# Checking the Brain Mapping Hypothesis: Predicting and Validating BOLD Curves for a Complex Task Using ACT-R

**Claus Möbus (claus.moebus@uni-oldenburg.de)**
**Jan Charles Lenk (jan.lenk@uni-oldenburg.de)**
**Arno Claassen (arno.claassen@ uni-oldenburg.de)**
Department of Computing Science, University of Oldenburg
D-26121 Oldenburg, Germany

**Jale Özyurt (jale.oezyurt@uni-oldenburg.de)**
**Christiane M. Thiel (christiane.thiel@uni-oldenburg.de)**
Department of Psychology, University of Oldenburg
D-26121 Oldenburg, Germany

**Abstract**

John R. Anderson proposed a correspondence between ACT-R modules and brain regions (Brain Mapping Hypothesis). Using a paradigm requiring rule-based matching of chemical structures (pseudo formulae) with their respective names, we compared ACT-R-generated blood-oxygen-level dependent (BOLD) signal curves with BOLD curves obtained from functional Magnetic Resonance Imaging (fMRI) scans. We found significant correlations between ACT-R generated and human BOLD curves for sensory and motor modules and regions in particular, whereas a lack of significant results was observed for mappings between internal modules and regions. This result was ascribed to the fact that in contrast to Anderson's studies, our subjects were not urged to follow a single strategy. Instead the task allowed them to construct their personal strategy within a constraint-based strategy space. Accordingly, the mapping hypothesis was tested strategy-specific. As subjects are generally not able to reliably identify their own in a retrospective manner, we used Response-Time (RT) data in combination with a Bayesian Belief Net to identify personal problem solving strategies.

**Keywords:** ACT-R; BOLD signal prediction, brain-mapping hypothesis

## Introduction

The ACT-R architecture (Anderson, 2004) provides a set of modules with sensory, motor, and internal functions. Anderson (2007a; Anderson, et al., 2008b) proposes a neurophysiologic analogy and postulates a mapping between these modules and brain regions (Table 1). For instance, the Procedural module is mapped onto the basal ganglia, while the Declarative module is mapped around the inferior frontal sulcus. The ACT-R 6.0 implementation provides a set of tools which directly predict BOLD signals for these brain regions. Indeed, Anderson has "[..] defined these regions once and for all and use them over and over again in predicting different experiments" (2007b).

Several studies were conducted by Anderson et al. in order to empirically validate the mapping hypothesis. These included experiments from various domains, like algebraic problem solving (Danker & Anderson, 2007; Stocco & Anderson, 2008), associative learning (Anderson et al., 2008a) or insight problems (Anderson et al., 2009). One particular feature in common of all these experiments was the fact that participants had to employ the same problem solving strategy on all tasks.

The empirical validation of the mapping hypothesis is among the research goals of our multidisciplinary research project (see Section Acknowledgements). While also the effects of affective and informative feedback on learning are being studied (Özyurt, Rietze, & Thiel, 2008) an accompanying fMRI study offers us the possibility to compare BOLD signal predictions generated from strategy-specific ACT-R models with BOLD signals obtained from actual fMRI scans.

Table 1: ACT-R module/regions mappings according to Anderson (2007a) with positions in Talairach coordinate and dimensions (D, W, H) in voxels

| Module | Region | X | Y | Z | D | W | H |
|---|---|---|---|---|---|---|---|
| Declarative | Prefrontal | ±40 | 21 | 21 | 5 | 5 | 4 |
| Imaginal | Parietal | ±23 | -64 | 34 | 5 | 5 | 4 |
| Manual | Motor | ±41 | -20 | 50 | 5 | 5 | 4 |
| Goal | ACC | ±5 | 10 | 38 | 5 | 3 | 4 |
| Procedural | Caudate | ±15 | 9 | 2 | 4 | 4 | 4 |
| Visual | Fusiform | ±42 | -61 | -9 | 5 | 5 | 4 |
| Aural | Auditory | ±46 | -22 | 9 | 5 | 5 | 4 |
| Vocal | Motor | ±43 | -14 | 33 | 5 | 5 | 4 |

Results of the present study suggest a further refinement of our modeling methods. In contrast to the experiments described by Anderson et. al. (2008a; Danker & Anderson, 2007; Stocco & Anderson, 2008), the tasks in our experimental setting were far more complex; because in order to solve these tasks, participants were free to choose their *personal* strategies. Because different strategies lead to different predictions of brain region activation, we had to model these different strategies and identify the chosen subject-specific strategy *without* using fMRI data (Möbus & Lenk, 2009). We would work unduly in favor of the mapping hypothesis if we would assign subjects to strategies according to similarity of their BOLD curves with the strategy-specific ACT-R-BOLD curves.

