Sequential Effects on Posterior Theta in the Classical Eriksen Task

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Abstract

The present study investigated whether the sequential effects on posterior theta in the classical Eriksen task can be understood better from the Conflict Adaptation Theory (CA) or the BRAC (Binding and Retrieval in Action Control) framework. Specifically, the study tested hypotheses derived from each theory regarding reaction time (RT), accuracy, and EEG theta power across eight conditions that varied in compatibility (compatible/incompatible), response transition (repeat/alternate). Participants completed a flanker task while EEG data were recorded. Behavioral data revealed that full repetition trials (e.g., CCR) produced the fastest RTs and highest accuracy, consistent with BRAC and CA predictions. However, CA predictions were all correct, while BRAC predictions only partially correct. Some findings deviated from BRAC predictions suggesting that motor response repetition may dominate retrieval under conditions of prior conflict. Posterior theta activity was biggest for sequences following incompatible trials relative to compatible trials, while also affected by some of the feature binding effects. These results suggest that neither theory alone fully accounts for the observed behavioral and neural dynamics. A novel integrative mechanism was proposed, which posits that feature-based retrieval and adaptive control operate in parallel, with their relative influence modulated by prior conflict, feature overlap, and the dominance of motor vs. perceptual retrieval. This framework would help to explain cases where full repetition does not guarantee facilitation (IIR) and provide new explanations of sequential cognitive control.

Introduction

Cognitive control, which is the ability to regulate behavior, allows an individual to operate in an environment with competing or conflicting information. It enables making adjustments after errors, controlling motor responses and decision-making, and suppressing irrelevant stimuli. Given its role in goal-directed behavior, developing theories that explain or predict cognitive control mechanisms holds significant practical and theoretical importance.

One of the ways to study cognitive control and selective attention is the classical Eriksen task. In this task, participants respond to the central target (letter or an arrow), which is flanked by distractors that are either response compatible or response incompatible with the target (Eriksen & Eriksen, 1974). Performance improves, as reaction times (RT) are faster and more accurate (PC) on compatible than on incompatible trials. This difference is known as the *compatibility effect* (Davelaar, 2013). Importantly, this effect on trial *n* is modulated following an incompatible trial *n-1* compared to a compatible trial *n-1*, which is called the *congruency sequence effect* (CSE; Gratton et. al., 1992). In practical terms, after an incompatible trial, RTs on a subsequent incompatible trial tend to be faster with fewer errors (iI) relative to an incompatible trial after a compatible one (cI). Conversely, responding to *n* compatible trial can be slowed if the *n-1* trial was incompatible (iC) relative to the compatible trial (cC). Therefore, the interference effect is lower after conflict. This pattern suggests dynamic adjustments of control, meaning an incompatibility on trial *n–1* triggers additional top-down control or inhibition that carries over, improving performance on trial *n*.

Conflict Adaptation Theory in CSE

According to the *conflict adaptation theory,* the CSE is connected to cognitive control adjustments. Moreover, *conflict monitoring* models argue that the anterior cingulate cortex (ACC) detects response conflict on an incompatible trial, and this triggers enhanced control on the next trial (Botvinick et al., 2001). Increased control sets higher filters specifically for stimulus processing (distractors are filtered stronger). The detection of conflict serves as a signal to the system to tighten inhibition or attentional focus, which allows for less interference from flankers on the subsequent trial. This increased control leads to smaller costs of RT and PC after incompatible trials. In other words, when the conflict is detected at trial *n-1*, it triggers enhanced cognitive control on trial *n* (Botvinick et al., 1999; Botvinick et al., 2001; and Kerns et al., 2004). Thus, the CSE is conceptualized as a form of top-down

adaptive control, a phenomenon wherein the cognitive system adjusts after conflict to prevent future performance decrements.

Negative Priming & Feature Repetition

Nevertheless, it can be argued that the CSE might not reflect modulations in active control but rather be attributed to bottom-up mechanisms including feature repetition and priming between consecutive trials. Practically, a compatible trial preceded by an incompatible trial (I→C) should be faster than I→I, regardless of whether the response repeats, because of carry-over control and compatibility effect. However, if a target response or distractor elements are repeated on the trial *n*, participants might experience an increase in performance from priming, especially if there is *response repetition*. On the other hand, if a distractor on one trial becomes the target on the next, responses slow down, a phenomenon known as *negative priming*. This effect, first demonstrated by Tipper (1985), suggests that it happens due to inhibitory bias applied during the initial act of suppression.

Studies have shown that CSE is reduced or absent when feature repetitions are controlled, arguing against the idea of conflict adaptation (Mayr et al., 2003; Nieuwenhuis et al., 2006). On the other hand, there are studies that confirmed the presence of CSE without feature repetition (Lee et al., 2025). These alternative perspectives have contributed to the development of a new theoretical framework that emphasizes episodic memory for event features as the underlying mechanism of sequential effects, in contrast to the classic conflict monitoring view.

Binding and Retrieval in Action Control (BRAC)

The framework of Frings et. al (2020), binding and retrieval in action control (BRAC), synthesized together concepts of feature integration, negative priming, repetition priming, and related effects into one model. This model suggests that sequential effects might not stem from adaptive control, but from two of its main mechanisms, which are episodic feature binding and retrieval. In the feature binding process, features of the stimulus (S), response (R) and a subsequent effect (E) are integrated into an event-file. Examples of those features are the target stimulus, distractors, the executed motor response, the outcome of the response, etc. When one of these features is repeated, the corresponding event-file is retrieved, which explains such phenomena as negative priming, response repetition, etc. Therefore, any

repeated component (S, R, or E) from the previous trial (n-1) can cue the entire response for the current trial (n). Moreover, depending on the situation, such retrieval can facilitate performance (an S-R link can be reactivated during response repetition), or interfere with it (negative priming). Interference can happen because of partial repetition, where only some of the feature repeats and the retrieved features compete with the new feature, which creates confusion. This leads to slower RTs and PCs (Lee et al., 2025). On the other hand, facilitation happens in the scenario of full repetition of all the features. Furthermore, no repetition of features results in no detected features, thus no confusion. So, full repetition and complete alternation benefits performance relative to a partial repetition.

It is important to note that because an event file survives for more than one trial, older files can still be cued, so the current response may be facilitated or disrupted by trial n-2. BRAC emphasizes that binding and retrieval are distinct mechanisms that can be influenced by both bottom-up stimulus factors and top-down context. Therefore, it does not deny that cognitive control can play a role, rather it emphasizes that much of the sequential variance may come from memory retrieval of prior episodes.

Posterior Theta

Neural oscillations in the theta band (~4–8 Hz) have been implicated in cognitive control and attention. Midfrontal theta power (maximal at frontal midline electrodes) increases during conflict or error processing, reflecting ACC engagement in control (Cohen & Cavanagh, 2011; Cavanagh & Frank, 2014). Most conflict tasks (also studies such as the one mentioned before) highlight frontal dynamics while posterior theta oscillations remain relatively understudied in the context of chosen theories and sequential effects. However, emerging evidence highlights that posterior theta activity may play a significant role in attentional control. Recent work from Haciahmet et al. (2021) found that in a flanker task midfrontal theta power rose for response conflicts, whereas parietal theta power was greater on compatible trials. In the same way, Asanowicz et al. (2023) reported that target anticipation and selection evoked a fronto-posterior theta network. Spatial cues elicited midfrontal and ipsilateral posterior theta before target onset, and after target onset a strong posterior-theta burst (ipsilateral to the target) was observed, tightly coupled with midfrontal theta. The authors suggested that this fronto-posterior theta coupling underlies the suppression of irrelevant visual information. Therefore, posterior theta is considered as an inhibitory control over distracting information.

Under this view, conditions requiring stronger inhibition should show enhanced posterior theta. Conflict adaptation theory implies that following an incompatible trial the system maintains an increased inhibitory state. Thus, larger posterior theta on trial *n* whenever trial *n–1* was incompatible. The BRAC framework, by contrast, would predict increased posterior theta whenever retrieval of a prior binding brings distractor features back (e.g. negative-priming conditions when a former distractor reappears) and other partial repetition conditions, requiring more suppression. Lower theta expected during full repetition trials and complete mismatch trials. In all cases, higher posterior theta power will be interpreted as evidence of greater visual inhibitory effort.

Current Study

Each theoretical framework offers a distinct perspective on the mechanisms underlying sequential effects and may account for different aspects of the phenomenon. Despite extensive work on flanker sequential effects, there is a lack of research on how Conflict Adaptation theory and BRAC account for both behavior and posterior EEG dynamics. Studies of theta-band activity have predominantly focused on midfrontal sources, leaving a gap in how oscillatory dynamics in visual cortical regions can be understood within theoretical models of cognitive control. This thesis aims to fill that gap by comparing how well Conflict Adaptation theory and BRAC feature-binding model account for observed patterns of behavior and posterior theta oscillatory activity across flanker trial sequences. In doing so, this study raises a critical question: *Which theoretical model, Conflict Adaptation or BRAC, best accounts for both the behavioral sequential effects and associated EEG (theta-band) patterns in the Eriksen flanker task?*

Specific behavioral and EEG predictions (see Table 1 and Figure 1) were derived from each theoretical framework to explore this question (Previous Compatibility [C/I] → Current Compatibility [C/I] × Response Transition [Repeat/Alt]). Conflict Adaptation theory proposes a smaller compatibility cost after incompatible trials. So, Hypothesis 1 (H1) is that RTs on an incompatible trial will be faster and accuracy higher if the previous trial was incompatible (I→I) compared to when the previous trial was compatible (C→I). In contrast, a compatible trial after an incompatible (I→C) will be slightly slower and less accurate than after a compatible (C→C). If the previous trial was compatible, no extra control is engaged. Putting it all together, C→C is going to be the fastest due to no conflict after compatible previous trial. Then I→C where prior trial induces more filtering and less conflict with the current

compatible trial. In this case the current compatible trial has suppressed typical flanker facilitation. I→I (CSE) is going next because of the previous trial upregulation and current incompatible trial. Current incompatible trial is intrinsically slower than current compatible trial and reduction of interference for *n = I* do not exceed loss on facilitation for *n = C*. The worst performance will be C→I as there is no prior conflict to engage control making the system unprepared for the interference.

