

# Exploring if EEG can be used to constrain cognitive models

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**Abstract:** Cognitive architectures such as ACT-R can be used to get a better understanding of the underlying processes in human cognition, but they can be hard to evaluate based on behavioral measures alone. Therefore, neural data can be used as additional information to inform models. There is a good connection between ACT-R and fMRI, but the connection between EEG is a lot less elaborated. EEG can be especially useful to get a better understanding of fast paced tasks because of the excellent temporal resolution of EEG. In this project we examined whether EEG could be used to constrain cognitive models. This is examined by evaluating the results from a model-based EEG analysis of an algebra solving task. Model-based analysis is a method to investigate new connections between model constructs and brain areas or to evaluate existing mappings between model constructs and brain areas. Model-based analysis uses the predictions from a cognitive model as regressors in a general linear model to examine the connections between EEG data and the model constructs. The model-based EEG analysis in this project showed promising results; the visual ACT-R module showed correlation between EEG data channels around the fusiform gyrus in the occipital lobe and the manual ACT-R module showed correlations between EEG channels around the motor cortex. These results show the connections between EEG data and model constructs and suggests that EEG data could be used to constrain cognitive models. However, the imaginal and declarative ACT-R modules did not show correlations between the module predictions and the EEG data channels around areas where we expected them. Therefore we suggest that our cognitive model of the algebra task needs refinement.

## 1. Introduction

Problem solving is a human skill that occurs in many forms, in many cases unnoticed. For example, when shopping groceries for dinner, several different steps such as remembering the ingredients and their quantities, where they are located in the store, and planning the quickest route, all require some sort of problem solving. In other tasks the problem-solving aspect is clearer. For example, when trying to solve a Rubik's cube as fast as possible where you have to remember the steps to move specific colored squares to other sides, keep track of the steps you made and plan ahead how to make sure that all the same colors end up at the same side.

A vast amount of research has been done to find out how problem solving works in the brain. Based on brain imaging techniques such as fMRI, a good understanding has emerged of which areas of the brain are active during different stages of problem solving (Fink et al., 2009; Newman et al., 2003). Generally, problem solving consists of declarative memory retrievals, working memory updating, and cognitive control. In the Rubik's cube example one would have to retrieve the sequence of steps needed to move the squares to other sides from declarative memory, use working memory to keep track of the intermediate steps and plan ahead, and use cognitive control to select appropriate perceptual information to keep track of the changes made. Imaging studies have located declarative memory retrievals, working memory updating, and cognitive control all to the fronto-parietal brain network, shown in Figure 1. This is a network that includes portions of the lateral prefrontal cortex and the posterior parietal cortex (Cabeza et al., 2003; Cole & Schneider, 2007; Dosenbach et al., 2007).

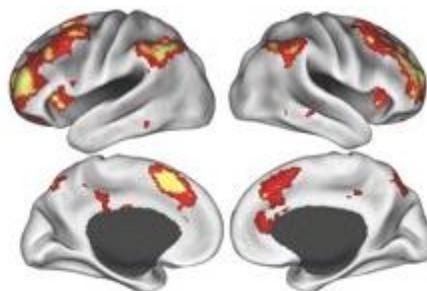


Figure 1. The fronto-parietal network. (Vincent, Kahn, Snyder, Raichle, & Buckner, 2008)

However, just knowing which areas are active is not enough to fully understand the process of problem solving. Knowing the active areas does not specify the underlying processes and the exact information flow during problem solving. More insight is needed in the underlying processes.

A method to get more insight into the underlying processes of cognition in the human brain is by modeling cognitive processes. Cognitive models simulate human cognitive processes in a computational simulation. These models aim to give precise predictions of the underlying cognitive processes and human behavioral measures such as reaction times and accuracy. Cognitive models can be developed within a so-called cognitive architecture. Cognitive architectures do not simply predict performance of a single specific task, but they model general cognitive processes of the brain, from perception to the final response, using general components that work for different tasks.

In this thesis, we use the cognitive architecture ACT-R (Adaptive Control of Thought-Rational). ACT-R consists of several modules and buffers (Anderson, 2007). For example, ACT-R has a declarative module that can retrieve facts from memory and a visual module that is able to process visual information. ACT-R has been used extensively to model human behavior in problem solving. For example, the game Towers of Hanoi (Anderson, Albert, & Fincham, 2005) and mathematical problem solving (Stocco & Anderson, 2008) have both been successfully modeled in the ACT-R cognitive architecture.

Cognitive models can give precise predictions of cognitive processes, but they can be hard to evaluate based solely on behavioral data such as response times and error rates (Turner, Forstmann, Love, Palmeri, & Van Maanen, 2016). Take solving of the Rubik's cube as an example, solving a complete cube takes dozens of steps but trained solvers can do this in a couple of seconds – the current world record is 4.73 seconds (Guinness World Records, 2017). Consequently, a cognitive model of this task requires dozens of module actions: Several visual, manual, declarative and working memory actions have to be modeled. Evaluating an extended model such as this with the complex underlying processes based on a single metric such as the total solving time would just not be enough.

To be able to evaluate cognitive models on more than response times or error percentages a mapping between the different modules and brain areas has been developed based on fMRI data (Anderson, Fincham, Qin, & Stocco, 2008). With such a mapping one can evaluate the predictions from a cognitive model by comparing the measured fMRI activity in the brain with the locations where the modules from cognitive models are mapped. When this shows deviations this might suggest that the cognitive model needs refinement. Due to this mapping ACT-R models are also able to predict fMRI data and these predictions can also be used to evaluate cognitive models. A good mapping of the modules to the brain is beneficial to constrain and evaluate models because when analyzing these models they should not only have to fit the behavioral data but also the fMRI BOLD response. The original mapping was based on literature and later this mapping was refined with model-based analysis (Borst, Nijboer, Taatgen, Van Rijn, & Anderson, 2015). Model-based analysis is a method that uses the predictions from cognitive models to locate neural correlates of model processes and representations.

To have fMRI as an extra constraining measure is useful for many models. However, ACT-R modules can work on timescales as small as milliseconds, and fMRI has a temporal resolution in the order of seconds. Thus, fMRI is less useful for examining fast tasks such as the Rubik's cube solving that only takes 4.73 seconds: fMRI would not be able to differentiate between the different stages in the solving process. EEG could be more suited to answering questions about differences in the modules' time courses of activation as well as the interactions between the modules because of the excellent temporal

resolution of EEG. Unfortunately, research towards the connections between EEG and ACT-R is less elaborated than the connection between fMRI and ACT-R. However, some steps have already been taken; for example, Van Vugt (2014) already showed that the activation of different cognitive resources from the ACT-R cognitive architecture correlate with specific patterns of brain oscillations recorded with EEG during an attentional blink task.

The goal of this project is to further investigate whether EEG data can be used to constrain ACT-R models and thereby utilize the great temporal resolution of EEG. This will be an explorative research that will investigate the correlations between data from EEG channels recorded during a cognitive task and an ACT-R model of this task. Correlations between ACT-R modules and EEG channels that are located around locations on the scalp where one would expect activity for that module would suggest that EEG data is usable to constrain cognitive models. For example, when predictions from the manual ACT-R module correlate with data from the EEG channels located around the motor cortex this would suggest that EEG channel data could be used to constrain cognitive models.

A task that requires activity in several ACT-R modules is needed to be able to investigate the correlations between EEG channel data and the ACT-R modules. Stocco & Anderson (2008) modeled an algebra solving task in the ACT-R cognitive architecture and their model showed activation in five different ACT-R modules; the procedural module, the imaginal module, the retrieval module, the visual module and the manual module. An advantage of algebra is that most people learned how to solve simple algebra problems in school and that the difficulty of the problems is adaptable. Therefore, we decided to use an algebra problem-solving task for this project.

The analysis method to investigate the correlations between the module predictions from the cognitive model and the EEG channel data is model-based analysis. This is a relatively new method that can be used to investigate new connections between model constructs and brain areas, or evaluate existing mappings. Standard EEG and fMRI analysis methods mostly use the condition-structure of the experiment as the basis for regressors in a General Linear Model (GLM). Model-based analysis uses the module predictions from a computational model as regressors. A linear model is fit to each EEG data channel, and when the EEG channel correlates significantly with one of the modules this channel is assumed to be involved in the simulated process. The advantage of model-based analysis over analysis that uses the condition structure is that a different predictor can be used for each trial, and that multiple processes can be active simultaneously and to different degrees within each trial. This makes model-based analysis more powerful (Borst & Anderson, 2017). Model-based analysis has been successfully applied in combination with fMRI data, but not yet in combination with EEG data (Borst & Anderson, 2017). When model-based EEG analysis in this project shows connections between ACT-R modules and EEG data channels located at the scalp where one would expect activity of the module based on prior research, this would be an indication that EEG data could be used to inform and constrain cognitive models.

## 2. Theoretical background

In this section we will discuss the theoretical background relevant for this project. We will start with describing cognitive architectures and ACT-R. This project uses an algebra task to investigate the connections between EEG data and a model of an algebra problem-solving task. Therefore, an existing algebra ACT-R model by Stocco & Anderson (2008) will be discussed. Then model-based cognitive neuroscience will be described with special interest in model-based analysis, which is the analysis method that we will use for this project. To be able to interpret the future results from the model-based analysis more information is needed about problem solving and algebra problem solving. The brain regions associated with these tasks will be discussed in the final section.

