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When the brain goes "Aha!": a study on Event-Related Potentials during the moment of insight

Bachelor's Project Thesis

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Abstract: A moment of insight is the experience of sudden comprehension when, for example, solving a puzzle. Insight in the brain is often studied using functional magnetic resonance imaging (fMRI), which has the disadvantage of not recording a continuous data stream. Electroencephalography (EEG), which is recorded continuously, could be a useful alternative to fMRI when looking at insight in the brain. EEG data from twenty-five participants was used to analyse whether there are patterns in electrical activity in the brain when one experiences insight. Possibly, this can be useful to investigate the use of EEG data for studying insight in the brain. Participants were experienced chess players who were asked to solve 100 chess puzzles. On EEG data, an Event-Related Potential (ERP) analysis was applied, in which data was averaged over all trials and all participants. Results confirmed an N200 component and a P300 component found in previous studies investigating ERPs and insight. However, no response-locked ERP components were found preceding preparedness to answer, and no previously reported stimulus-locked ERP components could be attributed to insight prior to a response.

Keywords: moment of insight; electroencephalography; event-related potentials; chess puzzles

1 Introduction

When solving a puzzle, listening to a joke, or trying to remember something, one can experience sudden comprehension. You see the solution to the puzzle; you get the punch line; you remembered! This is often referred to as an "Aha!"-moment, but can also be called the moment of insight (Kounios & Beeman, 2009). Insight can result in a new interpretation of a situation, which in turn can point to the solution to a problem (Sternberg & Davidson, 1995). The cognitive process behind insight is different from processes such as memory retrieval or search (Novick & Sherman, 2003), because it unlocks the way around a problem instead of 'only' solving the problem.

When studying what happens in the brain during a moment of insight, data from functional magnetic resonance imaging (fMRI) experiments is often used (Heeger & Ress, 2002). fMRI is a non-invasive method used to look for changes in neural activity that correlate with particular cognitive processes (Heeger & Ress, 2002). However, a clear understanding of how neuronal activity influences the fMRI signal is needed to correctly interpret the data.

When using fMRI to study insight, one needs to have a clear idea of when insight happens before setting up an experiment. That is because fMRI machines are relatively slow: it takes approximately 2 seconds per scan to collect data (Heeger & Ress, 2002). This means that time between two scans is not measured, and there is no continuous recording of the brain. It might be difficult to draw a definitive conclusion on when the moment of insight happens in fMRI data, because scans are taken at distinct time points. However, the occurrence of insight means rethinking some basic assumptions about the problem content, which happens in a relatively sudden and unpredictable manner (Köhler, 1925; Scheerer, 1963).

Another functional imaging method is electroencephalography (EEG), where synchronized electrical activity of thousands of active neurons is detected by means of electrodes that are attached to the scalp. In contrast to fMRI, EEG does provide a continuous recording and has a high temporal precision (Crosson et al., 2010). Results from previous studies about insight using EEG show that neuroelectric studies of insight are more consistent than neuroimaging studies (Dietrich & Kanso, 2010), and that insight can be broken down into multiple sub-processes when using EEG to study problem solving (Sandkühler & Bhattacharya, 2008).

1.1 Event-Related Potential

Event-related potentials (ERPs) are electrical potentials generated by the brain that are related to specific internal or external events (Luck, 2012; Sur & Sinha, 2009). An ERP can be characterised as a change in electric potential. ERPs can occur when, for example, a stimulus is presented, a decision is made, or a response is expressed (Coles & Rugg, 1995).

Experiencing insight is an internal event, which poses the question: "**Are there patterns in an electroencephalography during a moment of insight?**". If an ERP occurs when someone experiences a moment of insight, this means that there are patterns in the EEG data. From this it can be concluded that excellent temporal resolution of ERPs can allow for observing insight.