## Experiment

All participants were lower-grade schoolchildren with ages ranging from 11 to 13. The exercises which the children had to solve came from the domain of the chemical formula language (Heuer & Parchmann, 2008), which is generally unknown to children of that age. However, instead of real-world chemical elements, pseudo-elements (like *Pekir* or *Nukem*) were used to ensure that the children exclusively applied the rules of the artificial formula language. The children were asked to answer 80 trials in two sessions during fMRI scans. A single trial consisted of the auditive and visual presentation of a chemical compound name and the visual presentation of a pair of structural formulae (Figure 1). The subjects were asked to decide which of the two structural formulae (one on the left, the other on the right matches the compound name. The total presentation of a structural formula lasted for 4.5 seconds. An additional time of 1 second for the answer has been granted, so that the maximum response time amounted to 5.5 seconds.

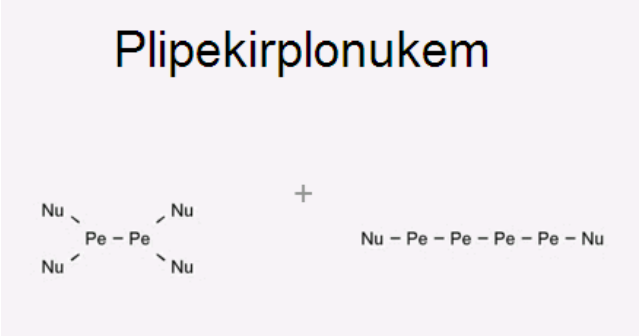


Figure 1: A typical experimental trial: The compound name is at the top, structural formulae left and right below.

If the response had occurred in time, a feedback was given after a jitter time of 2-18 seconds. The feedback consisted of two parts: one part informed about the participant's performance; a second, affective part informed about the performance of a fictional peer group. The total feedback presentation lasted for 2.5 seconds.

In order to find the correct structural formula for a compound name, six rules, which were part of the instruction given to all participants, had to be applied and checked for violations:

1. The abbreviation for an element is defined by two letters
2. The first letter of the abbreviation is the same as the first letter in the name of the element
3. Both letters appear in the element's name
4. An element may have a multiplicity from 1 to 4 in the compound. Distinct numerals are used to denote the multiplicity:
    - -/one
    - pli/two
    - pla/three
    - plo/four
5. The position of a numeral is always in front the element in the compound name
6. The central or inner element of the structural formula is always the first in the compound name

In Figure 1, the left structural formula actually matches the compound, while the right formula's cardinalities mismatch. These rules define the constraints of a strategy space from which correct *personal* strategies can be constructed by the subjects. There is no explicit order in which the rules should be applied. Either the left or the right formula violates at least one of the rules. The trials are thus classified by the position of the faulty formula (left/right) and by the number of the violating rule.

The rules were well known by the children because they went through an extensive instruction phase in multiple sessions. They familiarized themselves with the rules using age-based material and games especially designed for that purpose. They also passed 20 trials on a computer and another 40 in an fMRI simulator prior to entering the actual fMRI experiment.

Overall, 33 participants were included in our study concerning the brain-mapping hypothesis. They were distributed among five experimental groups defined by design matrices, which described the sequential order of trials and jitter times. These 33 participants scored an average 54.64 correct answers from a whole of 80 problems with a standard deviation of 11.9. On the average, they were able to signal the correct solution to the problem in a trial within 3.78 seconds with a standard deviation of 0.8s.