### 2.1 Cognitive Architectures & ACT-R

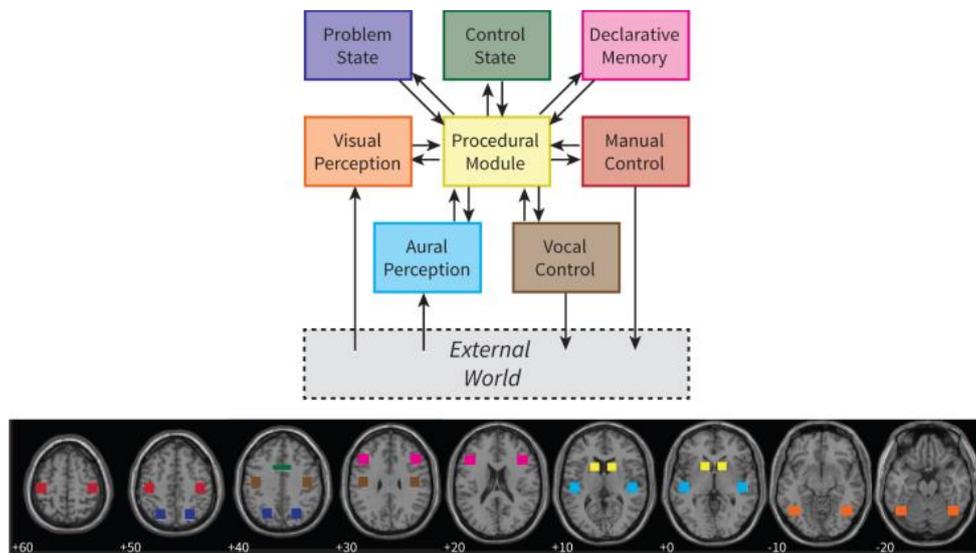
Cognitive architectures simulate cognitive processes of the human brain in a computational simulation. Cognitive architectures can be described as a combination of psychological theories which are able to simulate complete cognitive tasks from input to output. For example, they describe how visual information is processed as well as how the memory system works. Cognitive architectures have the ultimate goal to be able to describe the complete functioning of the human brain instead of a specific part; they are able to simulate many different kinds of tasks in the same architecture.

Several cognitive architectures have been developed, based on different underlying theories with different assumptions. Some are still actively being used and developed while others have been superseded by newer ideas. A cognitive architecture that is still being developed and improved is ACT-R (Anderson, 2007). Over the years, ACT-R has been used to successfully model people's behavior in many diverse tasks. Some examples are driving behavior, attentional blink, time perception and language learning (Ball, Freiman, Rodgers, & Myers, 2010; Salvucci, 2006; Taatgen, Juvina, Schipper, Borst, & Martens, 2009; Taatgen, van Rijn, & Anderson, 2007)

ACT-R will be the cognitive architecture used in this project to model the algebra task. ACT-R is chosen because this architecture is actively being used and it already has a mapping between fMRI activity and the different modules. This gives us some ground truth to judge the results from the model-based EEG analysis that will be discussed later. ACT-R consists of several modules and buffers, and cognition emerges through the interaction between these modules. Each module has a dedicated buffer and the modules in ACT-R are accessed through buffers. The contents of the buffers at a given moment in time represent the state of ACT-R at that moment (Anderson, 2007).

Figure 2 shows an overview of the different modules in ACT-R. In this project we use an algebra solving task for which we will create an ACT-R model. Stocco & Anderson (2008) already modeled an algebra task in the ACT-R architecture and we will discuss the different ACT-R modules that they used in their model. Our model will solve different types of algebra problems so the solving procedure will be different but the used modules used will be the same as Stocco & Anderson (2008). Their model was able to solve two types of problems; each equation was either entirely parametric or entirely numeric. For example participants had to find the value of 'x' for ' $a*x - a = a*b - a$ ' or ' $8*x - 2 = 36 - 6$ '. The equations had to be solved in three steps and participants had to report the transformations they made by pressing a certain finger on a keypad. For example, when solving ' $8*x - 2 = 36 - 6$ ' the first step was adding the addend from the left side to the right side to arrive at the next intermediate state ' $8*x = 32$ '. When participants did this they had to report '+' because they added 2

to the right side. The next step is to divide 32 by 8, so participants had to report ‘/’ by pressing the corresponding finger. Finally they had to report the correct answer on screen. This experiment approach divides the solving process into three separate steps to be able to analyze the three parts and their underlying processes separately.



**Figure 2. Overview of the different modules in ACT-R and the mappings of the ACT-R modules to the brain for fMRI data. The top part shows the ACT-R modules and their interactions between the external world and the other modules. The bottom part of the figure shows different dissections of the brain with squares of the corresponding colored ACT-R modules in areas that shows activation when a module is active (Borst et al., 2015).**

The central module in the model from Stocco & Anderson (2008) is the procedural module. The procedural model recognizes patterns of activity in other modules, and based on this, selects appropriate actions and transfers information to the other modules (Anderson, 2007). This module is responsible for cognitive control and keeps track of the different stages in the solving process.

The perceptual-motor modules handle interactions with the real world. In Stocco & Anderson’s algebra model the visual perception and the manual control module are used. The visual module detects and encodes the equations on the screen and the manual module controls the movements needed to select the correct answers. The declarative memory module handles memory retrievals from long term memory. The module consists of stored facts. In the Stocco & Anderson (2008) model several arithmetic facts have been stored in the modules memory, for example ‘ $36+2=38$ ’ and ‘ $38-6=32$ ’. They also stored transformation facts in memory. For example ‘The inverse of  $-$  is  $+$ ’ and ‘The inverse of  $/$  is  $*$ ’. These facts can be retrieved from declarative memory. The speed of this retrieval process depends on the activation of the fact. Facts which are frequent and recently used have a higher activation and can therefore be retrieved faster (Anderson, 2007).

The last module Stocco & Anderson (2008) used in their algebra task is the imaginal module. In Figure 2 this module is called the problem state module. The imaginal module is able to store information temporarily to allow short-term memorization. This module creates and transforms problem representations for algebra problems with sub-steps that have to be solved first. For example, in the case of ‘ $8*x - 2 = 36 - 6$ ’ the imaginal module would be used to hold the intermediate step ‘ $8*x = 32$ ’. This is also referred to as the working memory (Anderson 2007).

### **2.2.1 Model-based cognitive neuroscience**

Scientists have been trying to understand human cognition for many years. Two research traditions that try to get more insight in human cognition specifically are cognitive scientists and cognitive neuroscientists. These two groups used to approach the topic from different perspectives and coexisted independently. Cognitive scientists rely on the theoretical mathematical assumptions underlying cognitive processes, and apply these theories by developing formal models of cognition. An example is the ACT-R theory that was discussed above. The models simulate the cognitive processes in the human brain with mathematical equations and can be evaluated based on behavioural data. On the other hand, cognitive neuroscientists rely on statistical models to understand patterns of neural activity shown during experiments. The focus is on which brain regions show activity and how much activity they show rather than on the underlying computational processes.

Both methods yield disparate insights in human cognition, but the focus on one discipline has disadvantages. Turner et al. (2016) summarized the following limitations: “Without a cognitive model to guide the inferential process, cognitive neuroscientists are often (1) unable to interpret their results from a mechanistic point of view, (2) unable to address many phenomena when restricted to contrast analyses, and (3) unable to bring together results from different paradigms in a common theoretical framework” (p66). Cognitive models from cognitive scientists however, can be abstract and hard to evaluate when they only describe behavioural data. When two models with different approaches show the same behavioural results it is difficult to distinguish between them (Turner et al., 2016). These limitations inspired new approaches where models from cognitive scientists are combined with neurological data from the neuroscientists. The umbrella term for this combined approach is model-based cognitive neuroscience (Forstmann & Wagenmakers, 2015). This field has gained attention in recent years and is rapidly expanding. Model-based cognitive neuroscience already has been used to investigating many different phenomena, for example in the domains of perception, attention, memory, categorization and cognitive control (Palmeri, Love, & Turner, 2016; Pratte & Tong, 2016).

### **2.2.2 ACT-R and model-based cognitive neuroscience**

One example of a model-based cognitive neuroscience approach is mapping different modules in ACT-R onto regions in the brain. This mapping is shown in Figure 2 and is based on the literature (Anderson, 2007) and this is later refined with model-based analysis (Borst et al., 2015). The mapping shown in Figure 2 shows the colored squares on locations where fMRI activity would be expected when the corresponding colored ACT-R module are activated during a task.

The mapping of the modules to the brain enables us to use fMRI data to evaluate cognitive models. For example when the fMRI data of an experiment shows clear activation in an area where a module is mapped but the model itself does not show this, this could suggest that the model needs adjustments. This evaluation approach, however, already assumes a good mapping of the modules to the brain. EEG data is measured on the scalp and therefore a different mapping is needed, such mapping does not yet exist. A method to create mappings such as Figure 2 is model-based analysis. Model-based analysis will be discussed in the following section.

### **2.2.3 Model-based analysis**

Model-based analysis can be used to investigate new connections between model constructs and brain areas, or evaluate existing mappings. Most EEG and fMRI analysis methods use the condition-structure of the experiment as the basis for regressors in a General Linear Model (GLM). In standard fMRI analysis for each voxel in the brain a linear model is fit, and then the conditions are compared to

determine in which voxels the BOLD level differs significantly between conditions. This indicates the voxels that show activity during the different conditions. In model-based analysis, instead of the condition structure, the module predictions of the computational models are used as regressors in the GLM. In model-based fMRI analysis a linear model is fit to each voxel, and when the neurological data correlates significantly with one of the modules they are assumed to be involved in the simulated process. The advantage of model-based fMRI analysis over regular fMRI analysis is that a different predictor can be used for each trial, and that multiple processes can be active simultaneously and to different degrees within each trial (Borst & Anderson, 2017).

Borst & Anderson (2017) used model-based analysis to demonstrate how fMRI data could be used in combination with an ACT-R model. They located different ACT-R modules in the brain, for example declarative memory retrievals and manual actions. Model-based analysis is not only used in combination with the ACT-R modules but it can also be used with different kind of cognitive models. For example Ahn et al. (2011) successfully used model-based fMRI in combination with the Prospect Valence Learning model, which is a mathematical model of the decision-making processes in the Iowa Gambling Task.

#### **2.2.4 Model-based EEG analysis**

Model-based analysis has not yet been used in combination with EEG. EEG is a method by which the electrical current of the brain can be measured while it is performing tasks. This electrical activity is generated by the synchronized activity of thousands of neurons. When enough neurons fire in sync the electrical current is strong enough to spread through tissue, bone, and skull and therefore it can be measured non-invasively on the head surface. Figure 3 shows an EEG cap and the connected electrodes that measures the currents in the different channels. An advantage of EEG compared to fMRI is the excellent temporal resolution. The EEG response is in the order of milliseconds, where the fMRI bold response lags a couple of seconds. Therefore, EEG is more suited to answering questions about time differences and fast paced tasks. The spatial resolution of EEG is low due to the scattering of the signals through tissue and the skull.



**Figure 3. An EEG cap and the connected electrodes to measure electrical activity that is generated by the synchronized activity of neurons.**

A common method to investigate EEG data is by creating event-related potentials (ERPs) from the EEG data. ERPs show the average electric field measured in a channel reflecting the neural response to a certain event. Figure 4 shows an example of an ERP waveform.