In an earlier study by Qiu et al. (2008), it was demonstrated that solving a problem correctly elicited a positive ERP deflection (P300), indicating strong activity in the midline parieto-occipital scalp region. As there will be problem solving to stimulate insight during this experiment (more on this in section 2), it is expected to find a likewise component. Another study by Mai et al. (2004) showed peak latency in central midline components (Cz) at N380 which most likely reflects insight. However, all previous research is related to short problems, where ERP components were found as a result of a stimulus. In the present experiment, longer time periods of problem-solving were measured (opposed to other mentioned research). Before turning to the methods, let us first introduce the connection between chess and insight, which was used to operationalize insight in this experiment.

1.2 Chess as a research vehicle

To investigate the relationship between moment of insight and ERPs, chess can be used as a research vehicle. Since the rules of chess are universally specified and the environment of the game is well-defined, chess has often been used to research basic cognitive processes, such as perception, memory, and problem solving (Vaci & Bilalić, 2017). Another benefit is that chess has a precise rating system for measuring skill level - the ELO rating system (Elo, 1978) - and thus it is easier to define an objective skill level for a chess player for participation in an experiment (Charness, 1992).

To practice chess without an opponent, chess players often make use of chess puzzles. A chess puzzle is a situation in a chess game, where the player is only a certain amount of moves away from checkmate. For example, a checkmate-in-2 puzzle means that the chess player has to make two more moves to checkmate and be victorious. Since no opponent is required and the situation has a clear correct or incorrect outcome, chess puzzles can be used in research to study a chess player's reaction to chess events. Moreover, ERPs were used before to study chess. In Wright, Gobet, Chassy, and Ramchandani (2013), ERPs were used to determine the difference between the cognitive processes of experts versus novice chess players, and showed consistency with an N200 component reflecting matching of current perceptual input to memory in experts, relative to novices.

2 Methods

2.1 Participants

Twenty-seven volunteers participated in the experiment. They were recruited through various channels for chess enthusiasts (e.g. local chess associations or online chess communities). For the experiment, participants were invited to the University of Groningen, and received a compensation of €12. Data from two participants was excluded due to technical errors (the recordings were not saved). Thus, the data from twenty-five participants was used for the final analysis.

The mean age of the twenty-five participants (2 female, 23 male) was 29.96 years (SD = 9.04). Before their participation, participants signed informed consent and were informed about the experiment procedure. Participants were right-handed, had no neurological disorders, and had normal or corrected-to-normal vision.

The participants were experienced chess players, with an average KNSB (Royal Dutch Chess Association) ELO-rating of 1815.12 (SD = 290.53) and an average FIDE (International Chess Association) ELO-rating of 1806.76 (SD = 301.94). On average, participants had been actively playing chess for 13.96 years (SD = 8.48).

2.2 EEG procedure

The experiment required the participants to complete a set of 103 chess puzzles (see figure 2.1). The first three puzzles were used for practice, while the remaining 100 puzzles were presented in the main trials. The puzzles were compiled from real games using `www.chesspuzzle.net` as a source. For consistency, participants needed to play as the player using the white pieces throughout the experiment. All the puzzles were checkmate-in-two. Participants were required to specify only the first move.

Each trial began with a fixation cross, presented for 150 ms. Afterwards, a chessboard appeared with the chess pieces arranged as per the puzzle. Participants had no time limit to find the solution. First, they needed to indicate that they knew the answer with a mouse click using their right hand. Next, they responded with two clicks; first on the piece, and second on its desired location. After a completed trial, 50 ms would pass before the next trial began. The procedure repeated until all puzzles were completed, with breaks (for as long as the participants felt necessary) every 25 puzzles. In total, the experiment took 1.5 hours on average, with 1 hour for the execution of the experiment and 30 minutes for the equipment setup and breakdown. There was no feedback presented about individual puzzles during the experiment. Afterwards, participants were provided with the option to receive a document containing all puzzles and solutions.

