 4 shows the results for the right and left manual modules. R^2 -values are reported in the figures.

Problem State

ACT-R's problem state module is used for maintaining information that is necessary to perform a task (e.g., Anderson, 2007; Borst et al., 2010). It can contain one chunk of information at a time and is similar in that respect to working memory in recent theories (e.g., Oberauer, 2009).

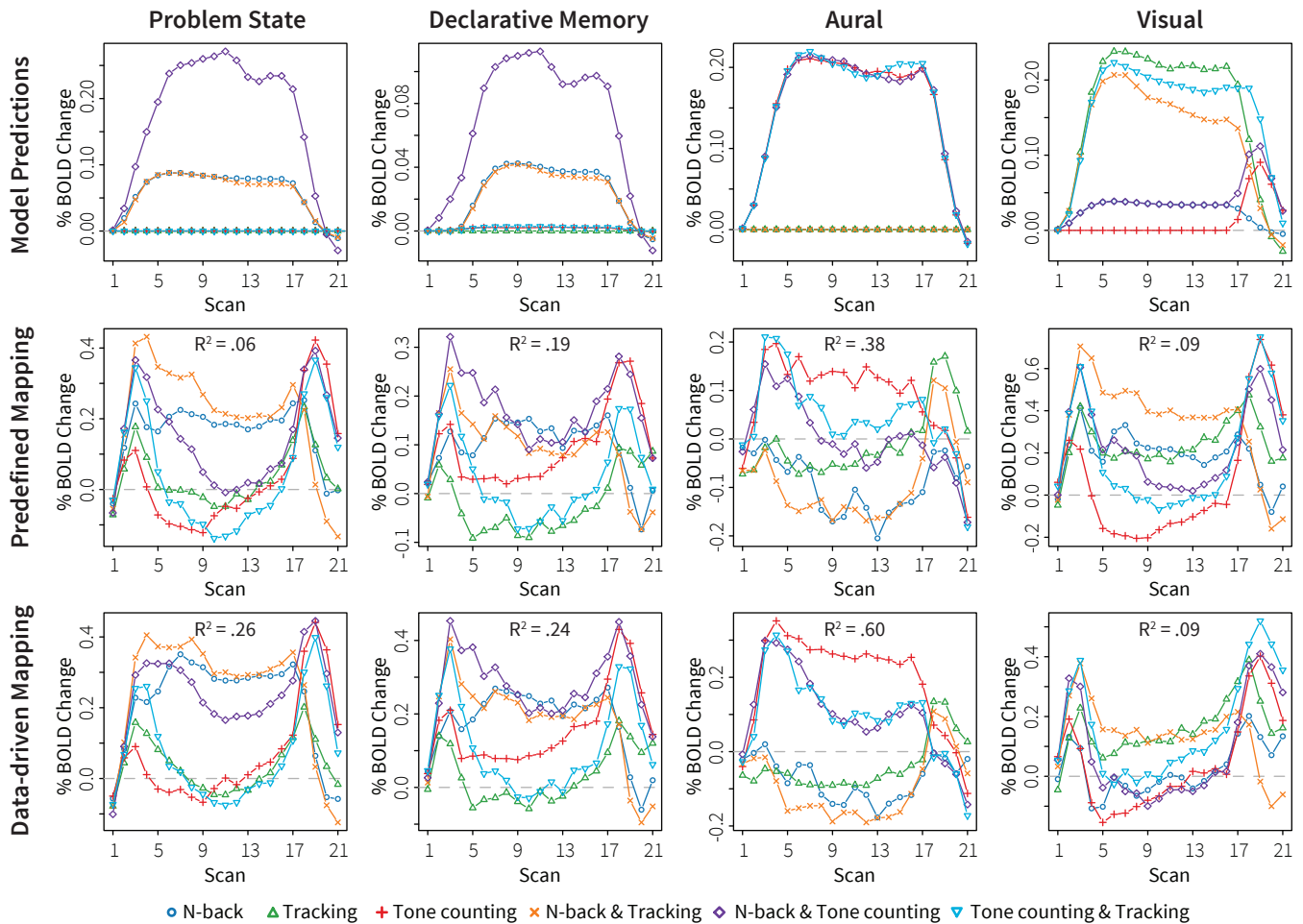


Figure 3. Model predictions and results for the problem state, declarative memory, aural, and visual modules.