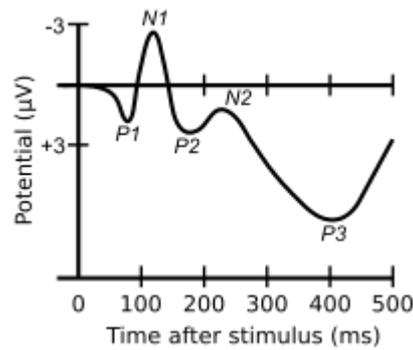


Figure 4. ERP waveform example.

ERPs capture neural activity related to both sensory and cognitive processes (Sur & Sinha, 2009). ERPs from different task conditions can be contrasted to each other to investigate differences, but individual ERPs can also be analyzed based on the different positive and negative peaks in the waveform. The peaks in the waveforms reflect different sensory and cognitive processes. There are two categories of ERP waves: the early waves and the later waves. The early waves peak within the first 100 milliseconds after stimulus. These are called the sensory ERPs because they depend on the physical parameters of the stimulus. The later ERPs are called the cognitive or endogenous ERPs because they reflect how the subject evaluates the stimulus and therefore how they process information (Sur & Sinha, 2009). A considerable amount of research has investigated the different ERP components, where they are associated with and how they can be manipulated. In this project however, we focus on model-based analysis and we only use ERPs to contrast the different task conditions. The contrasted ERPs can evaluate the quality of the EEG data and validate whether the assumption that the different task conditions elicit different neural responses holds or not.

Model-based analysis has been used in combination with fMRI data and an ACT-R model (Borst & Anderson, 2017). In model-based fMRI analysis the fMRI BOLD signals and the ACT-R module predictions are used in a GLM to find the voxels in the brain that correlate significant with the different modules. EEG channel data is measured on the scalp, so instead of voxels in the brain, model-based EEG analysis will be able to find correlating data channels on the scalp. With these results we will be able to plot the correlations between the different modules and the different EEG channels on the scalp. To be able to interpret the mappings between the modules and the EEG data, more information is needed about algebra problem solving and which brain areas are expected to show activity during this task. This will be discussed in the following section.

### 2.3 Problem solving and brain regions

To be able to evaluate and interpret the results from the model-based EEG analysis more information is needed about problem solving and the associated brain regions. Problem solving generally requires a combination of working memory updating, cognitive control and declarative memory retrievals.

Working memory refers to a system for temporary maintenance and manipulation of information in the brain, a function used for a wide range of cognitive operations (Goldman-Rakic, 1995). Most working memory tasks show connections with the pre-frontal cortex (PFC) and parietal areas. This was first hypothesized based on data from patients with prefrontal lesions that resulted in a loss of

immediate memory and several animal studies showing similar results (Goldman-Rakic, 1987; Müller & Knight, 2006; Verin et al., 1993). Later brain imaging confirmed the predictions of the connection between the frontal regions and working memory (Baddeley, 2003).

Cognitive control can be defined as the human ability of information prioritization for goal-driven decision-making (Posner & Snyder, 1975). It selects appropriate perceptual information for processing and ignores irrelevant stimuli, inhibits inappropriate responses and maintains relevant contextual information (Botvinick, Braver, Barch, Carter, & Cohen, 2001). Cognitive control and working memory are tightly coupled because most of the characteristics of cognitive control require some sort of temporary maintenance and manipulation of information. This also works the other way around: somehow cognition has to decide which information to maintain in working memory. Cognitive control processes have been mostly mapped to clusters in the posterior medial frontal cortex (pmMFC) in combination with the lateral prefrontal cortex (LPFC) (Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004). Also the anterior cingulate cortex (ACC) is involved in a form of attention that serves to regulate both cognitive and emotional processing (Bush, Luu, & Posner, 2000).

Declarative memory is the memory of facts and events that can be recalled. In the literature there is a distinction between autobiographical, episodic and semantic memory. During retrieval those different kinds of memory show overlapping activity in brain areas but also some areas showed memory-kind dependent activation. Burianova & Grady (2007) found activation for all memory types in the inferior frontal gyrus, the middle frontal gyrus, the caudate nucleus, the thalamus, and the lingual gyrus when retrieving from memory. Semantic memory will be most relevant for solving algebra problems where you have to retrieve arithmetic facts from memory. In contrast to the other memory types semantic memory showed activation in the left medial-temporal lobe in the anterior and superior areas. It also showed unique activations in the right inferior temporal lobe during retrieval (Burianova & Grady, 2007). Semantic memories are presumed to be encoded by the hippocampus, entorhinal cortex and perirhinal cortex. These are all located in the medial temporal lobe (Eichenbaum, 2004). The medial temporal lobe has been associated with the encoding, storage and retrieval of long-term memories (Simons & Spiers, 2003).

## **2.4 Algebra solving and brain regions**

In this study, we focus on solving algebra problems. Algebra is one specific case of problem solving that has been extensively investigated. To solve algebra problems, two types of knowledge are required: procedural knowledge of how to solve a problem and arithmetic knowledge facts. In more complex cases also the intermediate states of the problem must be maintained and updated during the solution process. The retrieval of arithmetic facts is similar to the declarative memory component from general problem solving. The procedural knowledge and the intermediate states are a combination of the working memory and cognitive control components from general problem solving.

During algebra problem solving several different brain areas are activated. The intraparietal sulcus (IPS) is involved in the manipulation of quantity representations and that the left Angular Gyrus (AG) is involved in the retrieval of arithmetic facts and the manipulation of numbers in verbal form (Dehaene, Piazza, Pinel, & Cohen, 2003). Both areas are located in the parietal lobe. The frontal brain areas are assumed to be involved in performance monitoring and working memory in complex calculations (Arsalidou & Taylor, 2011). However, there is no consensus on the distinction between those areas and their functions during algebra problem solving. For example Stocco & Anderson (2008) found evidence that the prefrontal area tracks the retrieval of algebraic facts, but Danker & Anderson (2007) showed that parietal activation and prefrontal activation were involved in both the

transformation and retrieval stages of an algebra task and that those were tightly intertwined. The brain areas and their exact involvement for algebra solving might still be in debate but the areas involved are the same areas that show activity in general problem solving.

Other studies focused on the different solving strategies in algebra, for example whether the answer is retrieved from memory or calculated. Research showed a larger activation in the angular gyrus when the solutions were retrieved from memory, and more activation spread over the pre-frontal cortex when procedural strategies were used to solve the problems (Grabner et al., 2009). The left parietal structures are more activated in simple arithmetic fact retrieval and the frontal areas are more involved in complex calculation processes. This is shown with children, when they started learning algebra they were heavily dependent on the frontal brain areas but when they gained experience this activation shifted to the parietal areas (Zamarian, Ischebeck, & Delazer, 2009). Equations that need to be calculated require more retrievals and more working memory and activate the pre-frontal cortex. This corresponds to the working memory aspect in general problem solving that is described as a combination of pre-frontal and parietal brain activation.

Stocco & Anderson (2008) used five ACT-R modules to model their algebra task. They used the procedural module, the visual module, the manual module, the retrieval module and the imaginal module. As shown in the mapping between the ACT-Modules and the brain dissections in Figure 2 the procedural module is mapped on the basal ganglia, the visual module on the fusiform gyrus in the occipital lobe, the manual module on the motor cortex extending from the precentral gyrus, through the postcentral gyrus, into the parietal lobe (Borst & Anderson, 2013), the imaginal module on the parietal lobe in the intraparietal sulcus and the declarative module on a region in the inferior ventrolateral prefrontal cortex.

## **3 Present study**

### **3.1 Research question**

Can we find connections between EEG data from an algebra problem solving task and the predictions from a cognitive model of this task, to determine whether EEG data can be used to constrain cognitive models?

### **3.2 Approach**

The ultimate goal of this project was to investigate whether EEG data could be used to constrain cognitive models. Data from fMRI experiments are already used to constrain cognitive models but the connection between EEG and cognitive models is less elaborated. The great temporal resolution of EEG could be beneficial in evaluating models. We investigated the connections between EEG data and cognitive models by examining the correlations between EEG channel data from an algebra problem solving task and the modules from a cognitive model of this task in the ACT-R architecture.

An algebra task was chosen because previous efforts to model algebra tasks in the ACT-R architecture showed activity in five different modules when solving algebra problem; the procedural module, the manual module, the imaginal module, the visual module and the declarative memory module (Stocco & Anderson, 2008). Algebra is also a task that most people learned in school and the difficulty of the task is adaptable. An experiment was conducted where participants solved various algebra problems while EEG channel data was recorded. The difficulty of the algebra problems were varied by altering the amount of transformations and memory retrievals needed to solve the equations. A new cognitive model in the ACT-R architecture was created that made predictions of the same algebra problems as the participants had to solve.

The analysis method that we used to investigate the correlations between the collected EEG channel data and the ACT-R module predictions is model-based EEG analysis. In model-based EEG analysis instead of the condition structure of an experiment the ACT-R module predictions are used as regressors in a GLM. The advantage of using the module prediction as regressors is that a different predictor can be used for each trial, and that multiple processes can be active simultaneously and to different degrees within each trial (Borst & Anderson, 2017).

The results from the model-based EEG analysis showed the correlations between the different EEG data channels and the ACT-R modules. The correlations were mapped on an image of the scalp based on the location of the data channels. This resulted in activation maps that showed the correlations between the data channels and the modules used in the ACT-R model. For this analysis we used the manual module, the imaginal module, the visual module and the declarative memory module. The created activation maps were examined to find out whether they showed correlations between the model and the EEG data in areas where activation would be expected based on the literature. Correlations between the EEG data channels and the model predictions in expected locations suggest that model-based analysis is possible in combination with EEG data, and therefore also to constrain cognitive models in the future. For the manual module we expected the activation map to show correlations around the motor cortex, for the visual module around the occipital lobe, for the imaginal module parietal lobe and for the declarative module around the prefrontal regions.