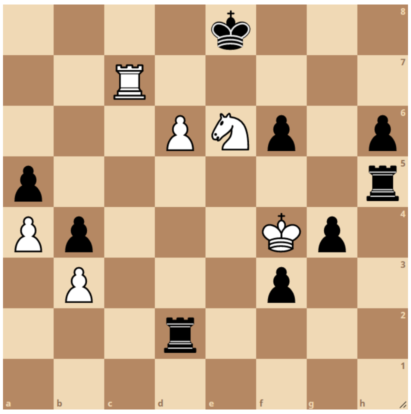

Figure 2.1: One of the chess puzzles that was used as a stimulus during the experiment. This puzzle is part of the condition group of non-sacrificial puzzles (more about this in section 2.6)

2.3 Equipment

EEG was recorded from 32 scalp sites using a Biosemi ActiveTwo system. For the recording, the electrodes were filled with conductive electrode gel. The electrodes were placed using the international 10-20 system layout. Two channels – Common Mode Sense (CMS) and Driven Right Leg (DRL) – were used as "ground". Vertical and horizontal eye-movements were recorded, as well as an average mastoid reference. The EEG data was amplified using an ActiveTwo AD-box and recorded using ActiView software from BioSemi instrumentation. The total input impedance was $<30k\Omega$.

2.4 Behavioural analysis

Practice trials were excluded for both accuracy and reaction times (RT) analyses. Additionally, all incorrect and incomplete trials were not taken into consideration in RT analysis. Lastly, trials that deviated more than 3 standard deviations from the mean per participant and conditions were removed.

A linear mixed-effects (LME; Bates and DebRoy (2004)) model was constructed in R to evaluate the accuracy rates and reaction times. A backward stepwise fitting procedure was used for construction. The first model contained all variables with interaction effects included. Each variable was then removed and evaluated to determine its significance. This procedure was done until all variables were tested. The `lme4` package was used to construct the models and their consecutive fits were compared. This was done for both the fixed-effects and random-effects structure.

2.5 EEG preprocessing

For the EEG data preprocessing, the open-source toolbox EEGLAB (Delorme & Makeig, 2004) was used. The average EEG signals of two external electrodes on mastoid bones were used as references. Bipolar channels of vertical and horizontal eye movement were calculated by subtracting EEG signals from two vertical external electrodes and two horizontal external electrodes, respectively. The referenced EEG data were then passed through a 1 Hz high-pass filter and a 40Hz low-pass filter. Next, the data was downsampled to 256 Hz . Manual detection of artifacts was performed on the data subsequently. From 25 participants, 20 had at least one noisy channel removed. On average, 1.68 channels per participant were removed. After manual artifact rejection, data was further decomposed using independent component analysis (ICA). Independent components of eye blinks and muscle movement were detected and removed. One or two independent components were substracted from the data for 20 out of 25 participants. For three participants, three, four and five components were removed.

2.6 ERP analysis

As described in section 1.1, ERPs can occur because of e.g. a stimulus, decision, or response. However, electric potential can also change because of several other sensory, cognitive or motor events, such as eye blinks or muscle movement. When measuring electrical potential using EEG, it is not only isolated ERPs related to the intended stimuli/decision/response that are recorded. This can make it hard to draw a definitive conclusion.

Classic ERP analysis was used to average out an ERP over multiple trials (Nidal & Malik, 2014). All incomplete trials were eliminated, and only correctly answered trials were used in the analysis. Baseline normalization (400 ms preceding the stimulus presentation) was applied to remove slow drifts in the signal. Data from 400 ms before and 800 ms after the stimulus was selected, as well as data from 800 ms before and 400 ms after the response. This was done for stimulus-locked and response-locked ERPs, respectively. Ultimately, average stimulus-locked and response-locked ERPs for each condition and each subject were generated, and their averages were plotted. Grand average event-related potential waveforms elicited were computed for all channels and visually inspected.

During the experiment, several participants noted that there was a pattern in the chess puzzles. They all identified some trials to be 'sacrificial' puzzles, where the key to solving the puzzle is to sacrifice a higher-order piece (a queen, knight, rook or bisshop), which results in a quick and immediate checkmate. Some participants said that, once they noticed this pattern, their focus in trials shifted: they would first check if sacrificing a higher-order piece yielded them a win, before looking at other options. When multiple participants reported the same observation, it became apparent that there was another interesting factor to analyse: the difference between sacrificial and non-sacrificial puzzles. From the 100 chess puzzles in the experiment, 40 could be solved by deploying the 'sacrifice' technique. In the end, this was marked as two separate conditions (sacrificial vs. non-sacrificial), and ERP analysis was performed in the two condition groups independently.