The model assumed that the problem state module was required for the n-back task and for the dual-task conditions involving the n-back task. For n-back & tone counting it predicted additional activity (see Nijboer et al., 2013, for details). The original, predefined ROI indeed showed activity for all conditions involving the n-back task. In addition, it showed an increase at the end of the trial for conditions involving tone counting, which is probably related to giving a response for this task. The new, data-driven ROI shows a similar pattern, except that the conditions were more clearly separated. That is, especially n-back & tone counting maintained activity throughout the trial. Neither ROI showed any evidence of the predicted large increase in the n-back and tone-counting condition (indicating that the model should be improved, see Nijboer et al., 2013).

Declarative Memory

Declarative memory is ACT-R's memory for facts. Activity in the ROI is assumed to reflect retrieving facts from memory, not passive storage. The model predicted a very similar pattern for declarative memory as for the problem state. It expected considerable activity in the various n-back

conditions, and a very small amount of activity in the tone-counting conditions (related to retrieving counting facts from memory).

Both the predefined and the new ROI show activity for the n-back conditions, and some activity for the tone-counting conditions. The results in the new ROI seem slightly cleaner, with higher activity levels overall, and therefore a little more activity in the tone-counting conditions. The differences were minor, however.

Aural

The aural module processes sounds. In the current model it was used to listen to the tones and determine whether they were high or low. Both the original and the new ROI showed a clear response to the tone-counting conditions. However, the new ROI showed sustained activity levels, while the levels returned to baseline halfway the trial in the original ROI for the dual-task conditions. In addition, the conditions *not* involving sounds were more closely together in the new ROI, thereby presenting a clearer separation between conditions with and without sound.

Visual

The visual module is used for processing visual stimuli. According to the model, it is activated most in the tracking task, to a lesser extent in the n-back task, and not at all in the tone-counting task. The results in both ROIs were dissimilar from the predictions. N-back & tracking reached the highest activation levels in the original ROI. In addition, the original ROI showed intermediate activity levels for n-back and tracking separately, and almost none or negative activity for the conditions involving tone counting. These results were not present in the new ROI, which seemed to exclusively reflect tracking activity.

Manual

Figure 4 shows the results for the manual module, separately for the left and the right hand of the model. Note that right-handed responses (tracking) will be reflected in the left motor cortex, and left-handed responses (n-back) in the right motor cortex. The final response in the tone-counting task was given with the right hand in the single task and tone counting & n-back conditions, and with the left hand in the tone counting & tracking condition. We therefore expected a late peak for the single tone-counting and tone counting & n-back conditions in the left motor cortex, and for tone counting & tracking in the right motor cortex. The model predictions reflect these considerations.

The results in the original, predefined ROI matched this pattern closely. The results in the new ROI, on the other hand, did not: most conditions show some activity in the left ROI. However, the alternative ROI, based on voxels in the precentral gyrus, did reflect the model predictions closely. It was very similar to the predefined mapping, but showed a less negative response in conditions that did not use the respective hands.

Discussion

The results in the new, data-driven ROIs were in general similar to the results in the original, predefined ROIs. This was not unexpected, given that the predefined ROIs have been applied successfully in a large number of studies. Although the differences were relatively minor, the new ROIs present a more principled, data-driven mapping of ACT-R on the brain, which follows anatomical brain structures. In addition, the new ROIs for the problem state, declarative memory, and aural modules were better at differentiating between the different conditions of the experiment. The BOLD response in the new manual ROI, based on all voxels, fitted badly to the model predictions. However, when we restricted the voxels to the precentral gyrus it also matched slightly better to the model predictions than the original ROI.