### **3.3 Execution**

The first step in this project is running the algebra experiment with participants to collect the EEG and behavioral data. The EEG data will be evaluated by creating ERPs to determine whether the different task conditions also elicited different neural responses. The results from the behavioral data will be used as input to create a cognitive model from the algebra task in the ACT-R architecture. This model will be adapted to fit the behavioral results. When there is a model of the algebra task, the model will be used to predict the same trials as the participants did. Then the model-based EEG analysis will be performed. The module predictions from the cognitive model will be used as regressors in a GLM. This will show correlations between the different ACT-R modules used in the model and the EEG data channels. These correlations will be mapped on activation maps and the results will be analyzed to evaluate whether EEG data could be used to constrain cognitive models.

## 4. Method

### 4.1 Algebra task

The experiment consisted of solving algebra problems. The task was to find the value of 'x'. The value of 'x' was always a number between 1 and 9. During the experiment five different problem types were presented to the participants. Each problem type had a different difficulty and required different actions to be solved. The amount of memory retrievals and transformations needed to solve the problems were varied because we expected that these differences would also result in different cognitive processes and therefore elicit differences in the EEG channel data.

The simplest question was problem type 1. Problem type 1 was in the format: 'x = a' where 'a' is a random generated number between 1 and 9. This can be solved instantly without any retrievals or transformations.

Problem type 2 had the format 'x (+ or -) b = a'. To solve this participants had to eliminate the addend on the left side by adding or subtracting b to a. One transformation and a simple memory retrieval of an addition or a subtraction fact was needed.

Problem type 3 was a division task in the format 'x = b/a'. To solve this, one memory retrieval is needed. Problem type 4 was in the format 'a\*x = b'. This can be solved by unwinding the unknown by applying the inverse operand of its factor. One transformation followed by one memory retrieval is needed.

The most complex problem type was problem type 5. The format is: 'a\*x (+or-) c = b'. To solve this problem two transformations are needed (adding or subtracting c to the right term and then the unwinding step), and two memory retrievals are needed. Examples of the five different problem types with the corresponding amount of retrievals and transformations to solve them are shown in table 1.

**Table 1. Overview of the different problem-types. An example problem and the estimated amount of memory retrievals and transformations needed to solve the problems.**

Problem type	Example problems	Retrieval	Transformation
1	$x = 8$	None	None
2	$x - 2 = 4$ / $x + 4 = 9$	One	One
3	$x = 32/8$	One	None
4	$8x = 32$	One	One
5	$8x - 4 = 28$ / $8x + 4 = 20$	Two	Two

### 4.2 Apparatus and Setup

Participants were tested individually in a small windowless room. They were seated in front of a 1366 by 768 21.5 inch screen with a density of 72dpi. Participants were asked to use a trackball to select the answers. A picture of the trackball is shown in Figure 5. The button on the side of the trackball had to be used to click when they knew the answer of the equation. A trackball was used because the same experiment will also be conducted with an fMRI setup in a future experiment and a trackball is easier to use while lying down in an fMRI machine. With the same setup the results from the two experiments will be comparable

EEG data was recorded with a sampling rate of 512 Hz from 128 scalp electrode channels, 4 ocular electrodes (2 VEOG and 2 HEOG), and 2 reference electrodes on the mastoids. The BioSemi Active Two system and the accompanying ActiView software were used. Participants were asked not to wear any make-up and no hair products during the experiment. After the set-up, including attaching the 6 face-electrodes, applying the EEG-cap and filling each of the 128 holes in the cap with conducting gel and connecting the 128 electrodes, the offset between the electrodes and the skull of the participants was inspected. Each active electrode should have an offset between  $\pm 40$  mV, and the signal had to be stable. When this limit was exceeded or the offset was unstable, the deviating electrodes were taken out of the cap and extra conducting gel was added. This process was repeated until all the electrode offsets were stable and between  $\pm 40$  mV. The complete set-up process took about 30 minutes per participant.

### 4.3 Procedure

During the set-up of the EEG-cap participants were given printed task instructions and they had the opportunity to ask any further questions about the upcoming algebra task. A timeline of the steps in an algebra trial is shown in Figure 5. Every trial started with a fixation cross (200 ms), followed by an algebra problem that had to be solved. Once the participant calculated the answer they were asked to use the button on the side of the trackball to click. When they clicked the equation disappeared and a circular keypad with the numbers 1-9 appeared where they had to select the answer. The maximum time the participants had to calculate the answer and click the trackball was 10 seconds, when there was no click registered before this the circular keypad appeared automatically. See Figure 5 for an image of the circular keypad. Participants were asked to use the trackball to move the cursor to the answer and click on it. The cursor started in the center of the circular keypad every trial. The maximum allowed time to select the answer on the circular keypad was 2000 ms. If no response was registered after 2000 ms the participant failed the trial and ‘Too slow’ was shown as feedback. This 2000ms click-limit was chosen to ensure that participants completely calculated the answer prior to the click to reveal the circular keypad. When the participant clicked an answer on the circular keypad, feedback (correct or incorrect) was shown on the screen for 995 ms before the next trial started.

The experiment started with 20 practice trials, four of each of the five problem type in random order. After the practice trial participants had the chance to ask questions and the electrode offsets were checked by the experimenter and adjusted. After the practice trials, the experiment started. The experiment consisted of four blocks of 100 algebra problems each. Every block presented 20 algebra problems of each of the five problem types in a random order. After every block the participants could have a break and the experimenter would check the electrode offsets again and tried to improve them when necessary. The participants could continue to the next block when they wanted by clicking the trackball button. After four blocks the experiment ended. In total each participant answered 400 algebra problems, 80 of each problem-type. Excluding setup, the experiment took approximately 50 minutes.

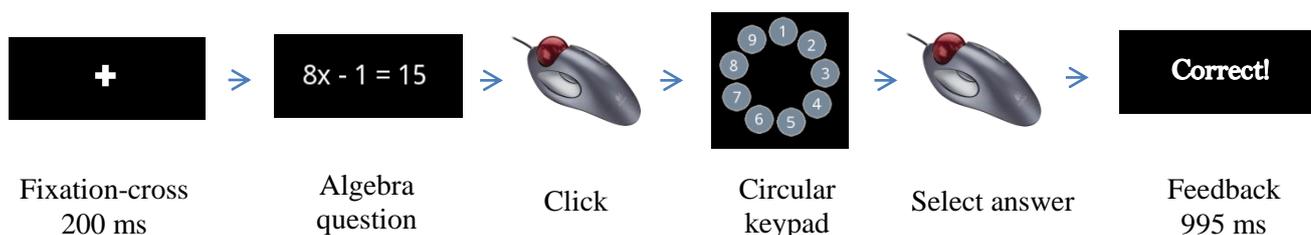


Figure 5. Timeline of the steps in the presentation and solving of 1 algebra problem.

## 4.4 Data preprocessing

EEG data preprocessing was performed using the EEGLab Matlab extension (Delorme & Makeig, 2004). First the EEG data was re-referenced to the average of the mastoids. The next step was rejecting artifacts from the data. A manual visual inspection of the dataset was performed by scrolling through the complete dataset, rejecting the parts with noise that could not be explained by eye blinks. If a channel was unstable throughout a larger part of the experiment, the complete channel was removed from the data. The amount of channels removed per participant ranged from 0 to 15 channels with a mean of 7.3 removed channels. These removed channels were later restored by interpolating the signal from the spherical channels around the removed channels. Then the data was resampled to 250 Hz and a high pass filter of 0.1 Hz and a low pass filter of 50 Hz were applied. To remove eye blink artifacts, the data was decomposed using Independent Component Analysis (ICA) and components associated with eye blinks were projected out of the data.

Finally, the continuous data was epoched in separate trials and only the complete and correctly answered trials were used. Onset-locked epochs from -500 ms to 1500 ms and response-locked epochs from -2000 ms to 500 ms were obtained for the ERP analysis. A mean baseline from -200 ms to 0 ms was obtained from the data. For the model-based analysis, for each trial -200 ms until the response was extracted from the continuous data, thus each trial had a different length. The response times were extracted from the behavioral data.

## 4.5 Model-based analysis

A practical guide to model-based fMRI analysis in combination with ACT-R is described in a tutorial paper by Borst & Anderson (2017). The approach they describe is used as the basis for the model-based EEG analysis in this project. Some adaptations had to be made to make this method applicable for EEG.

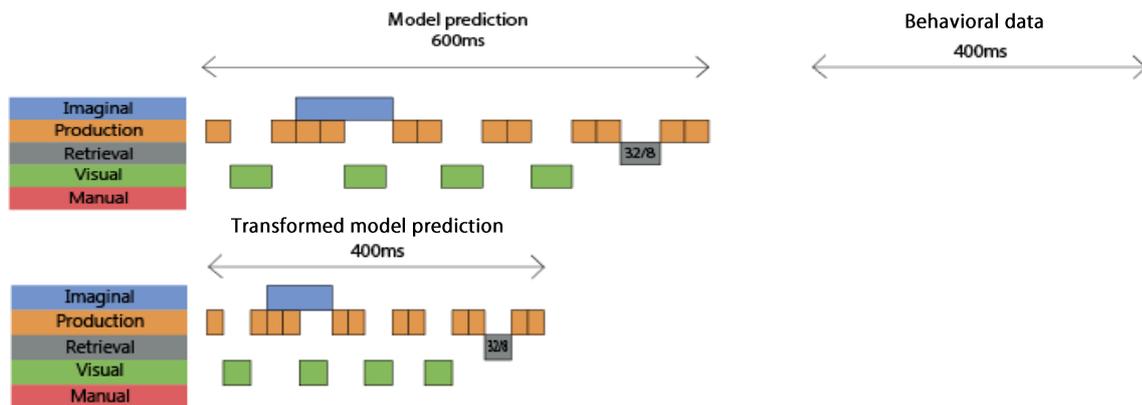
In model-based EEG analysis a multiple linear regression was used with the module predictions from a cognitive model as regressors. A multiple linear regression is a general linear model with more than one independent variable, and one dependent variable. The following equation was used:

$$y_{ij} = \beta_{0ij} + \beta_{ij \text{ Visual}} X_{i \text{ Visual}} + \beta_{ij \text{ Manual}} X_{i \text{ Manual}} + \beta_{ij \text{ Retrieval}} X_{i \text{ Retrieval}} + \beta_{ij \text{ Imaginal}} X_{i \text{ Imaginal}} + \epsilon_{ij}$$

Two datasets are needed to perform a model-based EEG analysis: EEG channel data (the  $y_{ij}$  in the multiple linear regression equation) and the module predictions from a cognitive model (the different  $X_i$  in the multiple linear regression equation). The  $i$  is the participant and the  $j$  the EEG data channel. During the preprocessing of the EEG data, epochs were obtained for all channels, for every trial from -200 ms until the response. The  $y_{ij}$  is the EEG data vector from one channel, from all the (correct and complete) trials merged together, of one participant. This data was resampled to 250 Hz.