Table 1

Behavioral and theta predictions

Sequence type	**Conflict adaptation**		**BRAC**	
	RT	**Theta**	**RT**	**Theta**
CCR (C→C, R)	1	4	1	8
CCA (C→C, A)	1	4	3	6
ICR (I→C, R)	2	2	5	4
ICA (I→C, A)	2	2	6	3
CIR (C→I, R)	4	3	7	2
CIA (C→I, A)	4	3	8	1
IIR (I→I, R)	3	1	2	7
IIA (I→I, A)	3	1	4	5

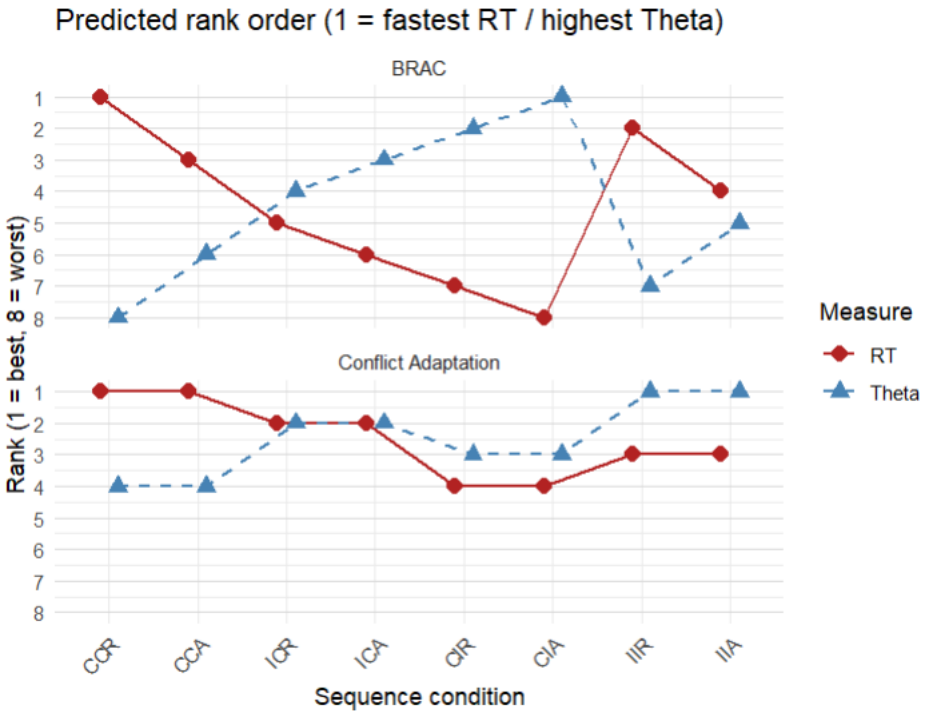
Note. Behaviorally: 1 = fastest RT, 8 = slowest RT. Theta: 1 = highest Theta, 8 = lowest. For the conflict adaptation theory RT (fastest to slowest) and Theta (highest to lowest) levels are ranked from 1-4, since it does not consider response priming.

From the BRAC perspective (Frings et al. 2020; Lee et al. 2025) Hypothesis 2 (H2) predicts that trials that are full stimulus–response (S-R) repetitions from the *n-1* trial will produce the fastest RTs. In other words, repeating all features of the prior event will facilitate performance via episodic retrieval of the just-executed response. Accuracy is also expected to be highest in full repetition conditions due to this retrieval. For example, CCR and IIR will have the fastest RTs and highest accuracy where CCR is faster than IIR due to compatible trials being intrinsically easier. Moreover, resolution of target-flanker competition may be attenuated but not fully abolished by response repetition. Hypothesis 3 (H3) predicts that complete alternation trials will produce slower RTs as it is a complete mismatch sequence, which does not produce interference or facilitation. So, the participant cannot leverage any memory from the last trial but also isn't confused by any partial overlap. Therefore, CCA and IIA. Later is slower due to the compatibility of trials. Lastly, Hypothesis 4 (H4) predicts that trials with a partial repetition of features will produce the slowest RTs, and more errors compared to either full repetitions or complete alternations. Moreover, negative priming

conditions will result in reduced performance. So, ICR is placed next and followed by IIA. Study of Frings et al. (2007) argues that repeating a distractor (stimulus cue) helps only when the same motor code is required again. So, it can be argued that retrieved motor code determines whether retrieval helps. ICR possesses the same response as the old target and same flankers on the current trial, while ICA as it is a typical negative priming example. CIR is going to be next as the key repeats itself, but the new distractor causes confusion. CIA has the worst performance out of all the conditions as it cannot benefit from the same distraction due to the change in response and it is a negative priming example.

Figure 1

Behavioral and theta predictions



Note. RT: 1 = fastest RT, 8 = slowest RT. Theta: 1 = highest Theta, 8 = lowest. For the conflict adaptation theory RT (fastest to slowest) and Theta (highest to lowest) levels are ranked from 1-4, since it does not consider response priming.

In terms of theta, all models expected to predict greater posterior theta in conditions demanding more inhibition. For example, according to the conflict adaptation, Hypothesis 5 (H5) predicts that posterior theta power will be greater following an incompatible trial than after a compatible trial. Sequences with prior conflict on trial n-1 will show elevated posterior theta (upregulated visual distractor inhibition) relative to sequences on trial n-1 with no prior conflict. This reflects the hypothesis that conflict triggers heightened attentional control.

Hypothesis 6 predicts that during partial repetitions posterior theta power will be higher on partial repetition trials than on full repetitions or total alternations (with alternations having higher theta than full repetitions). Thus, conditions with feature overlap/mismatch should elicit greater theta, whereas a full repetition or an entirely novel trial (no overlap) will require less theta power for conflict resolution. However, they may differ in exactly which sequences have maximum theta. The table and figure below outline these theory-specific predictions for RT, PC, and posterior theta in each of the eight conditions.

Methods

Participants

A total of 14 adult participants aged 18-35 years old (mean age: 23.7, male: 6, female: 8) were recruited, primarily students from the University of Twente. To be part of the experiment, they had to fit the inclusion criteria, which were being right-handed (assessed via the Annett Handedness Inventory), fluent in English (to understand task instructions), and having normal or corrected-to-normal vision (self-report). Exclusion criteria included self-reported neurological or psychological conditions (ADHD, ADD, epilepsy, depression, or anxiety disorders), history of brain injury or concussion, dyslexia, use of medication that affects cognitive functioning, severe visual impairments that cannot be corrected. The activities during the experiment were communicated to all participants in advance, and an informed consent form was obtained in writing. Participants eligible for course credits were rewarded for their participation. The University of Twente's Ethical Committee (Netherlands) approved the followed procedures (nr. 250455).

Stimuli, apparatus, and procedure

A central white fixation dot appeared on a black background for 1-2 seconds. Immediately after a five-letter array was shown for … ms. The target in the center, flanked on each side by three identical letters. Arrays were either compatible (SSSSSSSSS or HHHHHHHHH) or incompatible (SSSSHSSSS or HHHHSHHHH). Participants were instructed to respond by pressing the left Ctrl key for the target letter S and the right Ctrl key for H. The response window lasted for … ms. If an incorrect response was made or participant failed to respond, the word "ERROR" appeared on the screen. The experimental

session consisted of 4 blocks of 80 trials each. Within each block target letters and compatibility were randomized to ensure balanced trial sequences.

The experiment was conducted in a controlled laboratory setting at the University of Twente. Stimuli were presented on a computer screen positioned at a viewing distance of 0.3-0.6m. Responses were collected via a standard QWERTY keyboard. The laboratory was kept in a comfortable temperature and luminance. Stimulus presentation and response collection were managed using custom Presentation software.

EEG data were recorded with an ActiCap 32-channel cap using the extended 10/20 system (Appendix C). Electrode impedance was maintained below 10 kΩ. Vertical EOG was measured from electrodes above and below the left eye, and horizontal EOG from electrodes at the outer canthi of both eyes, near the temple. Grounds were placed in the middle of the forehead above the nasion, and at the placement point GND on the EEG cap, which was above the other ground. EEG and EOG signals were recorded using BrainVision Recorder software and later preprocessed BrainVision Analyzer software.

After completing the informed consent forms, a demographic questionnaire, and the Annett Handedness Inventory (Appendix B), participants were fitted with the EEG cap. A brief calibration procedure was conducted before starting the trails. Following calibration, participants were presented with on-screen instructions and completed 20 practice trials. Once they confirmed understanding of the stimulus-response mapping, the first experimental block commenced.

Participants were instructed to respond as quickly and accurately as possible while minimizing unnecessary movements. Throughout the session, the experimenter continuously monitored electrode impedance and signal quality in real time, conducting additional impedance checks between blocks if necessary.

After the experiment, participants were debriefed, and all data were anonymized and securely stored. The entire session lasted approximately 120 to 180 minutes.

Data Analysis

Behavioral Measures

Separate analyses were conducted for reaction times (RT) and proportion of correct responses (PC). All statistical procedures were carried out in R using the following packages: *tidyverse*, *readxl*, *writexl*, *stringr*, *tibble*, *kableExtra*, *afex*, *effectsize*, *emmeans* and *dplyr*.

Dependent variables were analyzed using repeated-measures within-subjects ANOVAs to examine main effects and interactions. Behavioral ANOVA analysis used 2 × 2 × 2 factorial structure: PrevComp (compatible vs incompatible), CurrComp (compatible vs incompatible) and RespTrans (repetition vs. alternation).

The same analyses on descriptive statistics were used for the theta activity. Dependent variables were analyzed using repeated-measures within-subjects ANOVA with the factors: PrevComp (compatible vs incompatible), CurrComp (compatible vs incompatible), RespTrans (repetition vs. alternation), Electrode (PO7 vs PO8). The 150 – 200 ms post-stimulus time window was used as it is the most sensitive to the theta power modulations.

An alpha level of .05 was used for all statistical tests. Effect sizes (e.g., partial η^2) was reported to facilitate interpretation the results. All statistical procedures followed APA guidelines for reporting results, ensuring that the analysis is transparent and replicable by other researchers.

EEG preprocessing

Continuous EEG data were preprocessed using BrainVision Analyzer 2. The raw signals were band-pass filtered between 0.1 and 30 Hz using a zero-phase filter. Additionally, a 50 Hz notch filter was applied to eliminate line noise. Ocular and other artefacts were removed using independent component analysis (ICA) with the Infomax algorithm. Following ICA correction, any residual artefacts were addressed by excluding individual epochs exhibiting excessive peak-to-peak amplitudes (e.g., exceeding ±100 μV). This preprocessing pipeline ensured the quality and reliability of the EEG signal for subsequent time–frequency analyses. Data was re-referenced to the average of 31 scalp channels. Additional artefact rejection was performed with stricter criteria, which is a maximal voltage step of 50 μV/ms, a maximal allowed difference of 200 μV in 200 ms intervals, and low activity detection as above.

Because the study examined inter-trial CSE, the segmentation had to isolate only those epochs that belonged to pre-defined two-trial sequences. In other words, the trial had to contain the same stimulus code (S111 or S121) both five seconds earlier and at the current stimulus onset. For each satisfied rule, a 7-s epoch (−6000 ms → +1000 ms) was extracted. Overlapping was permitted so that every qualifying trial sequence was retained. Thirty-five such segments were obtained in the example shown above.

Time-frequency decomposition was performed using a Morlet complex wavelet transform (Morlet parameter = 5). Frequencies from 4 Hz to 20 Hz were analysed in 7 logarithmic steps, with a focus on theta band activity. Spectral power was normalized as percent change relative to a pre-stimulus baseline (-500 ms to -100 ms).

EEG data were imported from four Excel files, each corresponding to a specific post-stimulus time window (100–150 ms to 250–300 ms). Posterior electrodes, PO7 and PO8, were selected based on prior literature implicating these regions in theta activity associated with conflict processing.

Results

Behavioral measures

Means (M) and standard deviations (SDs) of RT and PC across each condition are presented in Figure 2, 3 and Table 2. Participants responded fastest on CCR trials, M = 507.0 ± 74.4. In contrast, responses were slowest on the CIR trials, M = 585.2 ± 91.5. On average, current compatible trials showed faster RTs than for incompatible trials, M = 522 ms vs. M = 567 ms, respectively. The 8 conditions, ranked from the slowest to fastest based on mean reaction times, are as follows: CIR→IIA→CIA→IIR→ICR→ICA→CCA→CCR.

Accuracy was high across all conditions. Mean percent-correct ranged from about 93% to 98%. The highest accuracy can be seen on the CCA trials, M = 98.5 ± 1.8, whereas lowest accuracy on the IIA and CIR trials, M = 93.2 ± 6.1 and M = 93.1 ± 5.1, respectively. On average, current compatible trials showed higher PCs than for incompatible trials, M = 97.6 vs. M = 94.5, respectively. However, response alternate trials showed slightly higher accuracy, M = 96.2, compared to the response repeat trials, M = 95.9. The 8 conditions, ranked from the least to most accurate based on mean accuracy, are as follows: CIR→IIA→CIA→ICR→IIR→CCR→ICA→CCA. The comparison of the observed RT pattern vs. CA and BRAC predictions is in Figure 4.