A SONATA MRI system (Siemens, Erlangen, Germany) operating at 1.5T was used with a standard whole-head coil to obtain T2*-weighted echoplanar (EPI) images with BOLD contrast (matrix size: 64x64, pixel size: 3x3 $mm^2$). Participants completed two experimental runs consisting of 40 trials each. During each functional run 408 volumes of 30 three mm-thick axial slices were acquired sequentially with a 0.6 mm gap (TR = 2 sec, TE = 50 msec). Data were preprocessed with the Statistical Parametric Mapping software SPM5[1]. Following rigid body motion correction, the time series of each voxel was realigned temporally to the middle slice to correct for differences in slice acquisition time. Structural and functional volumes were coregistered and spatially normalised to a standard T1 template based on the Montreal Neurological Institute (MNI) reference brain (resampled to 2x2x2$mm^3$ voxel). The data were then smoothed with a Gaussian kernel of 8 mm full-width-half-maximum to accommodate intersubject anatomical variability.

## Models

Two input channels are available to the problem solver. The visual input channel is mandatory, while the auditory input channel is auxiliary. This fact adds to the complexity of the problem, especially as both channels may be perceived in parallel or consecutively. Either the left or the right formula

[1] http://www.fil.ion.ucl.ac.uk/spm/software/spm5 6/16/2010

or both have to be evaluated visually. This results in a variability of conceivable strategies, which differ in efficiency as well as module activation. A set of *basic tasks* is derived from the rules. These tasks are shared by all strategies, though not necessarily in the order presented here:

1. Visually and/or auditorially perceive and encode the different parts of the compound name (mandatory for any successful strategy)
2. Count the outer elements of a structural formula and compare them with the second numeral in the compound name
3. Count the inner elements of a structural formula and compare them with the first numeral
4. Compare the inner element with the first element of the compound name
5. Compare the outer element with the second element of the compound name
6. Indicate the correct formula

Tasks 2-5 may be applied to both formulae, or, more efficiently, to either the left or the right formula. It should be noted that some concurrency can take place if the compound name is encoded using only auditory input. Tasks 4 and 5 may be split into two different tasks as the abbreviation of an element always consists of two letters. Since the first letter is easier to compare with the name, it may be more appropriate to prioritize the first comparison and leave the second letter for later. A second open question which is not reflected within the above list of tasks is the position of the retrieval for the numerals. It can take place very early when encoding the compound name, but there is also the possibility to retrieve the numeral later on between the counting and comparison stages.

A strategy is defined by the order of task processing and the formulae Tasks 2-5 are applied to. While all the strategies share the same basic set of tasks, they all perform differently on each trial. Some trials may only be solved by counting the elements as in Figure 1, others by name-element comparisons, still others by both. A strategy shows higher performance (shorter response time) if it concentrates on a single structural formula to decide whether it matches or not. Each trial class (the violated rule and location of the violating formula) may have an impact on the performance of the strategy.

Several, though so far not all possible, strategies were modeled, at first on an abstract layer as UML activity diagrams, and subsequently within the ACT-R environment as a set of production rules. As only expert participants were modeled, all modeled strategies find the correct answer but with a large variation in performance. So far, four different strategies, S1 to S4, have been modeled (Table 2). They differ in that they either process the structural formula and the compound name simultaneously using the different input channels, or by processing the compound name first and then proceed to the structural formulae. Thus they either process the trial single- or multithreaded, or single-formula or both formulae.

Table 2: Characteristics of strategies/models

| | Multi-Thread | Single-Thread |
|---|---|---|
| Single Formula | S1 | S3 |
| Both Formulae | S2 | S4 |

Apart from these single- vs. multi-tasking and single vs. both formulae considerations, even more design options are available to the modeler yet. For instance, the exact time when certain tests are carried out may be varied. Thus, the model could compare the element's abbreviations with their respective names before comparing the cardinalities. Also, the costly checking of the second letter of the abbreviation may be postponed by the strategy in order to save time. A heuristic approach could leave the second letter out of consideration completely.

The models perform quite differently on the various trials, which is reflected in the ACT-R module traces. This affects the BOLD prediction. Any realization of Task 1, perceiving and encoding the compound name, would surely engage ACT-R's Visual or Aural module, if not both, and the Imaginal module. Tasks 2 and 3, which encompass encoding and counting the structural formulae, would involve the Imaginal, the Visual and the Declarative module. Tasks 4 and 5 would also require at least the Imaginal module, but it could involve the Visual module if the second letter of the symbol has to be checked for occurrence in the compound name. As Tasks 2-5 can be arranged in any arbitrary order, or even be split into subtasks which could run in parallel, quite different patterns of module activation would emerge. This implies that even models which produce similar behaviors may predict distinct BOLD signals, if the productions involved activate different modules.