The different  $X_i$  (visual, manual, retrieval, imaginal) are the module activity predictions from the ACT-R model. When ACT-R models predict task performance they specify when each module is active during the solving process. A visual example of the module activity from five ACT-R modules is shown in Figure 6. The predicted activity of the different modules from ACT-R models are used as

regressors on a trial-by-trial basis. Therefore, the ACT-R module predictions have to be matched to the participants' behavior, so the model needs to run and predict the exact same trials as the participants did. Before a GLM can be fit, the length of the module predictions has to be matched to the behavioral data. Figure 6 shows an example of the transformation of the module predictions to match the behavioral data. The module predictions have to be scaled and linearly transformed trial-by-trial to exactly match the length of the trials in the behavioral data. For example when a module prediction of a trial took 600 ms but the behavioral of the same trial showed 400 ms the module predictions had to be transformed linearly to 400 ms.



**Figure 6. An example of module activation in an ACT-R model over time. The colored blocks indicate that a module is active. The figure also shows an example of the linear transformation of the module predictions from 600 ms to 400 ms, to match the behavioral data.**

These module predictions also had to match the sampling rate of the EEG data, in this case 250Hz, so one second of trial data consist of 250 data points containing zeros when the module is inactive and ones when the module is active.

This resulted in two datasets, one with the neural data of the different EEG channels and trials from the participants and one with all the predictions of the different modules resized to exactly the size of the neural data. These two datasets can be used in a multiple linear regression model. Figure 7 shows a visual overview of how the  $y_{ij}$  data from one channel and the different  $X_i$  in the formula were obtained.

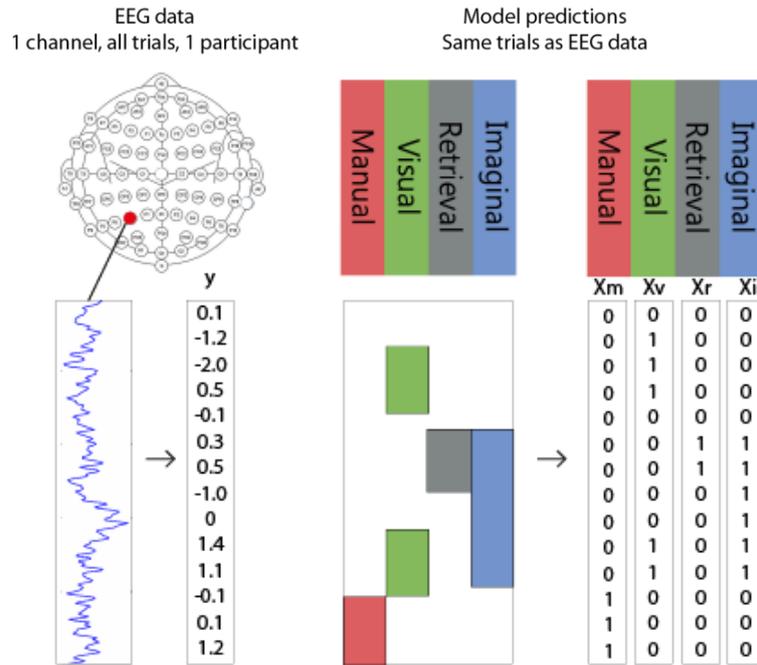


Figure 7. Visualization of the data needed in the general linear model. Data from 1 EEG channel of all trials from 1 participant is shown. This data is used as the  $y_{ij}$  data in the general linear model equation. The model predictions are transformed to binary data, where 0 means no module activity and 1 means that the module is active. These values are used as the different  $X_i$  values in the equation. The amount of time points from the EEG data and the module data are matched.

In the multiple linear regression formula,  $\beta_0$  is the intercept and  $\epsilon$  is the error term for the data that cannot be explained by the different modules. With the EEG data and the module data the multiple linear regression estimated the different  $\beta_{ij}$  (Visual, Manual, retrieval, Imaginal). The  $\beta_{ij}$  can be described as the weights of the different modules: how much of the specific module is needed to explain  $y_{ij}$ . The different  $\beta_{ij}$  were calculated for each participant per channels across all trials. Next, the different obtained module  $\beta_{ij}$  were averaged for all the participants per channel per module. An ANOVA was used to calculate whether the  $\beta_{ij}$  were significantly different from 0. A significance level of  $p < 0.05$  was used. An averaged  $\beta_{ij}$  that was significantly different from 0 indicated involvement of that channel in that module.

## 6. Results

We start this section by discussing the behavior results from the algebra experiment. The behavioral results were used as input for the ACT-R algebra model and therefore should be addressed first.

### 6.1.1 Participants

Twenty-eight right-handed participants were tested (age = 19–41 years,  $M = 22.7$  years,  $SD = 4.7$ , 12 women). Every participant received 12 euros compensation for their participation. Based on behavioral analysis one participant was removed because of the high percentage of errors. This participant scored 47.5% incorrect in problem type 5 and problem type 1 (e.g.  $x = 8$ ) was answered incorrectly 4 times. This result indicates that the participant was not paying full attention to the task and did not put effort in correctly solving the problems. During the visual inspection of the EEG data analysis five more participants were removed due to excessive noise in the recordings, leaving a final dataset of 22 participants.

### 6.1.2 Behavior results

Figure 8 shows an overview of the behavioral results from the algebra experiment. Reaction times (RTs) were measured from onset of the equation on the screen until the participant clicked the trackball. Only correct trials were included. Per participant the outliers per condition with a deviation larger than three SDs were removed.

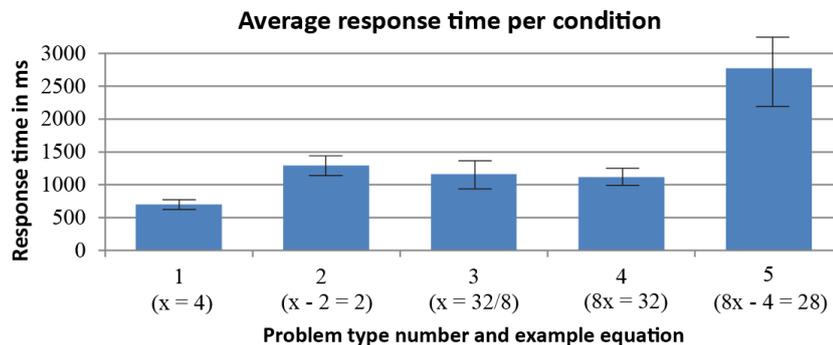


Figure 8. A graph of the behavioral results from the algebra experiment. The means of the correct trials per problem type and the confidence intervals (95%) are shown.

Table 2 shows an overview of the behavioral results and the estimated amount of memory retrievals and transformations the participants had to perform when solving the problems.

Table 2. Overview of the RTs SDs and error percentages per problem type from the behavioral data from all participants. Also the estimated amount of memory retrievals and transformation that participants needed to solve the equations are shown.

Problem type	Reaction time correct trials [ms]	SDs [ms]	Error percentage [%]	Memory retrievals	Transformations
1 ( $x = 4$ )	695	116	1.3	None	None
2 ( $x - 2 = 2$ )	1292	320	3.6	One	One
3 ( $x = 32/8$ )	1161	372	5.6	One	None
4 ( $8x = 32$ )	1117	276	6.0	One	One
5 ( $8x - 4 = 28$ )	2771	815	14.5	Two	Two

The first problem type was answered the quickest. Also, the error percentage of problem type 1 was the lowest. Problem type 2, 3 and 4 show similar RTs. Problem type 2 shows a smaller error percentage. Problem type 5 takes longer to solve than the other problem types. Also the error percentage with 14.5% is higher.

A one-way ANOVA analysis showed that there was a significant effect of the problem type on the RTs at the  $p < .05$  level for the five conditions [ $F(4, 105) = 68.45, p < .001$ ]. Post-hoc comparisons using the Tukey HSD test indicated that the mean RT from problem type 1 was significantly different from problem type 2, problem type 3, problem type 4 and problem type 5. Problem types 2, 3 and 4 mutually showed no significant difference, but they all showed significant difference compared to problem types 1 and 5. Problem type 5 was significantly different from problem types 1, 2, 3 and 4. Table 3 shows the results from the Tukey HSD test.

**Table 3. Results from the post-hoc comparisons using the Tukey HSD test.**

<b>Problem types</b>	<b>difference</b>	<b>p-value</b>
2-1	602	< .001
3-1	492	0.003
4-1	461	0.007
5-1	2126	< .001
3-2	-110	0.923
4-2	-140	0.831
5-2	1524	< .001
4-3	-31	0.999
5-3	1634	< .001
5-4	1665	< .001

### 6.1.3 Behavior discussion

Because the results from the behavioral data are used as input for the algebra model the results from the behavioral data will be discussed here.

As expected, problem type 1 took the shortest time to solve. The low error percentage makes sense because there is nothing to calculate, just a response. It would be expected that solving problem type 2 and 4 takes roughly the same amount of time because they both need one transformation action and one retrieval action to be solved. Problem type 3 requires one retrieval action and no transformation, and would therefore be expected to be faster to solve. The results, however, show no significant difference between problem types 2, 3 and 4. The lack of difference between problem type 2 and 3 might be explained because retrieving a subtraction or addition fact is easier and therefore faster than a division fact. But this would not explain the lack of significant difference between problem type 3 and 4. We assumed that when participants solve problem type 4: '8x=32' they first transform this to 'x=32/8' which is the same as problem type 3. Therefore we assumed that this extra transformation step would add a significant time to the solving process. The results show the opposite, problem type 4 shows actually a slightly shorter solving time. This result might suggest that participants do not start with transforming problem type 4 to problem type 3 but that they immediately start with the retrieval of the division fact. This might be because they are so familiar with this format of the equation that they automatically know how to solve it without the intermediate transformation step.

Problem type 5 has the largest RT. This is probably due to the two transformations and the two memory retrievals that are necessary to solve the problem. The differences with the other problem types in RT as well as error percentage is very large, which might suggest that there is more going on than just one extra transformation added to problem type 4.