Figure 4

Observed vs CA and BRAC

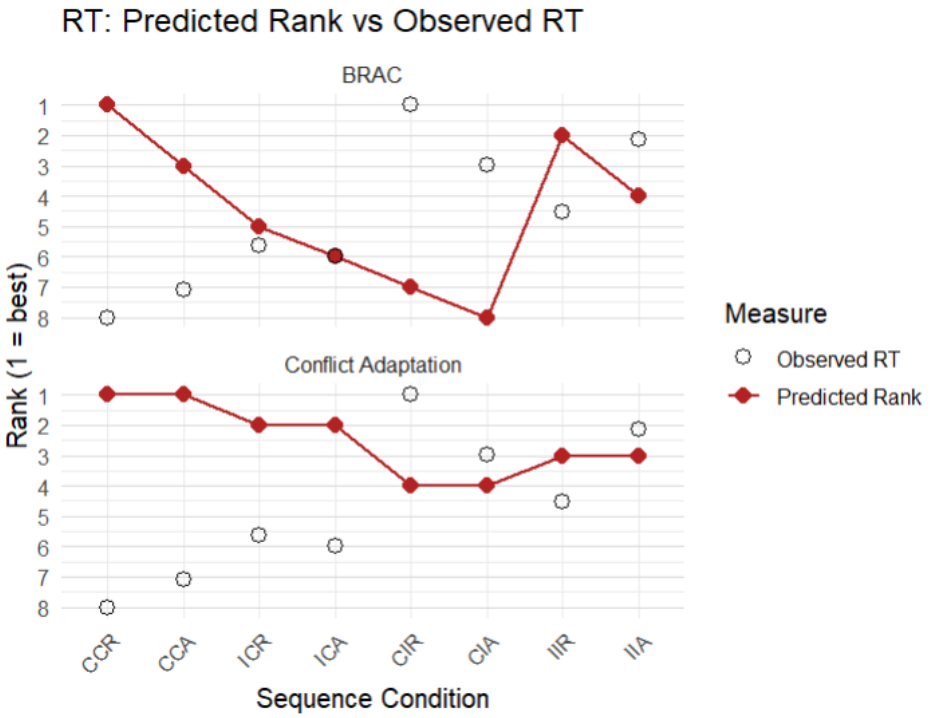


Figure 2

Reaction Time by Condition

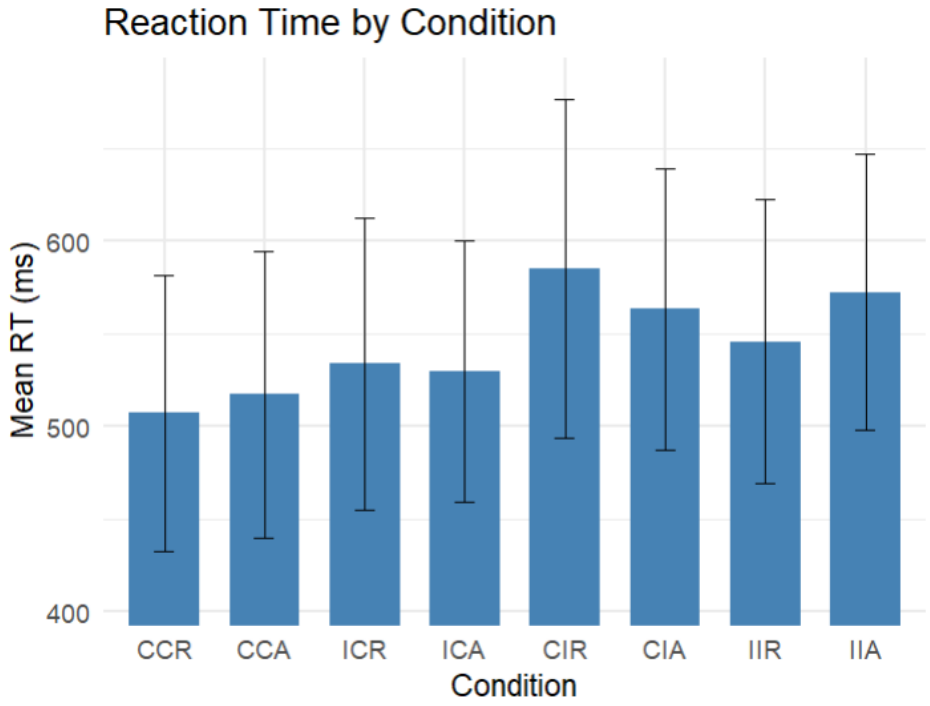
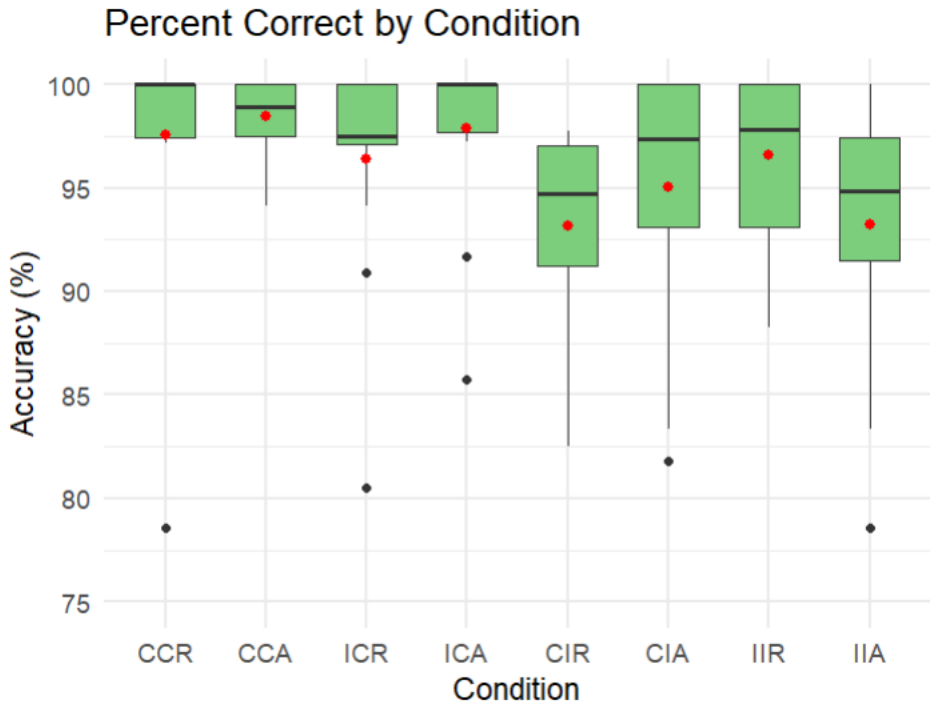


Figure 3

Percent Correct by Condition



A repeated measures ANOVA on RT showed main effect of CurrComp F (1,13) =29.77, p<0.0002, η_p^2 =0.7. Also, it revealed significant interaction between PrevCong X CurrCong, F (1,13) =16.69, p<0.002, η_p^2 =0.56, and PrevComp X CurrComp X RespTrans, F (1,13) =18.64, p<0.001, η_p^2 =0.59. Furthermore, an interaction between PrevComp X RespTrans revealed almost significant results, F (1,13) =4.57, p = 0.0519, η_p^2 =0.26. Even though response repeat trials produced slightly faster RTs, M = 543 ms, compared to the response alternate trials with M = 546 ms, the main effect of RespTrans was insignificant.

The same analysis on PC revealed significant main effect of CurrComp, F (1,13) =8.95, p<0.02, η_p^2 =0.41, and an interaction between PrevComp X RespTrans, F (1,13) =5.04, p<0.05, η_p^2 =0.28. Also, a significant three-way interaction with response transition was detected (PrevComp X CurrComp X RespTrans), F(1,13) =8.2, p<0.02, η_p^2 =0.39. There were no other significant or close to significant main effects or interactions, both in response time and accuracy data.

Theta measures

Table 1 displays the mean theta power for each trial condition. Topographic maps of the theta activity are provided in the Appendix (Appendix 1) to illustrate the scalp distribution of effects. Means (M) and standard deviations (SDs) theta power across each condition are presented in Figure 5, and Table 3. Generally, participants had highest theta on the IIR trials, M = 695.2 ± 362.73, and lowest on CCR trials with M = 444 ± 281.51. Current compatible trials had lower theta than incompatible trials, M = 535.63 ± 375.92 and M = 598.17 ± 364.61, respectively. Moreover, response alternate trials had M = 577.73 ± 369.37, which is higher than response repeat trials M = 556.07 ± 373.57. The 8 conditions, ranked from the lowest to the highest, are as follows: CCR→CIR→CCA→CIA→ICR→ICA→IIA→IIR. The comparison of the observed Theta pattern vs. CA and BRAC predictions is in Figure 6.

A five-factor repeated-measures ANOVA on the theta power showed significant main effects of PrevCong, F (1,13) =8.58, p < 0.02, η_p^2 =0.4, and CurrCong, F (1,13) =9.42, p < 0.009, η_p^2 =0.42. Only interaction between PrevComp X RespTrans was significant, F (1,13) =4.98, p < 0.05, η_p^2 =0.28. It is important to note that, although theta power at PO8 (M = 613) was higher than at PO7 (M = 521) in the 150–200 ms time window, this difference was not statistically significant (paired t(13) = –1.35, p = .202).

Table 3

Theta Means

Sequence type	Theta power	
	mean	**sd**
CCR (C→C, R)	443.99	281.51
CCA (C→C, A)	529.46	370.31
ICR (I→C, R)	584.20	470.03
ICA (I→C, A)	584.87	360.47
CIR (C→I, R)	500.9	323.87
CIA (C→I, A)	583.23	370.43
IIR (I→I, R)	695.19	362.73
IIA (I→I, A)	613.35	390.9