## Data Analysis

It is doubtful whether the participants are able to remember their problem solving strategy for each trial. It is also possible that they applied varying strategies to trials. The choice of strategy may be related to the trial class. However, we assume that the participants already settled for a *single* strategy after the extensive instruction and training phases. In order to determine which of our models is suitable to explain the performance of the actual strategy used by the participant, we devised a Bayesian Classifier with a Bayesian Belief Network (BBN) (Jensen, 2007) as diagnostic tool. The BBN (Figure 2) is trained with data from ACT-R model runs. Subsequently, behavioral data from the actual experiment is entered as evidence for identifying the personal trial-independent strategy of the subject. Strategies are thus classified by response times (RT).

The main idea is that all models produce distinct response times for each trial. We assume that response times for a strategy are dependent on the trial. This is reflected in the BBN in Figure 2. The probability tables of the BBN are

being learned by running all of the strategy-specific ACT-R models to generate cases. This results in a data matrix whose columns correspond to the nodes from the BBN and whose rows correspond to trials. During model runs, the default values of ACT-R's parameters were used.

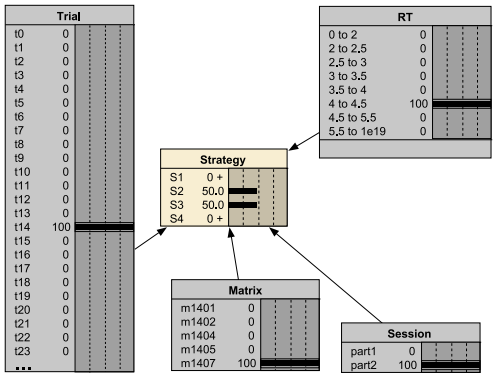


Figure 2: BBN for strategy classification

The trial is entered as evidence into the "Trial", "Matrix", and "Session" nodes. The response time of the participant is entered as evidence into the "RT" node. It is then possible to infer on the strategy most likely used by the participant in the "Strategy" node. In Figure 2, the trial in question is the 14th trial from the second session of the experimental group defined by design matrix 1407. In this particular case, for participant with a response time between 4 and 4.5 seconds, S2 and S3 are equally probable.

The collected fMRI data is analyzed by using the Regions of Interest (ROI) approach (Jäncke, 2005). The regions are specified by the module positions and dimensions given by Anderson's Brain Mapping Hypothesis in Table 1. The Talairach coordinates were transformed into MNI coordinates. The raw values of each voxel lying in the ROI are extracted from the images and averaged per region, resulting in an activation timeline for each person and region (Figure 3).

An averaged BOLD curve for each region is obtained by applying *a strategy-specific weighted means function* to and subsequent aggregation of the individual BOLD curves. For each trial $t$ of the 80 trials, a probability $p_{s,t}$ for a particular strategy $s$ is inferred with the BBN from Figure 2. In order to neutralize the effects of varying base levels of individual BOLD signals, we employed *ipsative measures*: the deviations from the individual's BOLD curve averages are aggregated as weighted averages using trial- and strategy-specific weights and compared with the deviations from the predictions.

For each ROI/Module pair, the averaged BOLD curve deviations are tested for correlation with the respective BOLD prediction computed from the ACT-R module activation (Anderson et al., 2008). The default parameters of the ACT-R BOLD module were used for this computation. Each time series consists of 400 data points.

As the Pearson's correlation coefficients were calculated independently for each experimental group, the resulting values were averaged among the experimental groups by using the Fisher-z transformation. Table 3 shows the final correlation results for each strategy separately for left and right brain hemispheres. If the correlation coefficient is higher than 0.098, the null hypothesis is rejected with $\alpha = 0.05$. In this case, nearly all correlations between the BOLD signal in the ROI and the ACT-R module's prediction can be considered statistically significant. This is due to the large $N$. The practical significance depends on the percentage of explained variance $r^2 \cdot 100$. This is the basis of our discussions.