## 6.2 Model

Stocco & Anderson (2008) already developed an algebraic problem solving model in the ACT-R architecture. Their model was designed to predict the results from equations such as ' $a*x - a = a*b - a$ ' and ' $8*x - 2 = 36 - 6$ '. These equations are different from the ones used in this project and therefore they require different solving strategies and models. However, we used the same ACT-R modules Stocco & Anderson (2008) did to solve the algebra problems. They used five different ACT-R modules: the production module, the visual module, the imaginal module, the retrieval module and the manual module. Figure 9 shows the module traces from the model we created to predict the five different problem types. The traces show the predictions from the models module activation from the different modules over time. This figure shows the different steps and lengths of the solving process per problem type.

An assumption we made for all problem types is that participants start by looking at the equation on the screen from left to right, symbol for symbol. For example, when ' $x=32/8$ ' is shown on the screen, first 'x' will be attended with the visual module, read and then stored in the imaginal buffer. When the first item is attended a chunk to store the information in the imaginal buffer is created which takes 200 ms. After attending the 'x' this will be followed by attending and processing '=', '32', '/' and finally '8'. Adding items to the slots in the imaginal chunk does not require extra time in this model. The equal sign is treated as a special case. When a visual-location contains an equal sign a production rule fires to look for the next item of the equation. The equal sign is not attended with the visual module and not stored in the imaginal chunk. This is because we assume that the equal sign is noticed to divide the equation into a left hand side and a right hand side but not interpreted and processed later on. When the complete equation is attended and added to the slots in the imaginal chunk, a production rule based on the contents of the imaginal chunk will decide how to further solve the problem. When there is only one slot filled in the left side and one on the right side of the created imaginal chunk, for example x on the left side and 8 in the right side slot, the problem is solved and no further actions are needed. Then a production rule is fired to start the manual module that simulates clicking the mouse button to reveal the circular keypad with the possible answers. When more slots are filled, additional steps are needed to solve the equation.

In problem type 2 (' $x - 2 = 2$ ') and 5 (' $8x - 4 = 28$ ') the first step is adding or subtracting the inverse of the addend from the left side to the right side. In the algebra model from Stocco & Anderson (2008) a memory retrieval was made to retrieve the inverse of + or -, in this model we assume that this is common knowledge and over trained and therefore we use a production rule that skips the transformation step. This was decided because the algebra problems in this experiment were solved a lot faster than the problems from Stocco & Anderson (2008) and adding another retrieval action to the solving process would make it unable to fit the model predictions to the behavioral data. Only one declarative memory retrieval for the addition fact, for example ' $2+2=4$ ', will be retrieved and the slots in the imaginal chunk will be updated.

To solve problem type 3 (' $x = 32/8$ ') only a single memory retrieval is needed of a division fact. In this case ' $32/8=4$ '. When this is retrieved the slots in the imaginal chunk are updated and the problem is solved. In problem type 4 (' $8x = 32$ ') it might be expected that the first step should be a transformation to ' $x=32/8$ ' and then a memory retrieval of ' $32/8=4$ ' to solve the problem. The behavioral data, however, showed no significant differences between the two problem types. Therefore, we decided to assume that participants skipped this transformation step and that they immediately knew that when the equation showed the format ' $8x = 32$ ' they should make a memory retrieval of the division fact ' $32/8=4$ '.

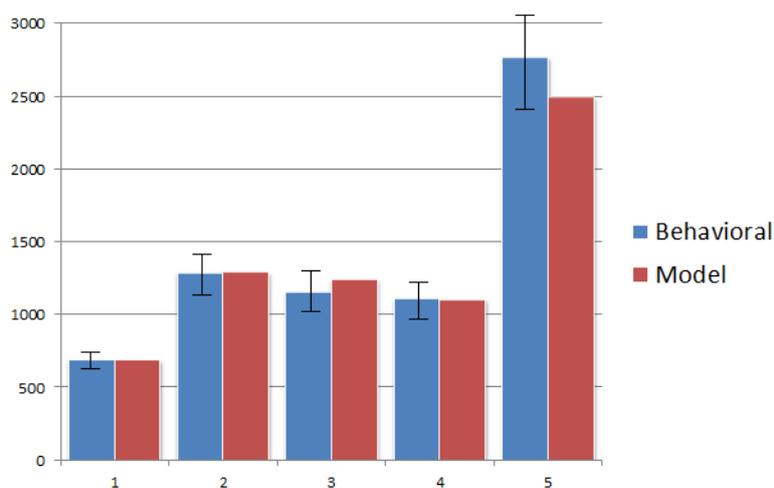


Figure 9. Overview of the module traces from the algebra model we created in the ACT-R architecture. The traces show the activations of the different modules over time. The figure shows the differences between the five problem types.

The behavioral data from the experiment showed that problem type 5 ( $8x - 4 = 28$ ) was harder to solve than the other problem types. This difference cannot be explained only by modeling another transformation to problem type 4 ( $8x = 32$ ). Therefore, a different approach was needed to make the model fit the behavioral data. For problem type 1-4 we assumed that an imaginal chunk was created with four slots for the left side of the equation and two slots for the right side after attending the first item. This took 200ms and adding the attended information to this chunk did not require any time and we modeled no other imaginal actions. Due to the more complex nature of problem type 5 we assumed that more imaginal updates were needed to be able to solve the problem. The first extra imaginal update was modeled after the attending of the complete equation. We assume that this is to process the equation and prepare the retrieval of the addition fact. This imaginal update takes 200 ms. Another imaginal update was modeled after the retrieval of the addition fact because this is an intermediate representation of the equation that has to be remembered by the participant. We assume that a participant at this stage will look back at the equation to recall the information on the left side of the equation. After looking back at the equation we modeled another imaginal update to make a representation of the complete equation in the intermediate state ( $8x = 32$ ). After this update the solving continued by retrieving the division fact to find the final answer of the equation.

We assumed that all participants knew the multiplication tables needed to solve the equations (1 to 9) by heart and therefore decided to model only one example of every problem type. This does not influence the model prediction because when we assume that they were equally good at retrieving for example  $15/3$  or  $18/6$ , modeling more than one example does not make any difference because retrieving those facts from declarative memory will take the same amount of time so the model's RT would not change. The standard time in ACT-R to retrieve a fact from declarative memory is 300 ms. Because of the simple nature of the addition and division facts for this task, the time needed for a memory retrieval was lowered to 80 ms. Stocco & Anderson (2008) also lowered the retrieval time, they lowered it to 60 ms. Because we only use correct trials in the model-based EEG analysis we made the assumption that people are flawless at retrieving the correct fact, so all the facts had the same activation and no errors were simulated in the model.

Figure 10 shows the behavioral response times and the model predictions per problem type. This shows a good model fit for problem types 1, 2, 3 and 4. The model's prediction of problem type 5 is a bit too short, but falls just within the CI bars of behavioral data. The difference between the behavioral data from problem type 5 and the model prediction is 272 ms.

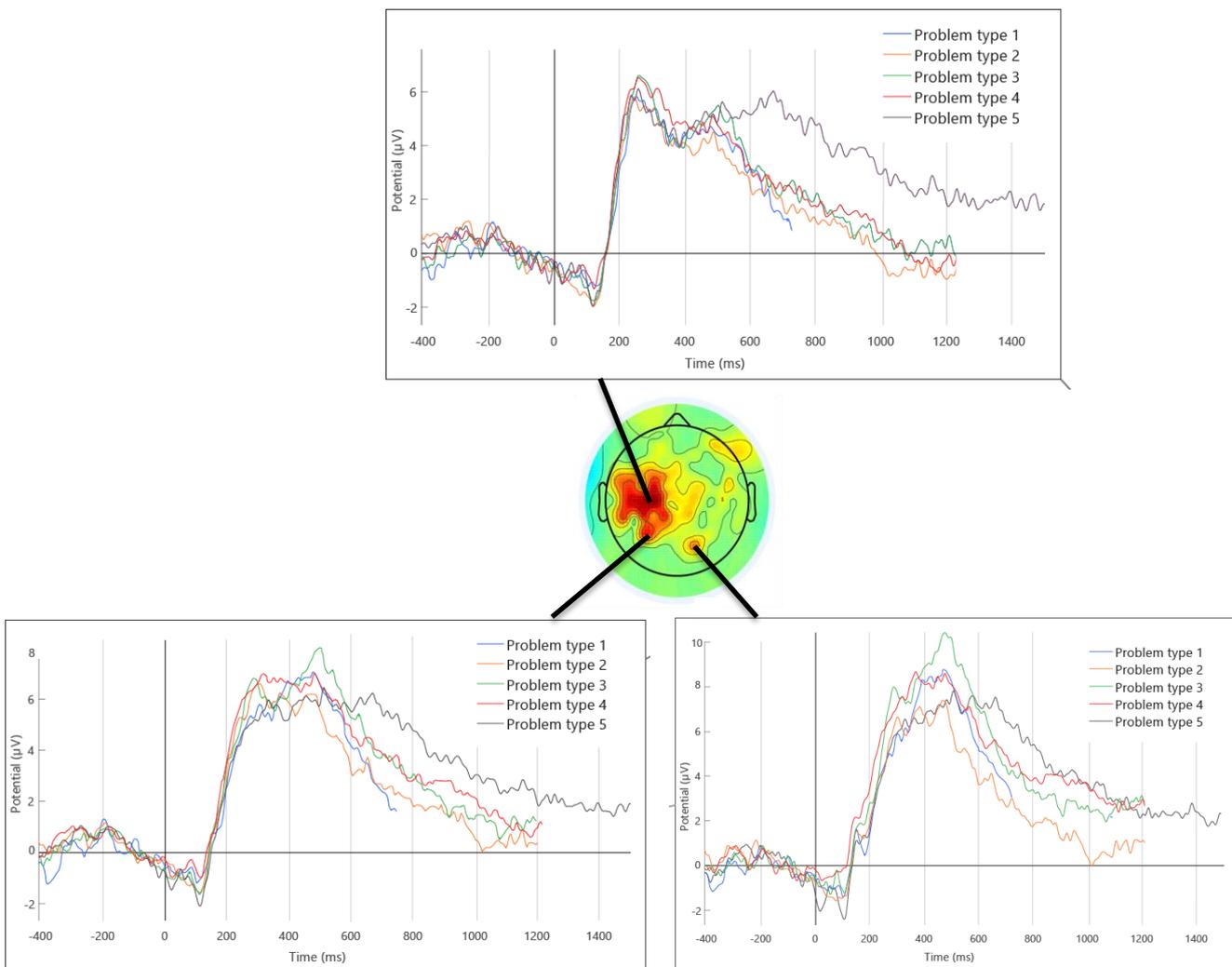


**Figure 10.** The behavioral results compared with the model predictions. The RTs from the five different problem-types are shown. The confidence intervals (95%) are shown for the behavioral data.