Figure 5

Theta Power

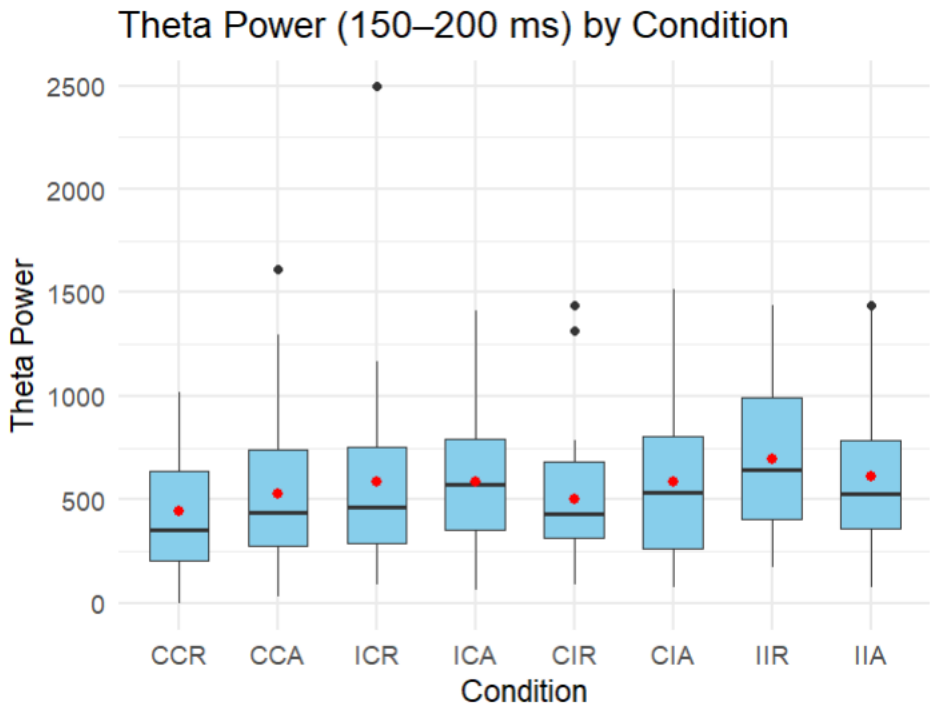
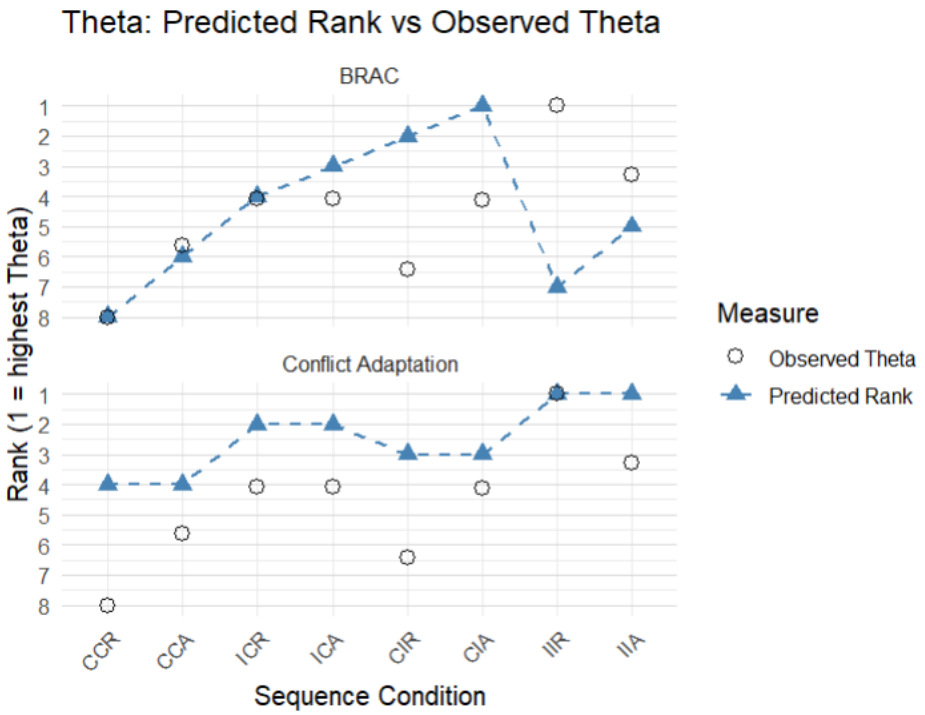


Figure 6

Theta Observed vs CA and BRAC Predictions



Discussion

This study investigated whether sequential effects on behavioral measures and posterior theta in the Eriksen flanker task can be best understood by Conflict Adaptation theory or by BRAC theory. Theoretical predictions were tested using both behavioral and neural measures.

Behaviorally, a classic CSE was observed with the significant interaction between previous and current compatibility trials, which is consistent with the conflict adaptation theory. Furthermore, strong interaction on the previous and current compatibility trials with added response transition suggest that episodic binding also played a role. The EEG data showed after incompatible indicating sustained visual inhibition after conflict trial.

Conflict adaptation effects and CSE were observed in the data, as predicted by H1 (see Table 2), which states that RTs on an incompatible trial will be faster and accuracy higher if the previous trial was incompatible (I→I) compared to when the previous trial was compatible (C→I). In contrast, a compatible trial after an incompatible (I→C) confirmed to be slightly slower and less accurate than after a compatible (C→C). Accuracy showed the same trend. These results suggest that cognitive systems use more control to resolve the following conflict. These results are consistent with the research of Gratton et al. (1992).

However, there are some results that cannot be explained by Conflict Adaptation. The evidence is in the comparison of full and partial repetition conditions, and complete mismatch conditions. According to the hypotheses 2-4 (Lee et al., 2025), BRAC predicts that full S-R repetitions (CCR, IIR) will show the fastest RTs (H2), complete alternations (CCA, IIA) will show slower RTs (H3), and partial feature overlaps (ICR, ICA, CIR, CIA) will be the slowest (H4). The data showed only partial support for these predictions. During full repetition performance improved only in CCR, which likely indicates retrieval mechanism of BRAC. However, IIR was mid-range in the RT ranking. Complete alternations were predicted to be after full repetitions, however only CCA was among the fastest conditions (2^{nd} fastest), while IIA was second slowest. Therefore, hypothesis 3 cannot be fully supported. Partial repetitions CIR and CIA were among the slowest, whereas ICR and ICA followed immediately after the fastest conditions (3^{rd} and 4^{th} rankings). Despite significant effect of previous compatibility and response repetition, accuracy revealed mixed results, which hints at repetition benefit. However, most of the times repetition trials showed lower accuracy and ranking results were not fully consistent with RTs. Therefore, BRAC cannot fully explain the pattern of conditions.

Posterior Theta and Inhibitory Control

Conflict Adaptation theory in hypothesis 5 predicted that posterior-parietal theta activity would index the engagement of visual selective attention and that this would increase after an incompatible trial, when control is engaged. In other words, how strongly the brain is filtering out flankers. The overall pattern of theta power strongly supported the conflict adaptation interpretation. Sequences where the previous trial was incompatible exhibited higher posterior theta than those where the previous trial was compatible. All four "I→" sequences showed greater theta power than any of the "C→" sequences. This suggests that the mere experience of conflict triggered a sustained enhancement of visual-processing control, carried into the next trial. Moreover, the highest theta was observed for sequences with two consecutive incompatible trials, which aligns with the idea that when conflict is encountered, the system is using maximal distractor suppression. So, the first incompatible trial activates control, and if the second trial is also incompatible, that control is fully used (and possibly further strengthened), resulting in strong theta-band activity to help filter out the conflicting flankers. In contrast, after a compatible trial the system's alert for conflict is lower, so when an incompatible trial appears it is unexpected and there is initially less inhibition. Results are also consistent with the research of Asanowicz et al. (2023) where subsequent targets evoke ipsilateral posterior theta bursts to suppress irrelevant stimuli.

BRAC might propose that theta reflects retrieval-induced conflict (i.e. the need to resolve interference from a partially mismatched memory of the previous trial). Theta findings only partly support this view. So, the prediction of hypothesis 6 was that partial-repetition trials should elicit higher posterior theta than full repeats or full alternations, reflecting the conflict between a retrieved episode and current stimuli. The data do not clealry support this view. Some conditions with partial overlaps showed elevated theta consistent with needing more inhibition. For example, ICR and ICA elicited high theta power, which could be seen as the brain handling a conflict between the retrieved prior response and the new response requirement. However, the overall ranking did not follow H6. Moreover, the peak theta was on IIR (full repetition) followed by IIA (complete mismatch, which is opposite to H6's predictions. A closer look shows that theta was more strongly driven by the presence of conflict and its anticipation (previous trial type) than by overlap. Importantly, the condition with the worst behavioral interference (CIR) did not show the highest theta. Its low theta, paired with poor performance, leans more towards the conflict adaptation theory. From the BRAC perspective, one might have expected high theta due to the retrieval mismatch, but the

results suggest that without a trigger for control (like a previous conflict), the system did not produce a large theta, and the outcome was an uninhibited, slow response. These findings suggest that the posterior theta reflects active control implementation rather than the passive presence of mismatch.

Theoretical Implications and Integrations

Egner (2007) argued that CSE is best understood as a combination of top-down and bottom-up influences. The results suggest that conflict adaptation theory accounts for the main sequential effects, especially in EEG. The presence of a significant CSE interaction in RT supports the idea of dynamic adjustments. Moreover, the results were similar with the classis conflict adaptation model of Botvinick et al. studies, which indicates that after an incompatible trial participants showed enhanced focus on task-relevant information and reduced distractor interference. This led to faster RTs and fewer errors on the following trial. Posterior theta power was higher after incompatible trials relative to compatible trials mirroring earlier findings that conflict produces increased theta-band activity related to attentional control. Overall pattern, both behavioral and neural, is best explained by the top-down control mechanism. So, conflict on trial *n-1* serves as a signal for more control on trial *n*.

In contrast, the pure feature-binding account (BRAC) only partially explained the data with the strong benefit of full repetition (CCR) and the overall mixed response-repeat trend that would fit BRAC. Despite significant ANOVA results on response effect, many predicted effects of BRAC were not observed. So, the data does not fully support the claim that full event-file repetition leads to facilitation, suggesting that intrinsic difficulty of incompatible trials, as emphasized by the Conflict Adaptation theory, continues to play a significant role. On the other hand, some of the results showed the facilitation during the repetition trials. Therefore, a hybrid explanation, where feature integration mechanisms (BRAC) interact with reactive control adjustments (Conflict Adaptation), may better explain the full pattern of results. From the theta perspective, conflict adaptation interpretation was favored over BRAC, suggesting that new explanation or mechanism is needed to understand the pattern from BRAC perspective.

Limitations, Future Suggestions & Conclusion

Several limitations were found in this study. Analysis was centered on a relatively early post-stimulus interval, even within this window multiple processes could overlap. For example, initial sensory encoding of the new stimulus (~100–150 ms) transitions into attentional processing (~150–200 ms), and theta-band measure could reflect a mixture of both. Secondly, the study had a small sample which limits the generalizability of the results. Then only 2 electrodes (PO7 & PO8) were used which restricts identification of the precise neural sources of the theta effects. Also, assessment on fronto-medial signals is lacking. Moreover, an ideal study design would manipulate target repetition and response repetition (for instance, using multiple stimuli mapping to the same response).

Future work should include larger and more diverse samples to ensure that observed effects are robust. More electrodes to map theta generators and better distinguish inhibition dynamics. It is also important to know which elements drive BRAC effects more strongly. Is repeating the flankers alone sufficient, or must the target or even the task context repeat? So holding two features constant while varying the third would help. Future works can also expand this type of research on other conflict tasks such as Stroop, Simon, etc. Moreover, these studies would benefit from new theoretical explanations on sequential effects and conflict tasks such as combining the multiple levels of feature integration (including identification on which feature is more dominant) and adaptive control, which would interact between each other.

In conclusion, this study aimed to evaluate whether sequential Effects on posterior theta in the classical Eriksen task are better understood by Conflict Adaptation Theory or the BRAC framework. Results showed that conflict adaptation mechanisms played a dominant role in both behavioral outcomes and posterior theta activity. This supports the idea that top-down control is used to manage conflict and optimize performance. However, feature binding effects predicted by BRAC were also observed, particularly in conditions involving full feature repetitions, where performance was facilitated. It is important to note that BRAC-related effects were only partially explained, suggesting that feature retrieval is more selective and less generalized than conflict-driven control. Overall, the data suggests an integrative model in which both conflict adaptation and feature binding contribute to adaptive control, with conflict adaptation as the primary driver and BRAC mechanisms as selective (secondary) modulatory effects when feature overlap allows.

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Appendix A

Table 1

Behavioral and theta predictions

Sequence type	Conflict adaptation		BRAC	
	RT	**Theta**	**RT**	**Theta**
CCR (C→C, R)	1	4	1	8
CCA (C→C, A)	1	4	3	6
ICR (I→C, R)	2	2	5	4
ICA (I→C, A)	2	2	6	3
CIR (C→I, R)	4	3	7	2
CIA (C→I, A)	4	3	8	1
IIR (I→I, R)	3	1	2	7
IIA (I→I, A)	3	1	4	5

Note. Behaviorally: 1 = fastest RT, 8 = slowest RT. Theta: 1 = highest Theta, 8 = lowest. For the conflict adaptation theory RT (fastest to slowest) and Theta (highest to lowest) levels are ranked from 1-4, since it does not consider response priming.