3 Results

3.1 Behavioural results

The participants' experience was reflected in their accuracy: on average, they solved 91.68% (SD = 7.89%) of the given puzzles correctly.

The average accuracy rates and reaction times, as well as the standard errors per participant, were computed across ELO rating (using KNSB rating) for both conditions. The relationship between ELO and the two dependent variables are shown in figures A.1 and A.2 in the Appendix. The influence of the conditions on the two dependent variables are shown in figures A.3 and A.4.

A binomial LME model was fitted to examine accuracy rates. A full model was fitted with both ELO and sacrifice condition variables and their interaction as the fixed-effects structure, and each individual puzzle and subject as random-effects structure. When the interaction effect was removed, there was no significant difference in fit between the full model and the no-interaction model ($\chi^2(1)$ = 1.0198, p >0.05, $\triangle$AIC = 0.9). The interaction effect was removed for simplicity. The full model also had no significant difference in fit when compared to a model without the sacrifice condition ($\chi^2(1)$ = 0.3479, p >0.05, $\triangle$AIC = 1.7). This finding corresponds to figure A.3, which shows no discernible difference between the mean accuracy of each condition. As such, the sacrifice condition was not included in the final accuracy model. A model with the ELO variable did, however, have a better fit compared to a model without ELO ($\chi^2(1)$ = 25.724, p <0.001, $\triangle$AIC = 23.7). This finding corresponds to the relationship seen in figure A.1. From these tests, the resulting fixed-effects structure only contains the ELO variable.

The same backwards selection procedure was done for the random-effects structure of the accuracy model. A model with the individual puzzles random-effect had a significantly better fit than a model without ($\chi^2(1)$ = 210.63, p <0.001, $\triangle$AIC = 208.6). Similarly, a model with the subjects as a random-effect had a significantly better fit than a model without the random-effect ($\chi^2(1)$ = 25.368, p <0.001, $\triangle$AIC = 23.4). Thus, the random-effects structure for the accuracy model includes the random-effects from each individual puzzle and subject.

For the reaction times, a Gaussian LME model was fitted. Before the model could be fitted, a logarithmic transformation had to be applied to the reaction times because a histogram revealed that they were right-skewed. As such, the LME model used the log reaction times as a dependent variable. A full model was first fitted as in the accuracy model; ELO, conditions, and their interactions as the fixed-effects structure, and individual puzzles and subjects as random-effects. The full model with the interaction effect between ELO and sacrifice condition had a significantly better fit than a model without the interaction ($\chi^2(1)$ = 14.708, p <0.001, $\triangle$AIC = 12.7). Similarly, the full model had a significantly better fit than a model without ELO ($\chi^2(2)$ = 43.72, p <0.001, $\triangle$AIC = 39.7) as well as a model without the sacrifice condition ($\chi^2(2)$ = 28.033, p <0.001, $\triangle$AIC = 24). This means the fixed-effects structure of the reaction times model includes ELO, sacrifice conditions, and interaction between these two variables.

For the random-effect structure, the random-effects from each individual puzzle and subject were checked. A model with the individual puzzle random-effect had a significantly better fit than a model without the random effect ($\chi^2(1)$ = 906.32, p <0.001, $\triangle$AIC = 904.3). Similarly, a model without the subject random-effect also had a significantly better fit than a model without subjects ($\chi^2(1)$ = 681.2, p <0.001, $\triangle$AIC = 679.2). Thus, as with accuracy model, the random-effects structure for the reaction time model includes the random-effects from each individual puzzle and subject.