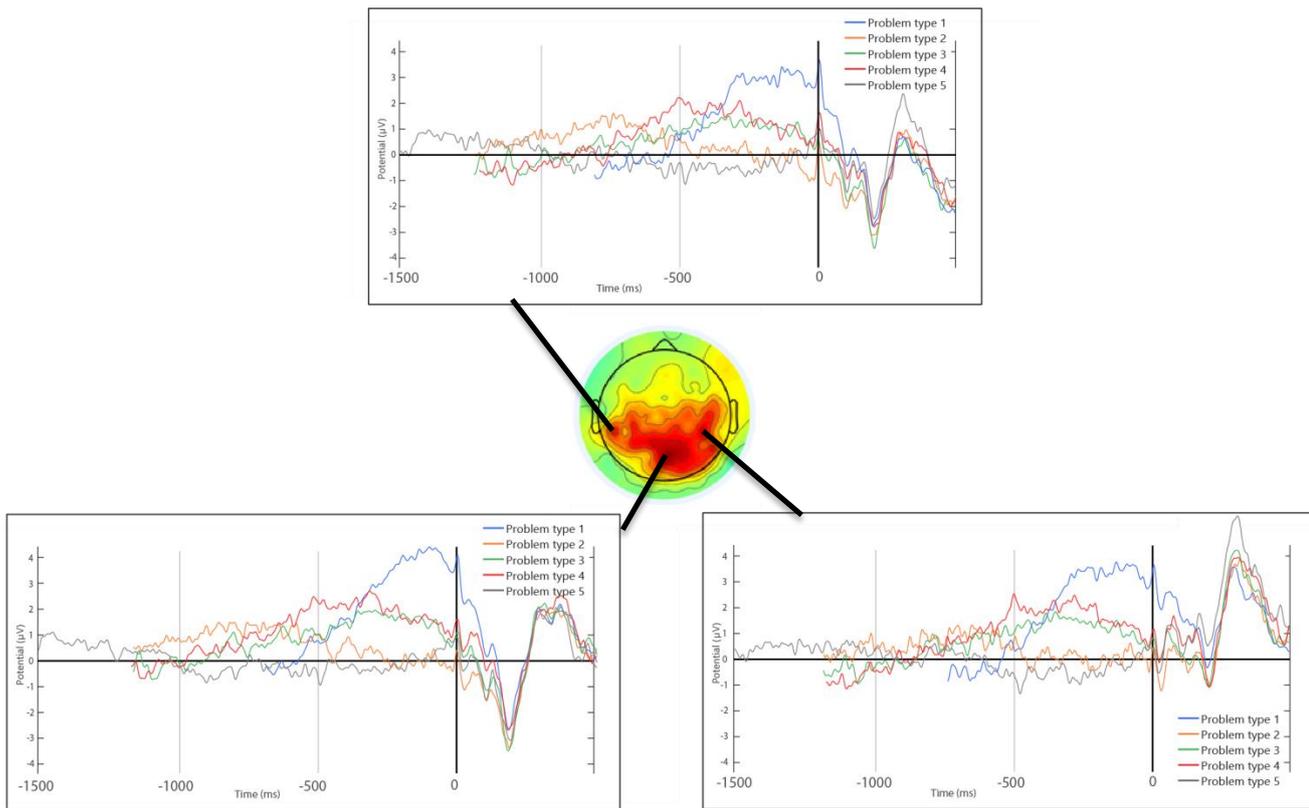
## 6.3 EEG results

### 6.3.1 ERP analysis

ERPs from different problem types for all channels in the EEG data were created to examine whether differences in problem type also elicited differences in neural responses. ANOVAs were used to determine whether there were statistically significant differences between the ERPs of the problem types. A significance level of  $p < 0.01$  and false discovery rate (FDR) correction per channel to correct for multiple comparisons were used. Figure 11 shows a topoplot based on the amount of significant time points that were measured with the ANOVA over the five problem types  $F[4, 105]$ . Darker red means more time points with significant F values. Figure 11 shows three onset-epoched ERPs from channels that showed many significant differences between the problem types. Figure 12 shows three response-locked ERPs with a high number of significant time points. The black lines indicate the location of the ERP on the scalp.



**Figure 11.** The topoplot shows the amount of significant F-values from the onset-locked ANOVA analysis of the five problem types. Darker red means more time-points with significant F-values. Three illustrative ERPs are shown from channels with many significant F-values. The black lines indicate the location from the ERP on the scalp.



**Figure 12.** The topoplots shows the amount of significant F-values from the response-locked ANOVA analysis of the five problem types. Darker red means more time-points with significant F-values. Three illustrative ERPs are shown from channels with many significant F-values. The black lines indicate the location from the ERP on the scalp.

In Figure 11 the onset ERPs show clear differences between the problem types, especially problem type 5. The top ERP from the mid-left channel on the scalp shows a clear delayed peak for problem type 5 compared to the other problem types. The other problem types do not seem to differentiate much from each other. The left and right channels at the back of the scalp both show a deviating peak for problem type 3. These ERPs also both show a delayed peak for problem type 5.

The three response-locked ERPs in Figure 12 all show a similar pattern. Problem type 1 peaks significantly higher than the other problem types from -400 ms until the actual click. Problem type 2 and 5 do not show a peak in this timeframe and 3 and 4 show a smaller peak. One might expect a similar motor bump for all problem types before the response click, but because only problem type 1 show this peak this peak is probably due to perception. Problem type 3 and 4 behave in a similar way in the three ERPs.

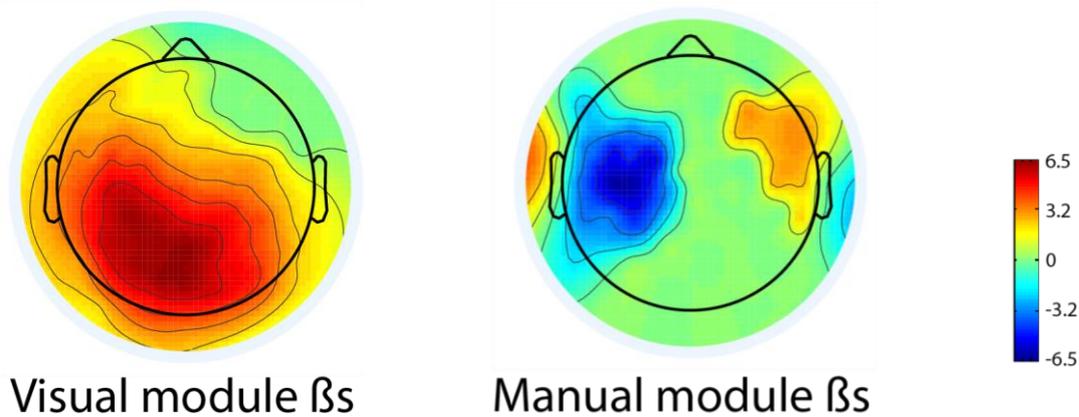
Based on the six ERPs shown in Figure 11 and Figure 12 we conclude that the data shows significant differences between the different problem types. This shows that the EEG data will be usable for further analysis in combination with the ACT-R model. In this project the ERPs will not be further analyzed or interpreted because we focus on a more theoretical-based approach: model-based analysis.

### 6.3.2 Model-based analysis

The model-based analysis was performed following the steps described in the method section. The calculated  $\beta$ s from the different EEG channels per participant in the multiple linear regressions were averaged over all participants per module. An ANOVA was used to calculate the  $\beta$ s significantly different from 0. A significance level of  $p < 0.05$  was used. The activation maps in Figure 13 and 14 show red for highly positive  $\beta$  values and they show blue for highly negative  $\beta$  values. Channels with  $\beta$ s not significantly different from 0 are shown in green. Therefore, the red indicates significant positive correlations between the module activities and the observed EEG data channels and blue indicates significant negative correlations between the module activities and the observed EEG data channels.

Figure 13 shows the results from the model-based analysis plotted on an activation map for the visual module and for the manual module. The visual module shows clear correlations with channels at the back of the scalp; strongest around the area where the visual cortex is located, but there is a large area around it as well. The activation map shows a stronger correlation on the left side of the scalp and is not completely balanced at the center.

The activation map from the manual module shows a significant negative blue area at the center-left side of the scalp and a positive area at the center-right part of the scalp. The total area with significant  $\beta$ s is smaller than in the visual module and is more focused on those two areas.



**Figure 13.** Activation map from the visual and the manual module showing the  $\beta$ s significantly different from 0. The  $\beta$ s were obtained using multiple linear regression with the module predictions as regressors. Blue indicates significant negative  $\beta$  compared to 0, red a positive significant different  $\beta$  compared to 0. Green areas did not show  $\beta$ s significantly different from 0.

Figure 14 shows the activation maps from the imaginal and the retrieval module. The imaginal module shows a large area of activation in the frontal part of the scalp. The most significant correlation lays over the left pre-frontal cortex but almost the complete frontal part of the scalp shows highly significant  $\beta$ s. The retrieval activation map shows fewer correlated channels compared to the other three modules. There is only some activation around the edges of the scalp. Some positive  $\beta$ s at the front are shown and a ring of negative  $\beta$ s are shown at the back of the scalp. Apart from the edges there were no channels significantly correlated with the retrieval module.