Table 2

RTs and PCs

Sequence type	RT		PC	
	mean	**sd**	**mean**	**sd**
CCR (C→C, R)	507.0186	74.36528	97.54136	5.605188
CCA (C→C, A)	517.1007	77.12124	98.48371	1.798981
ICR (I→C, R)	533.6543	79.21286	96.38779	5.252422
ICA (I→C, A)	529.6564	70.71920	97.86593	4.184226
CIR (C→I, R)	585.2236	91.54154	93.14457	5.115500
CIA (C→I, A)	563.3021	75.78799	95.05293	6.344378
IIR (I→I, R)	545.8550	76.89930	96.57893	4.240638
IIA (I→I, A)	572.4921	74.49746	93.24964	6.069709

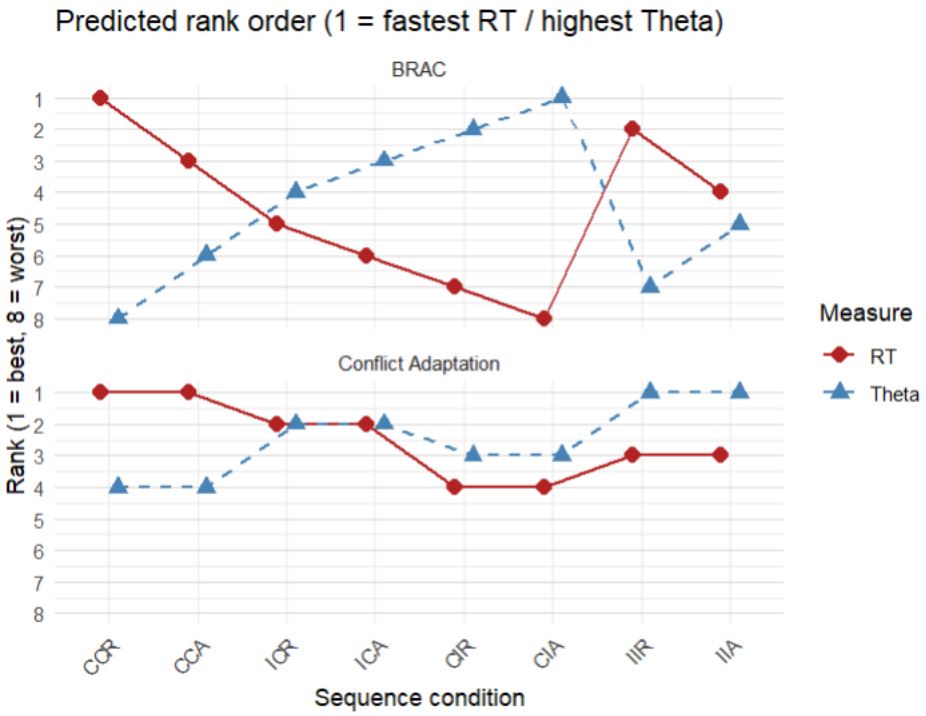
Table 3

Theta Means

Sequence type	Theta power	
	mean	**sd**
CCR (C→C, R)	443.99	281.51
CCA (C→C, A)	529.46	370.31
ICR (I→C, R)	584.20	470.03
ICA (I→C, A)	584.87	360.47
CIR (C→I, R)	500.9	323.87
CIA (C→I, A)	583.23	370.43
IIR (I→I, R)	695.19	362.73
IIA (I→I, A)	613.35	390.9

Figure 1

Behavioral and theta predictions



Note. RT: 1 = fastest RT, 8 = slowest RT. Theta: 1 = highest Theta, 8 = lowest. For the conflict adaptation theory RT (fastest to slowest) and Theta (highest to lowest) levels are ranked from 1-4, since it does not consider response priming. **Figure 2**