With the models fitted, they can now be examined for further analysis. The accuracy model found that the logit estimate significantly increased as ELO increased (β_{ELO} = 1.0673, SE = 0.1680, z-value = 6.351). The model suggests that subjects with higher ELO are more likely to respond accurately. Similarly, the reaction time model found that the time estimate significantly decreased when ELO increased (β_{ELO} = -0.502, SE = 0.077, t-value = -6.502). This would suggest that subjects with higher ELO solved the puzzles faster. The reaction time model also found that the time estimate significantly decreased when subjects were presented with sacrifice puzzles ($\beta_{sacrificePuzzle}$ = -0.377, SE = 0.100, t-value = -3.749). This finding implies that subjects solved sacrifice puzzles faster than non-sacrifice puzzles.

These results imply that the better chess players solved the puzzles quicker and more accurately. Higher ELO leads to more accuracy and quicker reaction times. Also, sacrifice puzzles lead to faster reaction times compared to non-sacrifice puzzles. Further investigation is required before suggesting a possible reason for this relationship.

3.2 ERP results

Grand average stimulus-locked and response-locked ERPs were calculated for both conditions. Figure A.5 in Appendix A shows average stimulus-locked ERPs, and Figure A.6 in Appendix A show average response-locked ERPs. Since it is interesting to look at ERP components across the scalp, in the final analysis 10 representative channels from across the scalp were selected. These were midline channel, along with channels from the side of the scalp. For a visual of where each channel is located on the scalp, see figure A.7.

When looking at data from stimulus-locked ERPs, an ERP component at N200 is detected, most present in midline scalp regions. This seems to be in line with the N200 component found in the previously mentioned study by Wright et al. (2013). Data from frontal, central and parietal midline scalp regions (Fz, Cz and Pz) shows an ERP component around P300, which corresponds to earlier findings by Qiu et al. (2008) where a P300 component was mentioned.

Data from response-locked ERPs was expected to show a N380 Cz component, as mentioned in section 1.1 (Mai et al., 2004). This was not found.

Unlike what was intended to be found, there were no ERP components observed in the 800 ms response window before a response.

4 Discussion

In earlier research (Mai et al., 2004; Qiu et al., 2008; Wright et al., 2013), there were no prolonged periods of time between a stimulus and an insightful response. Instead, ERP components after a stimulus were attributed to the experience of insight. With the current research, the intention was to differentiate between stimulus- and response-locked insight by using problems where insight was necessary over a longer period of time. This could yield both a confirmation of earlier found ERP components as actually being the result of insight, and a new look at ERP components preceding a moment of insight.

There is an absence of ERP components in the response window before the response. Although earlier found ERP components N200 and P300 components can be confirmed with findings of N200 and P300 components in stimulus-locked ERPs, there is a lack of an N380 component in central midline component Cz as reported by Mai et al. (2004). Furthermore, all identified components were indeed found as components resulting from the presentation of a stimulus, instead of preceding a response.

With the lack of new ERP components and the absence of familiar stimulus-locked ERP components preceding a response, we can conclude that there are no insightful ERP components that can be used to detect a moment of insight in the brain.

Bilalić et al. (2019) found that chess experts were better at problem solving in a chess context relative to novices, which required retrieval of chess-related information. However, it was also concluded that the experts' success came at a price, since they reported a diminished "Aha!"-experience compared to the control group. This difference in diminished moment of insight was not reported when participants were probed with a different problem, unrelated to their skill level in chess. Although in section 1.2 the benefits of chess as an operalization for this study were justified, based on findings by Bilalić et al. it might be interesting to repeat the study in a context where participants are less familiar and trained with the materials presented to them as stimuli.

Since the chess puzzles in this study were presented in the context of a realistic situation, namely the endings of played chess games, there were pieces on the board that did not play into the solution of the puzzle. Because of this, chess players use a heuristic tactic to evaluate their solution before making the intended move (Simon & Simon, 1962). In this study, data was analysed in a window 800 ms before a response. Perhaps this window was too small, and the heuristic tactic used to verify the solution takes longer than 800 ms (and as a result of this, the moment of insight and possible ERP components related to insight can be detected outside the taken response window).