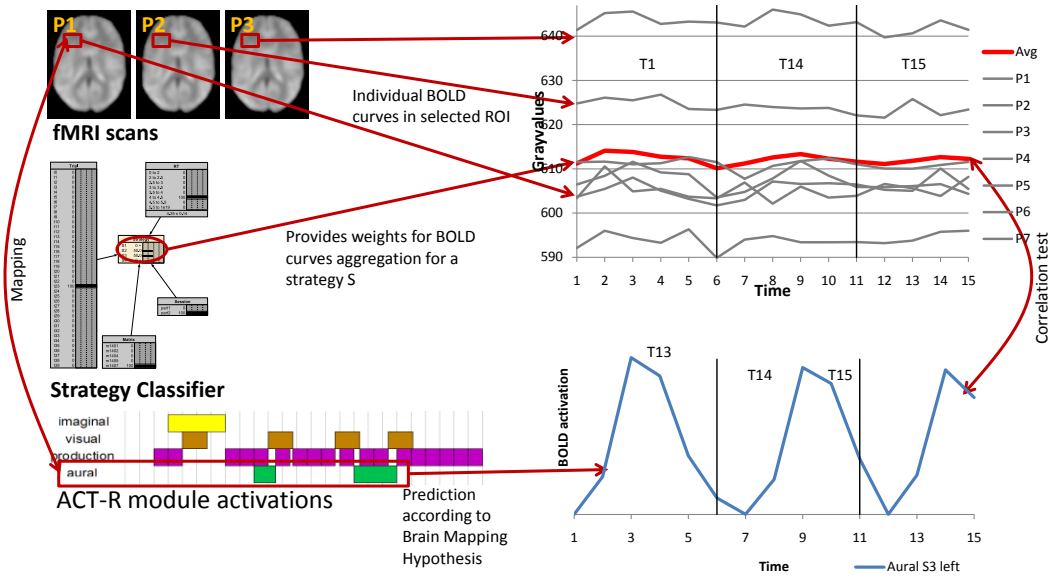


Figure 3: Aggregation of BOLD curve per ROI and correlation test with ACT-R prediction

Table 3: Correlations between ACT-R predictions and ROI activities. Each module's prediction has been tested for correlation with any of the regions from Table 1. Correlations marked with an asterisk are highest for the postulated mapping

| Hemisphere | Strategy | Production | Declarative | Imaginal | Visual | Goal | Manual | Aural |
|---|---|---|---|---|---|---|---|---|
| Left | S1 | 0.458 | 0.365 | 0.258 | 0.525 | -0.262 | 0.389 | *0.691 |
| | S2 | 0.489 | 0.402 | 0.259 | *0.647 | -0.267 | 0.403 | *0.691 |
| | S3 | 0.495 | 0.408 | 0.258 | *0.617 | -0.264 | 0.414 | *0.692 |
| | S4 | 0.489 | 0.414 | 0.246 | *0.367 | -0.265 | 0.194 | *0.693 |
| Right | S1 | 0.428 | 0.191 | 0.389 | 0.556 | -0.218 | -0.052 | *0.659 |
| | S2 | 0.438 | 0.220 | 0.397 | *0.606 | -0.218 | -0.049 | *0.660 |
| | S3 | 0.450 | 0.216 | 0.389 | *0.596 | -0.218 | -0.044 | *0.659 |
| | S4 | 0.432 | 0.231 | 0.397 | 0.295 | -0.218 | -0.065 | *0.660 |

## Discussion

Correlations between the Aural Module's predictions and left and right ROIs alike are high for every strategy. This might be expected, as the aural input is only available to each model for a short time, and thus the productions which perceive and encode that information fire at approximately the same time for all models.

The same applies to the Visual Module. The visual presentation lasts 4.5 seconds. During this time span, any model will perceive and encode visual information. Models S2 (multi-threaded, both formulae) and S3 (single threaded, single formula) perform with the highest correlation here. Both models show the same behavior regarding response times. However, the visual module is more engaged in the S2 model, which examines both formulae. Correlation is also the highest for this model.

The Manual Module's predictions are higher for the left than for the right hemisphere. This was expected as all subjects responded with their right hand. All strategies except S4 (single-threaded, both formulae) have a moderate correlation coefficient. The moderate correlation is surprising, as models were matched to the participants' BOLD signals according to their response time, which would suggest a higher correlation coefficient.