Reaction Time by Condition

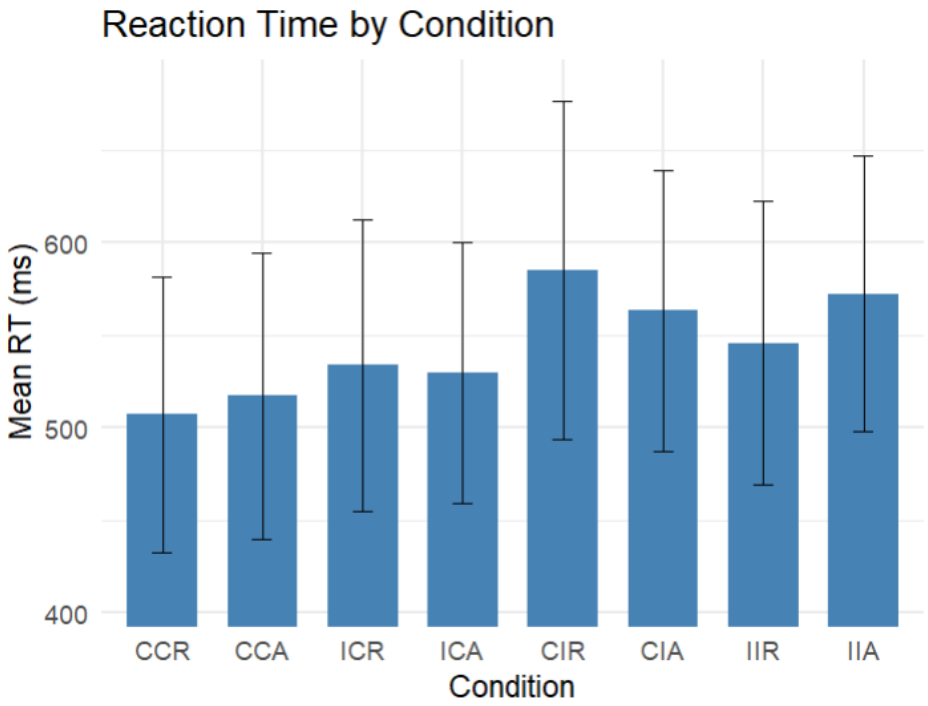


Figure 3

Percent Correct by Condition

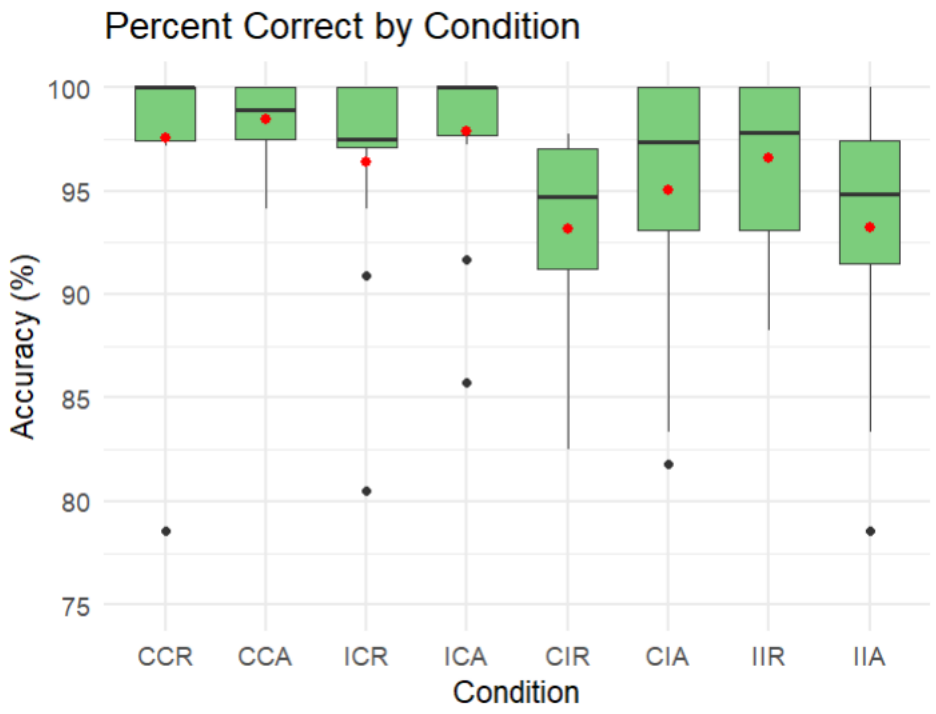


Figure 4

Observed vs CA and BRAC

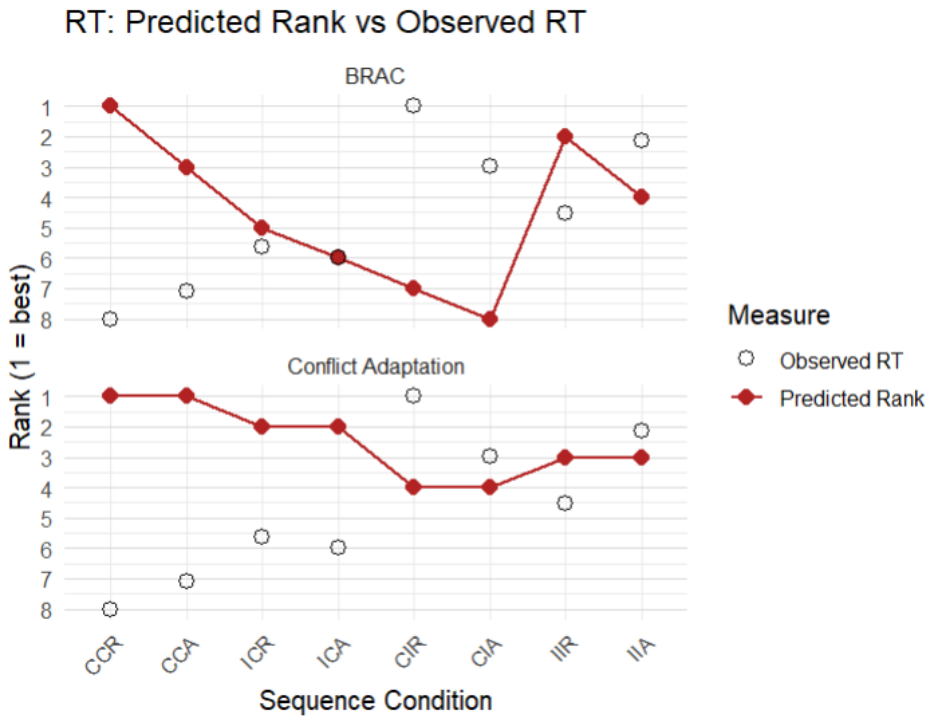


Figure 5

Theta Power

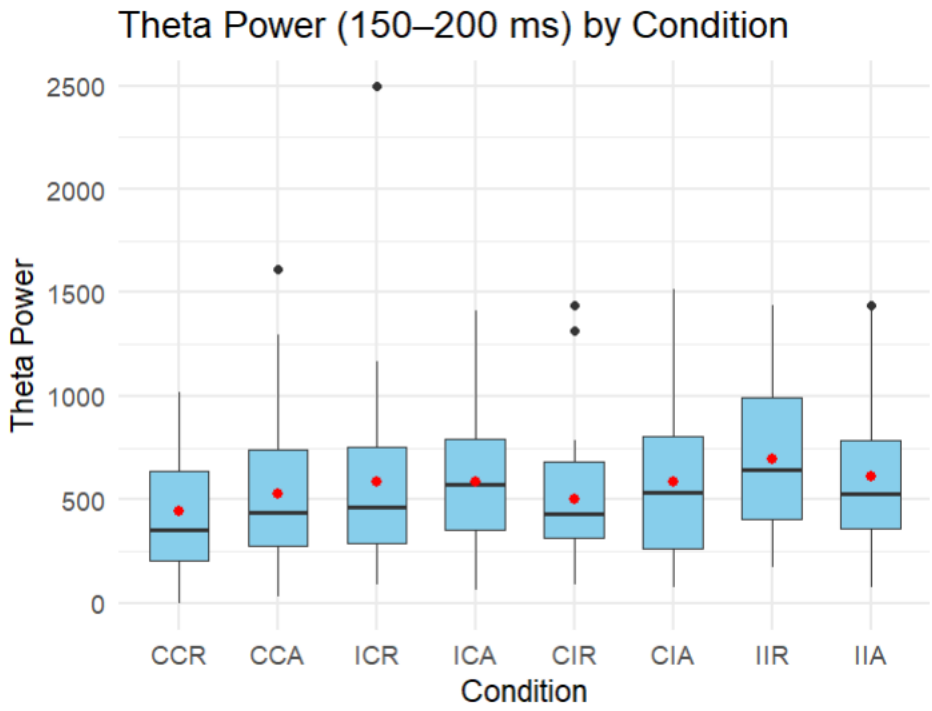
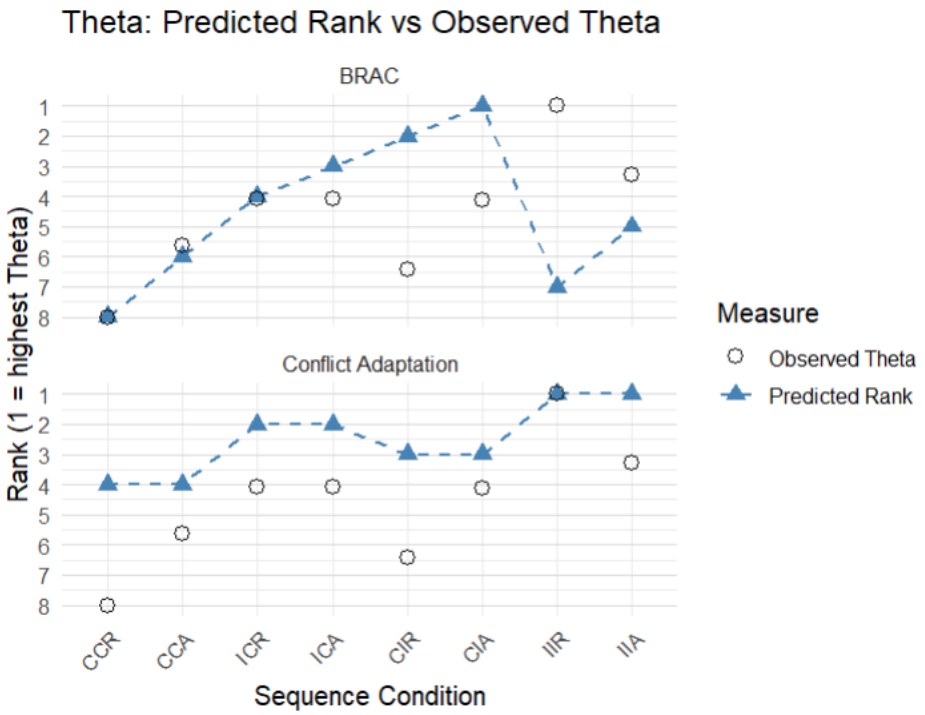


Figure 6

Theta Observed vs CA and BRAC Predictions



Appendix B

Annett Handedness Inventory

Name:

Indicate the preferred hand:

	Always left	Mostly left	No preference	Mostly right	Always right
Writing a letter					
Throw a ball to hit a target					
To play a racket in tennis , squash etc.					
What hand is up to handle a broom removing dust from the floor					
What hand is up to manipualte a shovel					
Lighting matches					
Scissors when cutting paper					
To hold a wire to move it through the eye of a needle					
To distribute playing cards					
To hit a nail on the head					
To hold your toothbrush					
To remove the cover from a jar					
	-2	-1	0	+1	+2

-24 tot –9 Left handed

-8 tot +8 ambidexter

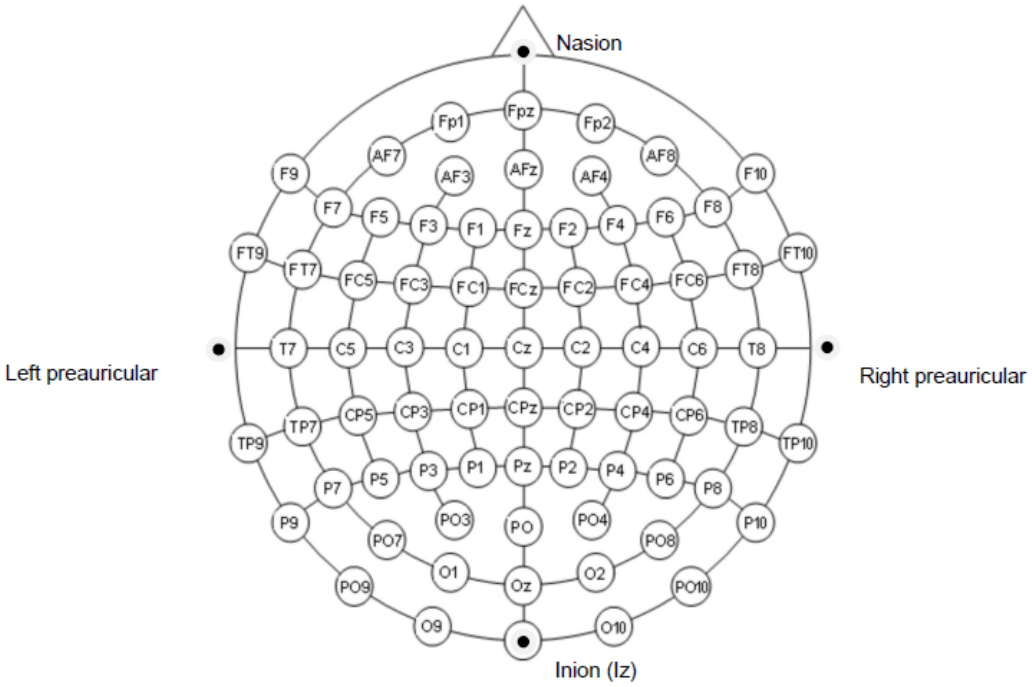
+9 tot + 24 right handed

Annett Handedness Inventory

Annet, M. (1970). A classification of hand preference by association analysis. British J of Psychol, 61, 303-321.