Moreover, other manipulations and analyses were performed on the same data set, namely a Hidden semi-Markov Model Multivariate Pattern analysis (HsMM-MVPA)). In that study, a 2-second model was used and eight bumps in a repeating pattern were detected before response. Since HsMM-MVPA takes different durations between bumps into accounts whilst the ERP technique analyses a set response window, perhaps the execution of a combined use of ERPs and HsMM-MVPA yields a more accurate result and makes findings more usable for future application.

5 Acknowledgments

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A Appendix

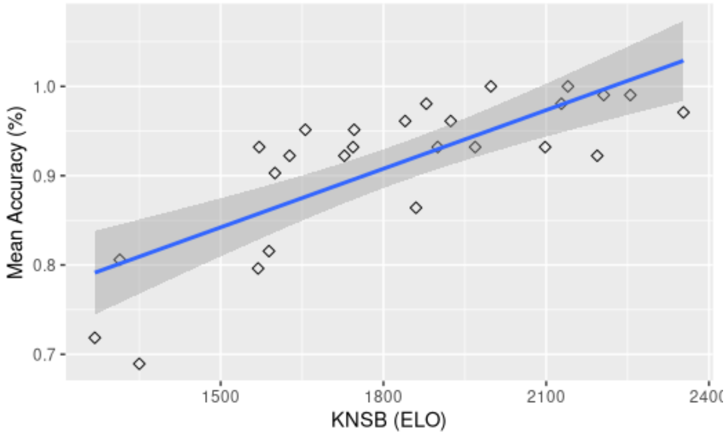

Figure A.1: Behavioural analysis results of the accuracy vs. ELO rating (using KNSB rating)

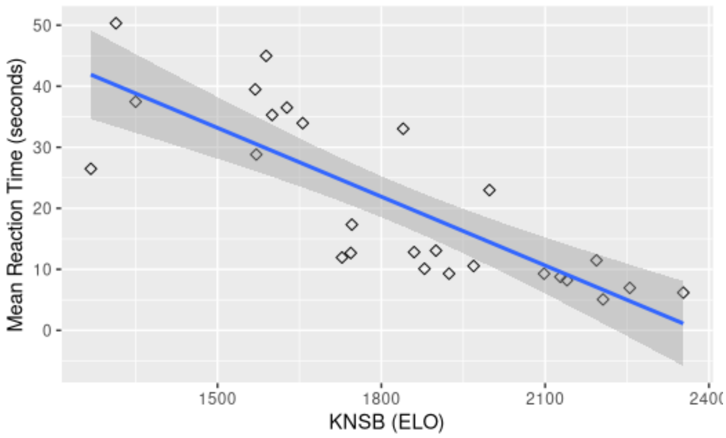

Figure A.2: Behavioural analysis results of the reaction time vs. ELO rating (using KNSB rating)

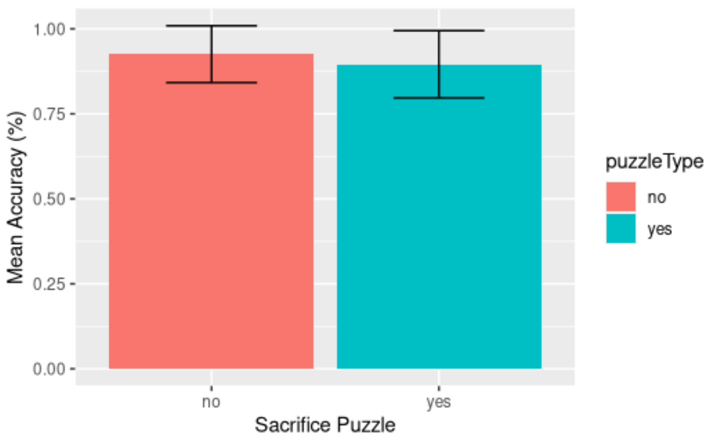

Figure A.3: Behavioural analysis results of the influence of condition (sacrifice vs. non-sacrifice) on mean accuracy