The results in the new visual ROI were clearly different from the results in the original ROI. Whereas the BOLD response in the original ROI responded both to the n-back and tracking conditions, the new ROI responded exclusively to the tracking task. It seems that the new ROI is only involved in visual-spatial perception, whereas the original

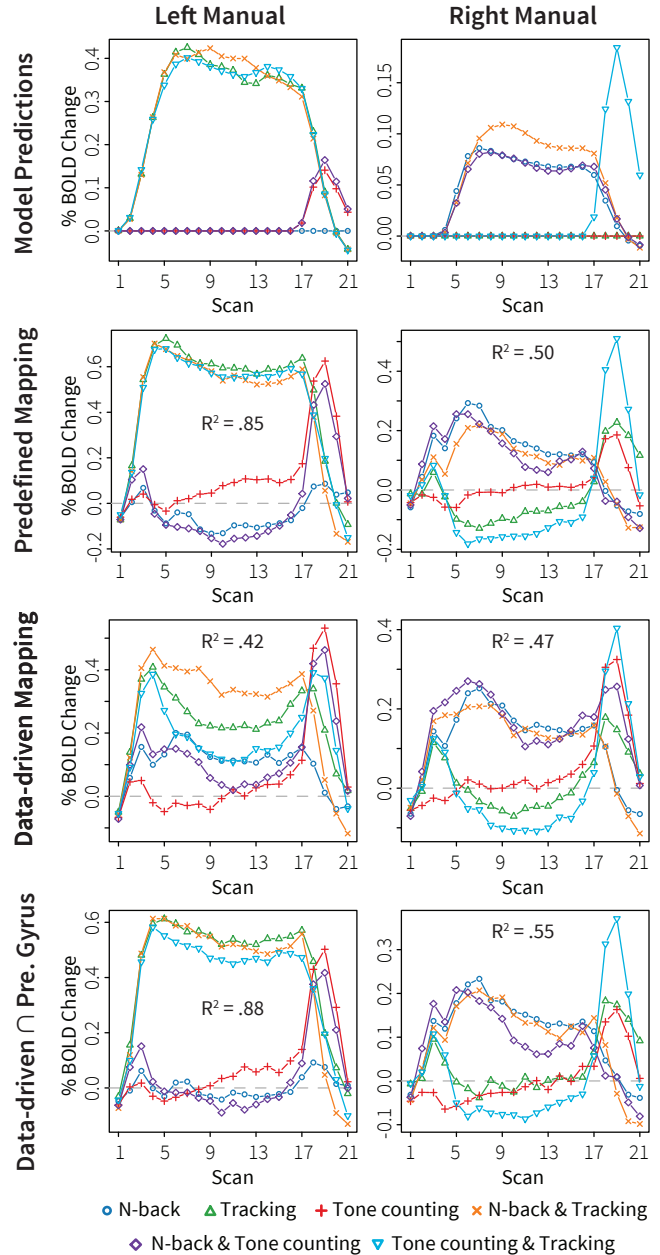


Figure 4. Model predictions and results for the manual module.

ROI also reflected detailed processing of the letters in the n-back task. The regions in the respective ROIs indeed correspond to the dorsal ‘where’ and ventral ‘what’ streams of visual perception (e.g., Haxby et al., 1991; Mishkin, Ungerleider, & Macko, 1983).

Because there is no ground truth, it was difficult to compare the two mappings (note that we do not claim that these are the only regions reflecting the modules’ processing, and neither that these regions exclusively reflect the modules). In the current paper we used a priori model predictions as a way of comparing the performance of the two mappings. However, the model is obviously not perfect (for instance, neither mapping reflected the predicted

activity in the problem state and declarative memory modules; see Nijboer et al., 2013, for a discussion on the model). We therefore judged the mappings both on how well they matched the model predictions, and how well they could differentiate between the different conditions.

Although the presented results are specific to the ACT-R cognitive architecture, we have shown that the methodology itself worked well. The methodology can be used for any cognitive architecture or model, and provides a powerful way of constraining and guiding modeling efforts.

In conclusion, we would recommend using the new ROIs for the problem state, declarative memory, aural, and manual (based on the precentral gyrus) modules. With respect to the visual module it seems better to use the original predefined ROI in the fusiform gyrus, at least for ACT-R's visual module. However, given that the new ROI seems to reflect visual-spatial activity, it might be used as an ROI for ACT-Rs visual-location buffer, which has not been mapped onto a brain region up to now.

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