Appendix C

10/20 system



Appendix D

R Code for statistical analysis

```
library(tidyverse)
library(readxl)
library(writexl)
library(stringr)
library(tibble)
library(afex)
library(emmeans)
library(kableExtra)
library(effectsize)
library(scales)
```

```
#----------------------------
# LOADIING LIBRARIES AND FILES
#----------------------------

file_list <- list(
  "L1_100-150ms_THeta_THesis.txt" = "100-150",
  "L1_150-200ms_THeta_THesis.txt" = "150-200",
  "L1_200-250ms_THeta_THesis.txt" = "200-250",
  "L1_250-300ms_THeta_THesis.txt" = "250-300"
)

# DATASET WITH ALL THETA
all_theta_data <- list()

# LOOPING THROUGH EACH FILE
for (file_name in names(file_list)) {
  time_label <- file_list[[file_name]]

  theta_data <- read.delim(file_name, sep = "\t", header = TRUE) %>%
    filter(if_any(everything(), ~ !is.na(.) & . != ""))

  po7_cols <- grep("^PO7", colnames(theta_data), value = TRUE)
  po8_cols <- grep("^PO8", colnames(theta_data), value = TRUE)

  theta_po7 <- theta_data[, po7_cols]
  theta_po8 <- theta_data[, po8_cols]
  subjects <- paste0("PP", sprintf("%02d", 3:16))

  long_po7 <- theta_po7 %>%
    mutate(Subject = subjects) %>%
    pivot_longer(-Subject, names_to = "CondLabel", values_to = "Theta") %>%
    mutate(Electrode = "PO7")
```

```
  long_po8 <- theta_po8 %>%
    mutate(Subject = subjects) %>%
    pivot_longer(-Subject, names_to = "CondLabel", values_to = "Theta") %>%
    mutate(Electrode = "PO8")

  combined <- bind_rows(long_po7, long_po8) %>%
    mutate(
      Subject = toupper(trimws(Subject)),
      Condition = str_extract(CondLabel, "[A-Z]{3}(?=_)"),
      Condition = toupper(trimws(Condition)),
      PrevCong = substr(Condition, 1, 1),
      CurrCong = substr(Condition, 2, 2),
      RespTrans = substr(Condition, 3, 3),
      PrevCong = factor(PrevCong, levels = c("C", "I")),
      CurrCong = factor(CurrCong, levels = c("C", "I")),
      RespTrans = factor(RespTrans, levels = c("R", "A")),
      TimeWindow = time_label
    )

  all_theta_data[[time_label]] <- combined
}

# COMBINE ALL INTO DATA FRAME

theta_all_windows <- bind_rows(all_theta_data)

# LOADING RTs and PCs

rt_data <- read.delim("RT_Thesis.txt", header = FALSE, sep = "\t")
pc_data <- read.delim("PC_Theses.txt", header = FALSE, sep = "\t")
conditions <- c("CCR", "CCA", "ICR", "ICA", "IIR", "IIA", "CIR", "CIA")
subjects <- paste0("PP", sprintf("%02d", 3:16))

#ADD COLUMN NAMES
```

```
colnames(rt_data) <- conditions
colnames(pc_data) <- conditions
rt_data$Subject <- subjects
pc_data$Subject <- subjects

rt_long <- rt_data %>%
  pivot_longer(-Subject, names_to = "Condition", values_to = "RT") %>%
  mutate(Subject = toupper(trimws(Subject)), Condition =
toupper(trimws(Condition)))

pc_long <- pc_data %>%
  pivot_longer(-Subject, names_to = "Condition", values_to = "PC") %>%
  mutate(Subject = toupper(trimws(Subject)), Condition =
toupper(trimws(Condition)))

# MERGE EVEYTHING

theta_all <- theta_all_windows %>%
  left_join(rt_long, by = c("Subject", "Condition")) %>%
  left_join(pc_long, by = c("Subject", "Condition"))

str(theta_all$Theta)

# HOW MANY NAs

sum(is.na(as.numeric(theta_all$Theta)))

# PROBLEMATIC ROWS

theta_all %>%
  filter(is.na(as.numeric(Theta))) %>%
  select(Subject, Electrode, CondLabel, Theta) %>%
  distinct()
```

```
theta_all <- theta_all %>%
  mutate(
    Theta = gsub(",", ".", Theta),      # convert comma decimal to dot
    Theta = trimws(Theta),              # remove whitespace
    Theta = na_if(Theta, ""),           # convert empty strings to NA
    Theta = as.numeric(Theta)           # final conversion
  )

# NOW NUMERIC

str(theta_all$Theta)

# CHECK NAs

sum(is.na(theta_all$Theta))

#MAKE AN EXCEL FILE

#write_xlsx(theta_all, "theta_all_export.xlsx")

#LAST CHECK

str(theta_all)
head(theta_all)

#------------------------
#SUMMARY OF MEANS AND IDs
#------------------------

summary_stats <- theta_all %>%
  group_by(Electrode, Condition, TimeWindow) %>%
  summarise(
    mean_RT = mean(RT, na.rm = TRUE),
    sd_RT = sd(RT, na.rm = TRUE),
```

```
    mean_PC = mean(PC, na.rm = TRUE),
    sd_PC = sd(PC, na.rm = TRUE),
    mean_Theta = mean(Theta, na.rm = TRUE),
    sd_Theta = sd(Theta, na.rm = TRUE),
    n = n()
  ) %>%
  ungroup()

print(summary_stats)

#THETA 150-200

summary_stats_150_200 <- theta_all %>%
  filter(TimeWindow == "150-200") %>%
  group_by(Electrode, Condition, TimeWindow) %>%
  summarise(
    mean_RT = mean(RT, na.rm = TRUE),
    sd_RT   = sd(RT, na.rm = TRUE),
    mean_PC = mean(PC, na.rm = TRUE),
    sd_PC   = sd(PC, na.rm = TRUE),
    mean_Theta = mean(Theta, na.rm = TRUE),
    sd_Theta   = sd(Theta, na.rm = TRUE),
    n = n(),
    .groups = "drop"
  )

print(summary_stats_150_200)

#MAKE AN EXCEL FILE

#write_xlsx(summary_stats_150_200, "summary_stats_150_200.xlsx")

#write_xlsx(summary_stats, "summary_stats_export.xlsx")
```

```
#-----------------
#ANOVA PREPARATION + DESCRIPTIVE STATISTICS
#-----------------

df <- read_excel("theta_all_export.xlsx")



df <- df %>%
  mutate(
    Condition = factor(Condition,
levels=c("CCR","CCA","ICR","ICA","IIR","IIA","CIR","CIA")),
    PrevCong  = factor(substr(Condition,1,1), levels=c("C","I"),
labels=c("Prev_C","Prev_I")),
    CurrCong  = factor(substr(Condition,2,2), levels=c("C","I"),
labels=c("Curr_C","Curr_I")),
    RespTrans = factor(substr(Condition,3,3), levels=c("R","A"),
labels=c("Resp_Repeat","Resp_Alt")),
    TimeWindow = factor(TimeWindow, levels=c("100-150","150-200","200-
250","250-300")),
    Electrode  = factor(Electrode, levels=c("PO7","PO8"))
  )

#CHECK THE DATA

str(df)

#Filter for 150-200 timewindow

df_150_200 <- df %>% filter(TimeWindow == "150-200")



#-----------
#ANOVA START
#-----------
```

```
#----
#RT
#----

rt_df <- df_150_200 %>%
  select(Subject, Condition, PrevCong, CurrCong, RespTrans, RT) %>%
  distinct()

#aov_rt <- aov(
 # RT ~ PrevCong * CurrCong * RespTrans +
 #   Error(Subject / (PrevCong * CurrCong * RespTrans)),
 # data = rt_df
#)

aov_rt <- aov_ez(
  id = "Subject",
  dv = "RT",
  within = c("PrevCong", "CurrCong", "RespTrans"),
  data = rt_df
)

eta_squared(aov_rt, partial = TRUE)

summary(aov_rt)

#RT means

rt_desc <- rt_df %>%
  group_by(Condition) %>%
  summarise(
    mean_RT = mean(RT, na.rm = TRUE),
    sd_RT   = sd(RT,   na.rm = TRUE),
    n       = n(),
```

```
    .groups = "drop"
  ) %>%
  mutate(
    RT_desc = sprintf("%.1f ± %.1f (n=%d)", mean_RT, sd_RT, n)
  )

rt_df %>%
  group_by(CurrCong) %>%
  summarise(Mean_RT = mean(RT))

rt_df %>%
  group_by(RespTrans) %>%
  summarise(Mean_RT = mean(RT))

# RT plot

ggplot(rt_desc, aes(x = reorder(Condition, mean_RT), y = mean_RT)) +
  geom_col(fill = "steelblue", width = 0.7) +
  geom_errorbar(aes(ymin = mean_RT - sd_RT, ymax = mean_RT + sd_RT),
                width = 0.2, color = "black") +
  labs(
    title = "Reaction Time by Condition",
    x = "Condition",
    y = "Mean RT (ms)"
  ) +
  coord_cartesian(ylim = c(min(rt_desc$mean_RT) - 100, max(rt_desc$mean_RT) +
100)) +
  theme_minimal(base_size = 14) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#----
#PC
#----
```

```
pc_df <- df_150_200 %>%
  select(Subject, Condition, PrevCong, CurrCong, RespTrans, PC) %>%
  distinct()

#aov_pc <- aov(
#  PC ~ PrevCong * CurrCong * RespTrans +
 #   Error(Subject / (PrevCong * CurrCong * RespTrans)),
 # data = pc_df
#)

aov_pc <- aov_ez(
  id = "Subject",
  dv = "PC",
  within = c("PrevCong", "CurrCong", "RespTrans"),
  data = pc_df
)

summary(aov_pc)

eta_squared(aov_pc, partial = TRUE)

#PC Means
pc_desc <- pc_df %>%
  group_by(Condition) %>%
  summarise(
    mean_PC = mean(PC, na.rm = TRUE),
    sd_PC   = sd(PC,   na.rm = TRUE),
    n       = n(),
    .groups = "drop"
  ) %>%
  mutate(
    PC_desc = sprintf("%.1f ± %.1f (n=%d)", mean_PC, sd_PC, n)
  )
```

```
pc_df %>%
  group_by(CurrCong) %>%
  summarise(Mean_PC = mean(PC))

pc_df %>%
  group_by(RespTrans) %>%
  summarise(Mean_PC = mean(PC))

#PC plot
ggplot(pc_df, aes(x = Condition, y = PC)) +
  geom_boxplot(fill = "palegreen3", color = "black", width = 0.6) +
  stat_summary(fun = mean, geom = "point", shape = 20, size = 3, color = "red") +
  labs(
    title = "Percent Correct by Condition",
    x = "Condition",
    y = "Accuracy (%)"
  ) +
  ylim(75, 100) +
  theme_minimal(base_size = 14) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#-----
#Theta
#-----

theta_summary <- df_150_200 %>%
  group_by(Subject, PrevCong, CurrCong, RespTrans, Electrode) %>%
  summarize(Theta = mean(Theta, na.rm = TRUE), .groups = "drop")

#aov_150_200 <- aov(
  #Theta ~ PrevCong * CurrCong * RespTrans * Electrode +
   # Error(Subject / (PrevCong * CurrCong * RespTrans * Electrode)),
  #data = theta_summary
#)
```

```
aov_theta <- aov_ez(
  id = "Subject",
  dv = "Theta",
  within = c("PrevCong", "CurrCong", "RespTrans", "Electrode"),
  data = theta_summary
)

summary(aov_theta)

eta_squared(aov_theta, partial = TRUE)



#Means Theta

desc_stats_by_condition <- df_150_200 %>%
  group_by(Condition) %>%
  summarise(
    Mean_Theta = mean(Theta, na.rm = TRUE),
    SD_Theta   = sd(Theta, na.rm = TRUE),
    N          = n(),
    .groups    = "drop"
  )

print(desc_stats_by_condition)



#Plots



ggplot(df_150_200, aes(x = Condition, y = Theta)) +
  geom_boxplot(fill = "skyblue", color = "black") +
  stat_summary(fun = mean, geom = "point", shape = 20, size = 3, color = "red") +
```

```
  labs(title = "Theta Power by Condition (150-200 ms)", y = "Theta Power", x =
"Condition") +
  theme_minimal()


#Means CurrCong
desc_by_currcong <- df_150_200 %>%
 group_by(CurrCong) %>%
 summarise(
  Mean_Theta = mean(Theta, na.rm = TRUE),
  SD_Theta   = sd(Theta, na.rm = TRUE),
  N          = n(),
  .groups    = "drop"
 )

print(desc_by_currcong)

#Means RespTrans
desc_by_resptrans <- df_150_200 %>%
 group_by(RespTrans) %>%
 summarise(
  Mean_Theta = mean(Theta, na.rm = TRUE),
  SD_Theta   = sd(Theta, na.rm = TRUE),
  N          = n(),
  .groups    = "drop"
 )

print(desc_by_resptrans)



# ANOVA Everything + TimeWindow and Electrode
#aov_tw <- aov(
 # Theta ~ PrevCong * CurrCong * RespTrans * TimeWindow * Electrode +
```

```
  #  Error(Subject / (PrevCong * CurrCong * RespTrans * TimeWindow * Electrode)),
  #data = theta_tw
#)
#summary(aov_tw)


#aov_tw_afex <- aov_ez(
#  id = "Subject",
#  dv = "Theta",
 # within = c("PrevCong", "CurrCong", "RespTrans", "Electrode"),
 # data = theta_summary
#)

#summary(aov_tw_afex)


gratton_means <- rt_df %>%
  group_by(PrevCong, CurrCong) %>%
  summarise(Mean_RT = mean(RT), .groups = "drop")

gratton_df <- gratton_means %>%
  tidyr::pivot_wider(names_from = CurrCong, values_from = Mean_RT)

gratton_df <- gratton_df %>%
  mutate(Delta_RT = Curr_I - Curr_C)

brac_means <- rt_df %>%
  group_by(PrevCong, CurrCong, RespTrans) %>%
  summarise(Mean_RT = mean(RT), .groups = "drop")

brac_wide <- brac_means %>%
  pivot_wider(names_from = CurrCong, values_from = Mean_RT) %>%
  mutate(Delta_RT = Curr_I - Curr_C)
```

```
repeat_df <- rt_df %>% filter(RespTrans == "Resp_Repeat")
change_df <- rt_df %>% filter(RespTrans == "Resp_Alternate")

anova_repeat <- aov_ez(
  id = "Subject",
  dv = "RT",
  data = repeat_df,
  within = c("PrevCong", "CurrCong")
)

print(anova_repeat)



#-----
#Plots
#-----

seq_order <- c("CCR","CCA","ICR","ICA","CIR","CIA","IIR","IIA")