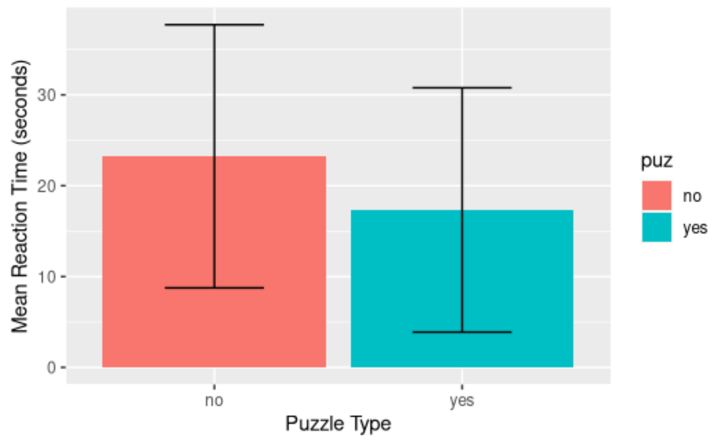

Figure A.4: Behavioural analysis results of the influence of condition (sacrifice vs. non-sacrifice) on mean reaction time

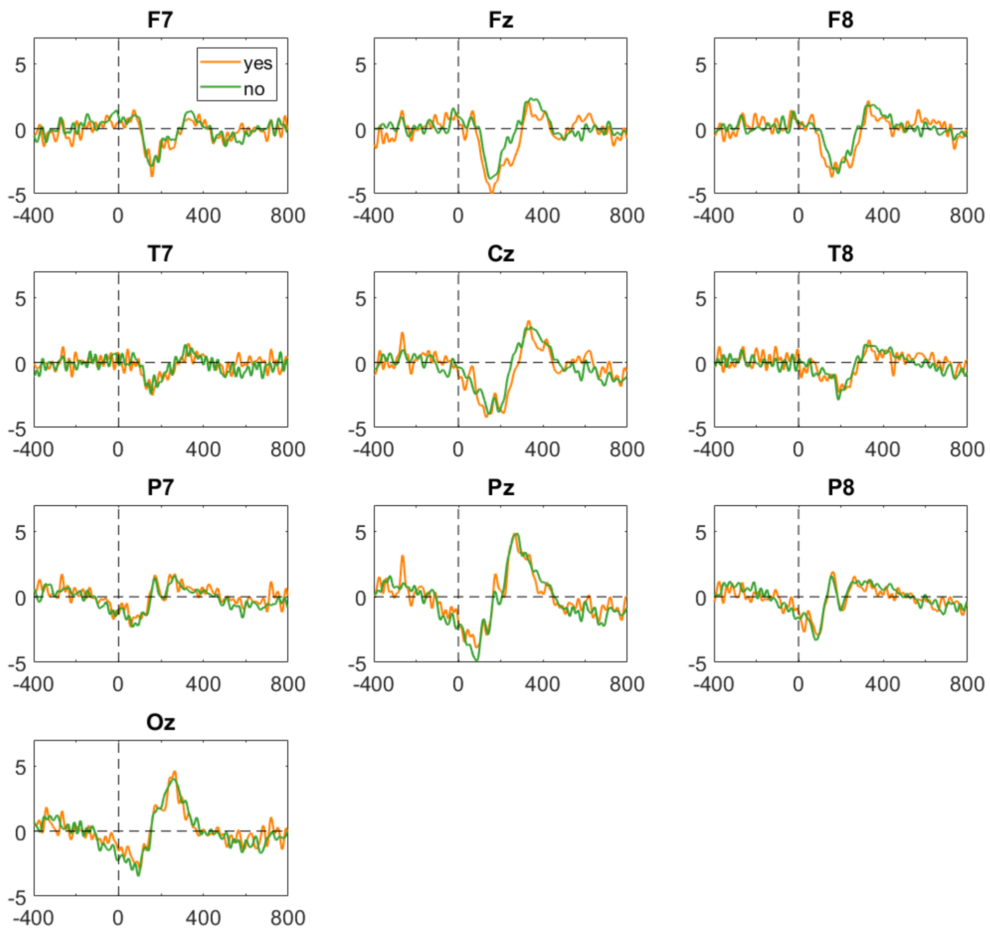

Figure A.5: Grand average stimulus-locked ERPs.