The Procedural Module offers fair correlations for both hemispheres and all strategies, even if the correlations for S1 are somewhat lower than those for the other strategies. The correlations of the Declarative Module's predictions are moderate for the left hemisphere and low for the right hemisphere. The higher prediction for the left Retrieval Module is in line with previous research showing a left hemispheric dominance for the retrieval of verbal information (Petrides Alivisatos, & Evans, 1995; McDermott, Buckner, Petersen, Kelley, and Sanders, 1999).

The opposite is the case for the Imaginal Module's prediction: These correlate better with the right than with the left hemisphere. The Goal Module's correlation is negative in all cases.

In general, the correlations are higher for the sensor modules, the Visual and Aural Modules. The internal modules, Procedural, Declarative, and Imaginal, show lower correlations alike. However, this cannot be ascribed to faulty assumptions in the modeling process, as they are still high when tested for significance. Rather, they suggest that participants may be occupied with other processes which the models do not account for. This could especially be the case as the experimental design provided large jitter times or delays, during which the participant remained inactive. This has also been observed by Danker and Anderson (2007).

All of our models assume a single goal which is created at the beginning of a trial. The negative correlation coefficients suggest that this assumption is wrong. Thus, the creation of sub-goals for individual tasks should be considered an alternative. A model using sub-goals would have a decreased performance and higher response times due to goal chunk creation costs. Using the Competing Strategies paradigm (Taatgen, Lebiere, & Anderson, 2006), the model would optimize performance by production rule learning.

The models' deficiencies are also evident from the scatter plots in Figure 4. These show predictions versus experimental evidence. Ideally, experimental evidence would increase with model predictions with little variance to the regression line, which would indicate similar peaks and depressions for both curves. This is clearly not the case for the Goal module on the right. Instead, both scatter plots show clustering on the prediction axis. This indicates monotonous activity patterns in the respective modules, which is due to the chunk loading and manipulation actions as implemented by the model.

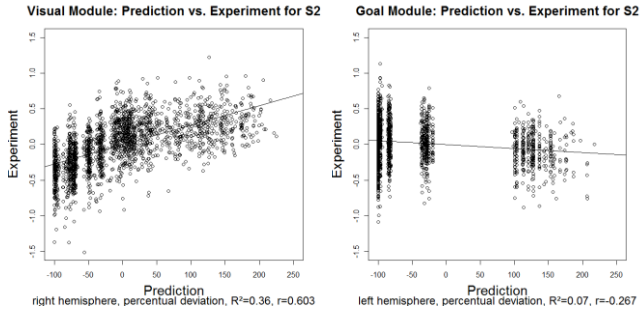


Figure 4: Scatter plots of predictions vs. evidence for S2

## Conclusion

The correlations presented here are generally lower than in previous studies (Danker and Anderson, 2007). However, the experimental design, which does not account for functional separation, might contribute to that fact. For a

complex task which allows for a multitude of strategies to be pursued, many models may reproduce similar human behavior but do not predict the same BOLD curves.

The ACT-R architecture features many free parameters which may be altered in order to fit the model to experimental data, even if this may seem contrary to the intention of a cognitive architecture (Taatgen & Anderson, 2008). Also, many different modeling paradigms exist which may be more or less appropriate to the task.

Thus, three options arise for the continuation of our research. First, we could redesign our experiment in order to separate functionalities, which is the approach currently done by other research groups. Second, we could refine our models by using a modified internal representation such as sub-goal chunks. Third, we could define other ROIs and look for correlations there.

So far, the second and third choices are being pursued by us. The second choice would also include the calibration of the modified model to the individual participant's behavior by adjusting ACT-R's parameters. This should have positive effect on BOLD prediction and signal correlations.

Especially the third choice of defining alternative ROIs is of great importance. As can be seen in Table 1, Anderson's brain mapping hypothesis covers only a very small portion of the brain. However, a review of imaging research attributes the functions of ACT-R's modules to a much wider range of areas (Kaspera, 2010). Also, many of these regions seem to interact when performing a certain function, a phenomenon which the one-to-one mapping presented by Anderson cannot account for.