# Prepare prediction table

# 1. Define eight theoretical predictions sequentially (1–8)
pred_tbl <- tribble(
  ~Condition, ~CA_RT, ~CA_Theta, ~BRAC_RT, ~BRAC_Theta,
  #  Conflict-adaptation  |  BRAC
  #  RT  | Theta          |  RT  | Theta
  "CCR", 1,    8,           1,    8,
  "CCA", 2,    7,           4,    7,
  "ICR", 5,    4,           3,    6,
  "ICA", 6,    3,           6,    3,
  "CIR", 7,    6,           5,    4,
  "CIA", 8,    5,           8,    1,
  "IIR", 3,    2,           2,    5,
  "IIA", 4,    1,           7,    2
```

```
)

# Tidy the data
plot_df <- pred_tbl %>%
  pivot_longer(-Condition,
               names_to = c("Theory", "Measure"),
               names_sep = "_",
               values_to = "Rank") %>%
  mutate(
    Theory = recode(Theory, CA = "Conflict Adaptation", BRAC = "BRAC"),
    Measure = factor(Measure, levels = c("RT", "Theta")),
    x_order = as.numeric(factor(Condition, levels = pred_tbl$Condition)),
    Offset = ifelse(Measure == "RT", -0.1, 0.1),
    x_pos = x_order + Offset
  )

plot_df <- pred_tbl %>%
  pivot_longer(-Condition, names_to = c("Theory","Measure"),
               names_sep = "_", values_to = "Rank") %>%
  mutate(
    Condition = factor(Condition, levels = seq_order),
    Theory    = recode(Theory, CA = "Conflict Adaptation", BRAC = "BRAC"),
    Measure   = factor(Measure, c("RT","Theta")),
    x_pos     = as.numeric(Condition) + ifelse(Measure == "RT", -0.1, 0.1)
  )

# Create the plot
ggplot(plot_df, aes(x = x_pos, y = Rank, group = Measure)) +
  geom_hline(yintercept = 1:8, linetype = "dotted", colour = "grey80") +
  geom_line(aes(colour = Measure, linetype = Measure), size = 0.8) +
  geom_point(aes(shape = Measure, colour = Measure), size = 3.5, fill = "white") +
  facet_grid(Measure ~ Theory) +
  scale_x_continuous(breaks = 1:8, labels = seq_order) +
  scale_y_reverse(breaks = 1:8) +
```

```
  scale_colour_manual(values = c(RT = "tomato3", Theta = "steelblue")) +
  scale_linetype_manual(values = c(RT = "solid", Theta = "dashed")) +
  scale_shape_manual(values = c(RT = 16, Theta = 17)) +
  labs(title = "Predicted RT and Theta Rank Patterns (1–8 scale)",
       x = "Sequence Condition", y = "Rank (1 = best)") +
  theme_minimal(base_size = 11)

# Corrected tribble block: each column name starts with ~
pred_long <- tribble(
  ~Condition, ~Theory,              ~Measure, ~Rank,
  "CCR",      "Conflict Adaptation", "RT",     1,
  "CCR",      "Conflict Adaptation", "Theta",  4,
  "CCR",      "BRAC",                "RT",     1,
  "CCR",      "BRAC",                "Theta",  8,

  "CCA",      "Conflict Adaptation", "RT",     1,
  "CCA",      "Conflict Adaptation", "Theta",  4,
  "CCA",      "BRAC",                "RT",     3,
  "CCA",      "BRAC",                "Theta",  6,

  "ICR",      "Conflict Adaptation", "RT",     2,
  "ICR",      "Conflict Adaptation", "Theta",  2,
  "ICR",      "BRAC",                "RT",     5,
  "ICR",      "BRAC",                "Theta",  4,

  "ICA",      "Conflict Adaptation", "RT",     2,
  "ICA",      "Conflict Adaptation", "Theta",  2,
  "ICA",      "BRAC",                "RT",     6,
  "ICA",      "BRAC",                "Theta",  3,

  "CIR",      "Conflict Adaptation", "RT",     4,
  "CIR",      "Conflict Adaptation", "Theta",  3,
  "CIR",      "BRAC",                "RT",     7,
  "CIR",      "BRAC",                "Theta",  2,
```

```
  "CIA",     "Conflict Adaptation", "RT",     4,
  "CIA",     "Conflict Adaptation", "Theta",  3,
  "CIA",     "BRAC",                "RT",     8,
  "CIA",     "BRAC",                "Theta",  1,

  "IIR",     "Conflict Adaptation", "RT",     3,
  "IIR",     "Conflict Adaptation", "Theta",  1,
  "IIR",     "BRAC",                "RT",     2,
  "IIR",     "BRAC",                "Theta",  7,

  "IIA",     "Conflict Adaptation", "RT",     3,
  "IIA",     "Conflict Adaptation", "Theta",  1,
  "IIA",     "BRAC",                "RT",     4,
  "IIA",     "BRAC",                "Theta",  5
) |>
  set_names(c("Condition","Theory","Measure","Rank"))

# fixed condition order for x–axis
seq_order <- c("CCR","CCA","ICR","ICA","CIR","CIA","IIR","IIA")
pred_long <- pred_long |> mutate(
  Condition = factor(Condition, levels = seq_order),
  Measure   = factor(Measure, levels = c("RT","Theta"))
)

#2.  Plot: one facet per Theory, overlay RT & Theta
ggplot(pred_long,
       aes(x = Condition, y = Rank,
           colour = Measure, shape = Measure, linetype = Measure,
           group  = Measure)) +
  geom_hline(yintercept = 1:8, colour = "grey85", linewidth = .15) +
  geom_line(linewidth = .8, position = position_dodge(width = .4)) +
  geom_point(size = 3, fill = "white",
             position = position_dodge(width = .4)) +
```

```
  scale_y_reverse(breaks = 1:8) +
  scale_colour_manual(values = c(RT = "firebrick", Theta = "steelblue")) +
  scale_shape_manual(values  = c(RT = 16, Theta = 17)) +
  scale_linetype_manual(values = c(RT = "solid", Theta = "dashed")) +
  facet_wrap(~ Theory, nrow = 2) +
  labs(title = "Predicted rank order (1 = fastest RT / highest Theta)",
       y = "Rank (1 = best, 8 = worst)", x = "Sequence condition") +
  theme_minimal(base_size = 11) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))



#--------------------
#Plot for Statistics
#--------------------

#RT PLOT

rt_desc <- tribble(
  ~Condition, ~mean_RT, ~sd_RT,
  "CCR", 507.0186, 74.36528,
  "CCA", 517.1007, 77.12124,
  "ICR", 533.6543, 79.21286,
  "ICA", 529.6564, 70.71920,
  "CIR", 585.2236, 91.54154,
  "CIA", 563.3021, 75.78799,
  "IIR", 545.8550, 76.89930,
  "IIA", 572.4921, 74.49746
)

# Define the sequence order
seq_order <- c("CCR", "CCA", "ICR", "ICA", "CIR", "CIA", "IIR", "IIA")

# Convert Condition to a factor with specified order
rt_desc <- rt_desc %>%
```

```
  mutate(Condition = factor(Condition, levels = seq_order))

# Create the plot
ggplot(rt_desc, aes(x = Condition, y = mean_RT)) +
  geom_col(fill = "steelblue", width = 0.7) +
  geom_errorbar(aes(ymin = mean_RT - sd_RT, ymax = mean_RT + sd_RT),
                width = 0.2) +
  labs(title = "Reaction Time by Condition",
       y = "Mean RT (ms)", x = "Condition") +
  coord_cartesian(ylim = c(min(rt_desc$mean_RT)-100,
                           max(rt_desc$mean_RT)+100)) +
  theme_minimal(base_size = 14)

#PC PLOT

ggplot(pc_df %>% mutate(Condition = factor(Condition, seq_order)),
       aes(Condition, PC)) +
  geom_boxplot(fill = "palegreen3", width = 0.6) +
  stat_summary(fun = mean, geom = "point", size = 2, color = "red") +
  labs(title = "Percent Correct by Condition",
       y = "Accuracy (%)", x = "Condition") +
  ylim(75, 100) +
  theme_minimal(base_size = 14)

#THETA PLOT

ggplot(df_150_200 %>% mutate(Condition = factor(Condition, seq_order)),
       aes(Condition, Theta)) +
  geom_boxplot(fill = "skyblue", width = 0.6) +
  stat_summary(fun = mean, geom = "point", size = 2, color = "red") +
  labs(title = "Theta Power (150–200 ms) by Condition",
       y = "Theta Power", x = "Condition") +
  theme_minimal(base_size = 14)
```

```
#OPTIONAL
rt_plot_df <- rt_df %>%
  group_by(Condition) %>%
  summarise(mean_RT = mean(RT, na.rm = TRUE), .groups = "drop") %>%
  mutate(Condition = factor(Condition, levels = seq_order))

ggplot(rt_df %>% mutate(Condition = factor(Condition, levels = seq_order)),
       aes(x = Condition, y = RT)) +
  geom_boxplot(fill = "lightblue", width = 0.6) +
  stat_summary(fun = mean, geom = "point", shape = 20, size = 4, color = "red") +
  geom_line(data = rt_plot_df, aes(x = Condition, y = mean_RT, group = 1),
            color = "tomato3", size = 0.5, inherit.aes = FALSE) +
  labs(title = "Reaction Time by Condition",
       y = "RT (ms)", x = "Condition") +
  theme_minimal(base_size = 14) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))



#-------------
#Overlay Plots
#-------------

#Make sure it is in this sequence

seq_order <- c("CCR", "CCA", "ICR", "ICA", "CIR", "CIA", "IIR", "IIA")

clean_condition <- function(df) {
  df %>%
    mutate(
      Condition = str_trim(Condition),
      Condition = factor(Condition, levels = seq_order) # lock desired order!!!
    )
```

```
}

# Observed RT data
rt_desc <- tribble(
  ~Condition, ~mean_RT,
  "CCR", 507.0186,
  "CCA", 517.1007,
  "ICR", 533.6543,
  "ICA", 529.6564,
  "CIR", 585.2236,
  "CIA", 563.3021,
  "IIR", 545.8550,
  "IIA", 572.4921
)

# Observed Theta data
theta_desc <- tribble(
  ~Condition, ~mean_Theta,
  "CCR", 443.99,
  "CCA", 529.46,
  "ICR", 584.20,
  "ICA", 584.87,
  "CIR", 500.90,
  "CIA", 583.23,
  "IIR", 695.19,
  "IIA", 613.35
)



# Add observed RTs
```

```
pred_long_rt <- pred_long %>%
  filter(Measure == "RT") %>%
  clean_condition() %>%
  mutate(Theory = as.factor(Theory)) %>%
  left_join(rt_desc, by = "Condition")


# RT Plot
ggplot(pred_long_rt, aes(x = Condition)) +
  geom_hline(yintercept = 1:8, colour = "grey85", linewidth = .15) +
  geom_line(
    aes(y = Rank, group = Theory, colour = "Predicted Rank"),
    linewidth = .8
  ) +
  geom_point(
    aes(y = Rank, colour = "Predicted Rank", shape = "Predicted Rank"),
    size = 3
  ) +
  geom_point(
    aes(y = rescale(mean_RT, to = c(8, 1)),
        colour = "Observed RT", shape = "Observed RT"),
    size = 3
  ) +
  scale_y_reverse(breaks = 1:8) +
  scale_x_discrete(limits = seq_order, drop = FALSE) +   # <- hard lock order
  scale_colour_manual(
    name   = "Measure",
    values = c("Predicted Rank" = "firebrick",
               "Observed RT"    = "black")
  ) +
```

```
  scale_shape_manual(
    name   = "Measure",
    values = c("Predicted Rank" = 16,
               "Observed RT"    = 1)
  ) +
  facet_wrap(~ Theory, nrow = 2) +
  labs(
    title = "RT: Predicted Rank vs Observed RT",
    y     = "Rank (1 = best)",
    x     = "Sequence Condition"
  ) +
  theme_minimal(base_size = 12) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Add observed Theta
pred_long_theta <- pred_long %>%
  filter(Measure == "Theta") %>%
  clean_condition() %>%
  mutate(Theory = as.factor(Theory)) %>%
  left_join(theta_desc, by = "Condition")

# Theta Plot
ggplot(pred_long_theta, aes(x = Condition)) +
  geom_hline(yintercept = 1:8, colour = "grey85", linewidth = .15) +
  geom_line(
    aes(y = Rank, group = Theory, colour = "Predicted Rank"),
    linetype = "dashed", linewidth = .8
  ) +
  geom_point(
    aes(y = Rank, colour = "Predicted Rank", shape = "Predicted Rank"),
```

```
  size = 3
) +
geom_point(
  aes(y = rescale(mean_Theta, to = c(8, 1)),
      colour = "Observed Theta", shape = "Observed Theta"),
  size = 3
) +
scale_y_reverse(breaks = 1:8) +
scale_x_discrete(limits = seq_order, drop = FALSE) +   # <- hard lock order
scale_colour_manual(
  name   = "Measure",
  values = c("Predicted Rank" = "steelblue",
             "Observed Theta" = "black")
) +
scale_shape_manual(
  name   = "Measure",
  values = c("Predicted Rank" = 17,
             "Observed Theta" = 1)
) +
facet_wrap(~ Theory, nrow = 2) +
labs(
  title = "Theta: Predicted Rank vs Observed Theta",
  y     = "Rank (1 = highest Theta)",
  x     = "Sequence Condition"
) +
theme_minimal(base_size = 12) +
theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

AI Statement

During the preparation of this work the author used ChatGPT to brainstorm, assist in debugging the code in R. After using this tool/service, the author reviewed and edited the content as needed and took full responsibility for the content of the work.