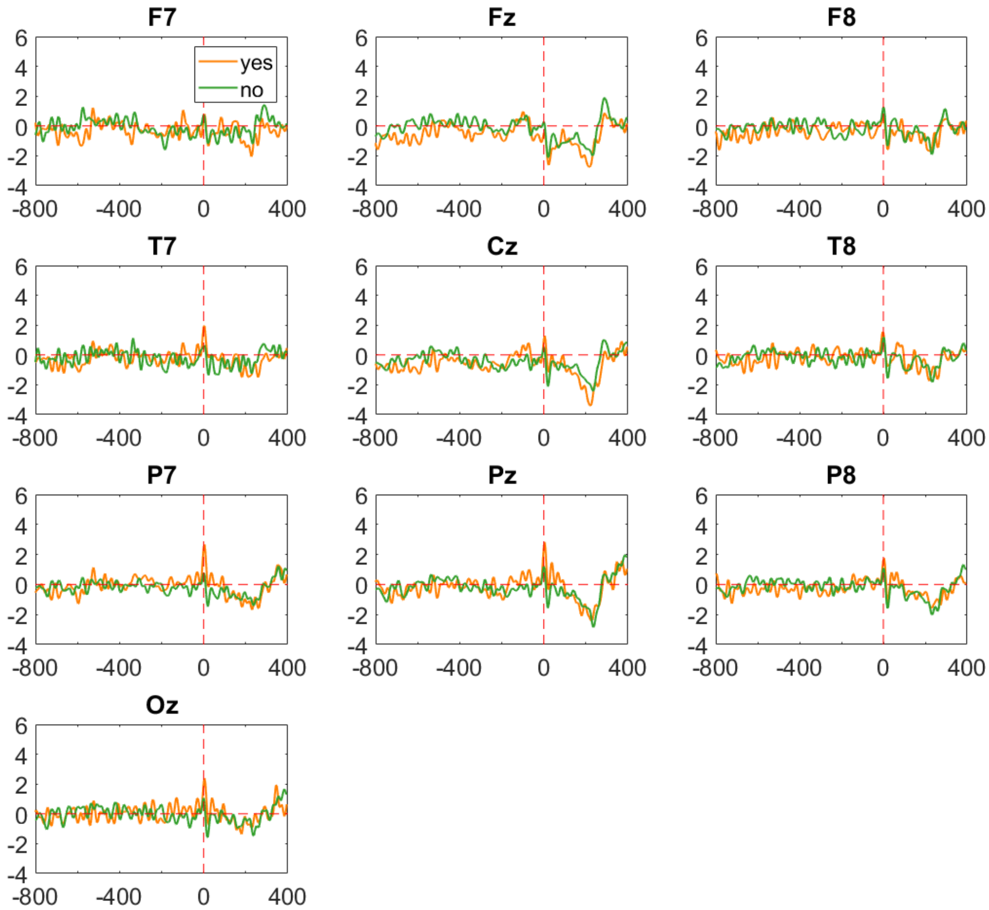

Figure A.6: Grand average response-locked ERPs.

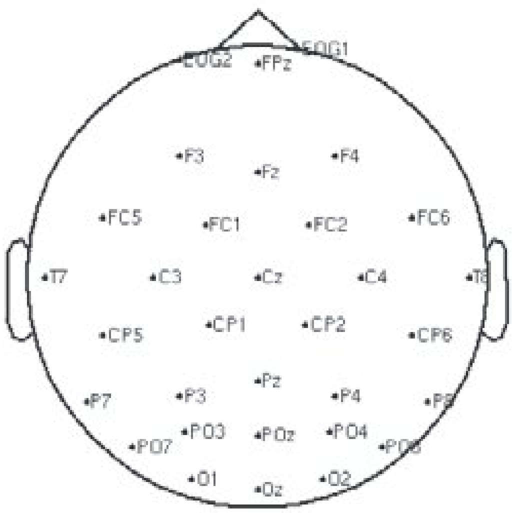

Figure A.7: Placement of EEG channels across the scalp. Image from Greco et al. (2006).