## Acknowledgments

*Cognitive Modeling and Bayesian Identification Analysis* (CoMBIAn), work package within project *Impact of affective and informative feedback on learning in children before and after a reattribution training: An integrated approach using neuroimaging, educational research and modeling*, Möbus, Moschner, Parchmann & Thiel (main applicant), BMBF-Program for the Promotion of Scientific Collaboration between the Neurosciences and Research on Learning and Instruction, 03/01/2008 - 02/28/2011.

We wish to thank Mrs. P. Arndt, Mrs. B. Moschner, Mrs. I. Parchmann, Mrs. A. Anschütz, and Mr. S. Bernholt for the experimental design and support by discussing our results.

## References

Anderson, J. R. (2007a). *How can the human mind occur in the physical universe?* Oxford University Press

Anderson, J. R. (2007b). Using Brain Imaging to Guide the Development of a Cognitive Architecture, in: Gray, W. D. (ed.), *Integrated Models of Cognitive Systems*, Oxford University Press

Anderson, J. R., Anderson, J. F., Ferris, J. L., Fincham, J., & Jung, K. J. (2009). The lateral inferior prefrontal cortex and anterior cingulate cortex are engaged at different stages in the solution of insight problems, *Proceedings of the National Academy of Sciences*, 106, 10799-10804

Anderson, J. R., Bothell, D., Byrne, M., Douglass, S., Lebiere, C., & Qin, Y. (2004). An integrated theory of the mind, *Psychological Review*, 111, 1036-1060

Anderson, J. R., Byrne, D., Fincham, J., & Gunn, P. (2008a). Role of prefrontal cortices in associative learning, *Cerebral Cortex*, 18, 904-914

Anderson, J. R., Fincham, J., Qin, Y., & Stocco, A. (2008b). A central circuit of the mind, *Trends in Cognitive Science,* 12, 136-143

Danker, J. & Anderson, J. R. (2007). The roles of prefrontal and posterior parietal cortex in algebra problem solving, *Neuroimage*, 35, 1365-1377

Heuer, S. & Parchmann, I. (2008). $Son_2e$ oder $Fus_2bal_2$ – wie Sechstklässler die chemische Formelsprache interpretieren, *Naturwissenschaften im Unterricht*, 106/107, 20-24

Jänke, L. (2005). *Methoden der Bildgebung in der Psychologie und den kognitiven Neurowissenschaften*, Kohlhammer

Jensen, F. V. & Nielsen, T. (2007). *Bayesian Networks and Decision Graphs*, Springer

Stocco, A., & Anderson, J.R. (2008), Endogenous control and task representation: An fMRI study in algebraic problem solving, *Journal of Cognitive Neuroscience*, 20, 1300-1314

Taatgen, N., & Anderson, J. R. (2008). Constraints in Cognitive Architectures, in: Sun, R. (ed.) *Handbook of Computational Psychology*, Cambridge University Press

Taatgen, N., Lebiere, C., & Anderson, J. (2006). Modeling Paradigms in ACT-R, in: Sun, R. (ed.), *Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation*, Cambridge University Press

Kaspera, R. (2010). *ACT-R: Zur Überprüfung der Brain Mapping Hypothese (On Validation of the Brain Mapping Hypothesis)*, Technical Report, University of Oldenburg

McDermott, K. B., Buckner, R. L., Petersen, S. E., Kelley, W. M., & Sanders, A. L. (1999). Set- and code-specific activation in frontal cortex: an fMRI study of encoding and retrieval of faces and words, *Journal of Cognitive Neuroscience*, 11, 631-640.

Möbus, C. & Lenk, J. C. (2009). Bayesian Identification of Problem-Solving Strategies for Checking the ACT-R/Brain-Mapping Hypothesis, in: Schmid, U., Ragni, M., & Knauff, M. (eds.), Proceedings of the KI 2009 Workshop Complex Cognition, Paderborn, Germany, *Bamberger Beiträge zur Wirtschaftsinformatik und Angewandten Informatik*, 82, 37-47

Özyurt, J., Rietze, M. & Thiel, C. (2008). fMRI of feedback processing in children and adults, *Frontiers in Human Neuroscience*

Petrides, M.,Alivisatos, B., and Evans, A. C. (1995). Functional activation of the human ventrolateral frontal cortex during mnemonic retrieval of verbal information, *Proceedings of the National Academy of Sciences*, 92, 5803-5807.