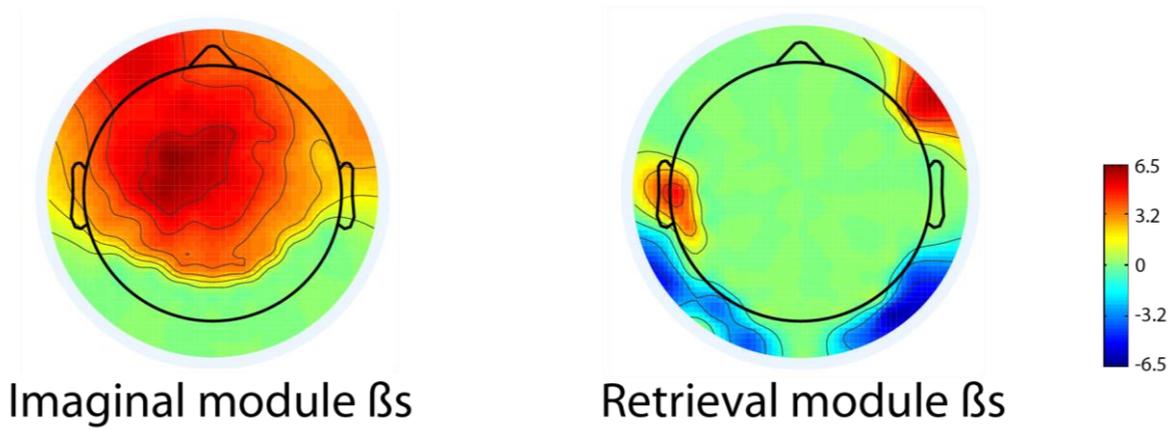


Figure 14. Activation maps from the imaginal and the retrieval module showing the  $\beta_s$  significantly different from 0. The  $\beta_s$  were obtained using a multiple linear regression per channel. Blue indicates significant negative  $\beta$  compared to 0, red a positive significant different  $\beta$  compared to 0. Green areas did not show  $\beta_s$  significantly different from 0.

## 7. Discussion

This project examined whether it was possible to use EEG in combination with cognitive models to be able to use EEG data to constrain cognitive models. This was tested by performing a model-based analysis with EEG channel data from an algebra task, in combination with a cognitive model in the ACT-R architecture. To be able to determine whether model-based EEG analysis was possible we mapped the correlations between the EEG channels and four different ACT-R modules on a scalp map. Correlations between different modules and the EEG channels in areas where activation would be expected based on the literature suggested that model-based analysis is possible in combination with EEG data. This connection between the ACT-R modules and EEG data indicates that EEG data could be used as extra fitting parameters in future modeling projects and therefore constrain cognitive models.

The activation maps from the visual and manual modules in Figure 13 show promising results: both modules show correlations between areas that would be expected to be active for visual and manual tasks. The activation map from the visual module shows clear activation on the back of the scalp, over the visual cortex that is involved in processing visual information. The activation area is spread out over a large part of the upper back of the scalp. The ACT-R module mapping in Figure 2 shows that the visual module is mapped to the fusiform gyrus in the occipital lobe, which is located at the lower back in the scalp. Our results show this as well and they also show activation in the higher areas of the scalp. This corresponds with the results from a project by Borst et al. (2015) where they made a mapping of the ACT-R modules with model-based fMRI analysis. They used a spatial visual processing task and showed that for this spatial visual task the visual module correlated with an area on the parietal cortex instead of the occipital lobe. The activation map from the visual module show a scattered activation around the visual cortex on the scalp, this could be expected due to the distortion of the EEG signals when passing through tissue and skull.

The manual response in the algebra experiment was a right-handed trackball movement-and-click action. Therefore, according to literature and the ACT-R module mappings in Figure 2, correlations at the left motor-cortex would be expected. The activation map shows a large blue area with significant negative  $\beta$ s around the area of the left motor cortex. On the right side of the scalp an area with significant positive  $\beta$ s is shown. The locations with correlation are all around the area of the motor cortex but the exact source of the signal is hard to determine with this activation map. Further analysis with dipole-fitting could be used to find the exact source of the signal to investigate whether the prediction of activation in the left motor-cortex holds. However, the correlations are clearly around the location of the motor cortex and therefore this shows a connection between EEG data and the manual module predictions.

The activation map of the imaginal module shows strong correlations between the module and the EEG data channels at the frontal part of the scalp. The spread in this plot is very large and almost three quarters of the channels show statistical significant involvement of the imaginal module. The activation in frontal area of the scalp could be expected based on the literature that relates working memory to the pre-frontal cortex (Baddeley, 2003). Working memory is involved when making the intermediate representations of the algebra equations. However, the mapping of ACT-R in Figure 2 is located at a different area: on the parietal cortex, specifically on the intraparietal sulcus. The activation map from the imaginal module does not show this. An explanation for results could be that because the imaginal and retrieval module are correlated in problem type 5, it was not possible to distinguish between them with the model-based analysis. Therefore, the activation map of the imaginal module

and the retrieval module could be combined in the imaginal activation map, because the retrieval module would be expected to show correlations in the pre-frontal area.

The retrieval activation map shows an unclear pattern. Only some EEG channels at the edges show correlations. Activation would be expected in the pre-frontal regions and the hippocampus, although the hippocampus is located deep inside the brain and therefore difficult to measure with EEG. The activation map from the retrieval module clearly does not show activation in the pre-frontal regions and the current results could be entirely due to noise. This result also could suggest that the current model does not correctly predict the activation from the retrieval module and that the model needs refinement. The model's limitations will be discussed in the limitations section.

Even though the imaginal and the retrieval modules did not show the desired results, this initial version of the algebra model already showed promising results towards using EEG in combination with model-based analysis. The correlations between the EEG data and the module predictions in the visual and manual model appear in areas that were expected and show a clear connection between the EEG data and the modules. Therefore, we give the preliminary conclusion that model-based EEG analysis in combination with a cognitive model is possible. Being able to use model-based EEG analysis would give cognitive modelers extra parameters to fit their models. This project turned out to be an example that extra fitting parameters can be very useful when modeling because even though the RTs from the behavioral data of the experiment fitted the model predictions well, the model itself probably needs more refinement to also be able to find correlations between the EEG data and the imaginal and retrieval modules.

The project was exploratory research that investigated whether EEG data was usable in combination with cognitive models. The method we used to investigate this was model-based EEG analysis. With our findings that model-based EEG analysis showed promising results with correlations between the ACT-R modules and the EEG data, we give the conclusion that EEG could be used in combination with cognitive models. The great temporal resolution of EEG can give new insights in several fast-paced tasks that might not show up in fMRI analysis. Another advantage of using EEG instead of fMRI is the cost and effort of an experiment. A complete Biosemi 128 channel EEG setup, similar to the one used for this experiment, costs around €44,000 (Biosemi, 2017). An fMRI scanner can easily cost over a million euros and fMRI experiment is much more time consuming.

## 7.1 Limitations

Model-based analysis strongly depends on a correct model of the task. It is possible that the current model of the algebra task, even though the RTs fitted quite well, was not accurate enough. Therefore reevaluating the current model could improve the results. When modeling the algebra task, every possible model should always start with a visual action (looking at the algebra equation at the screen), and always end with a manual action (using the trackball). Therefore we assume that the current algebra model correctly predicted the visual and manual modules and that this might be the reason that the results of those two modules showed the strongest effects. The timing of activations from the imaginal and retrieval modules are less strictly predefined and these can be modeled in different ways and still be able to solve the algebra problems. Therefore these modules are more prone to modeling faults and this is probably where the current model needs improvement.

The assumptions made for the imaginal and retrieval modules might need to be revisited. For the imaginal module we assumed that an imaginal buffer was created after the appearance of an equation. This took 200 ms and adding items to the buffer later on did require added module activation. As a result of this there was only one use of the imaginal module at the beginning of the solving process in

the problem types one to four. In problem type 5, because of the increased difficulty of the problem and the intermediate representations, there were three more imaginal updates modeled to solve the equations. In total four different imaginal module updates were modeled taking 200 ms each. To improve the results from the imaginal activation map one could try to only model the imaginal module for algebra problems that require transformations. This could result in more focused areas of correlations around the parietal cortex in the imaginal module activation map and this could also induce clearer results for the retrieval module activation map.

Another issue with the algebra model could be the difficulty of the facts that had to be retrieved from memory. One may argue that solving for example ' $2+2=4$ ' is so trivial that there is almost no effort needed to solve this, and therefore the ACT-R retrieval time is short. We tried to take this into account by shortening the retrieval times compared to the ACT-R defaults, but this assumption could be incorrect. We decided to give every memory chunk the same activation and therefore the same retrieval time. The results from the retrieval module activation map could possibly be improved with modeling different activations for the algebra facts in declarative memory, for example that retrieving ' $2+2=4$ ' would take less time than retrieving ' $32/8=4$ '.

Besides reevaluating the algebra model, additional analysis of the current data could also give more concluding results. In the current model-based analysis we averaged the data from the different problem types to create a single activation map per module. Expanded the analysis of the separate problem types could reveal more information about the correctness of the modeling assumptions as well as a more precise mapping of the correlations between the EEG data and the module predictions. For example one could investigate the activation maps from problem type 5 and when this would show unexpected results this might be because the imaginal module assumptions were incorrect because most of the imaginal actions were modeled in problem type 5. Another method to extend the current analysis is dipole-fitting. This can be used to locate the exact source of the signals; this would yield more exact results that are better comparable to the existing mapping between ACT-R and fMRI. The ERP analysis is also a section that could be extended. In this project the ERPs from the different problem types were only used to determine whether the data showed significant differences between problem types. This ERP analysis could be extended to get a better understanding of the cognitive processes involved when solving algebra problems and this could inform the algebra model.

## **7.2 Future work**

A next step would be to make a complete mapping of all the modules on the scalp. Model-based EEG analysis should therefore be applied to several different tasks to rule out task dependent effects. This is similar to what Borst & Anderson (2013) did for fMRI data. They used fMRI in combination with model-based analysis to create a mapping between fMRI data and the ACT-R modules. They used five different tasks to locate the various ACT-R modules. A mapping such as this for EEG data could be an additional method to evaluate existing models and inform new models with EEG data. With a mapping of the ACT-R modules on the scalp, cognitive architectures would also be able to predict the EEG signals of models. For fMRI a mapping and the ability to predict the signals already exist, but EEG in combination with a mapping and the ability to predict the signals has great advantages because of the great temporal resolution of EEG. Many tasks and especially problem solving tasks such as the Rubik's cube example are very fast, and many cognitive processes occur inside the brain during this short period to complete the task. EEG and model-based EEG as an analysis method would be much more suited to find out more about these fast problem solving tasks than the existing fMRI analysis methods.

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