(200-300 words)

Opt 1**: Engagement of personalized resting-state and task-activated brain states during inter-task intervals predicts working memory task performance in healthy adults.**

**Introduction:** Functional neuroimaging traditionally averages brain activity across time, obscuring transient shifts in whole-brain connectivity. Yet, mounting evidence shows that the brain dynamically shifts between discrete brain states both during periods of rest and while engaged in cognitively demanding tasks (REFs). Fair et al. (2007) demonstrated that individuals transition into a resting-state-like brain state during inter-block intervals during task fMRI. Furthermore, more recent studies have identified canonical patterns of resting-state brain states in healthy adults, ranging from the principal functional gradient that extends from sensorimotor to association regions to a limited set of brain activation patterns (Margulies et al., 2016; CAP state papers). **However, it is unclear if some individuals preferentially engage specific resting-state or task-like brain states during task transitions, and whether this engagement relates to performance on a cognitive task.**

**Proposed methods:** To determine if some subjects preferentially engage specific resting-state or task-activated brain states during inter-block intervals, we will use resting-state and task fMRI during a working memory (WM) task from 339 unrelated healthy adults from the Human Connectome Project (HCP). We will do k-means clustering on the resting-state and WM block-specific time-series data (Kim et al., 2025 Biorxiv) after concatenating each subject’s cortical area by time matrices. Identified clusters will be canonical group-level brain states. We will then extract inter-block intervals from the WM task and, for each subject, compute the similarity of their average inter-block activity to each of the canonical brain states using Spearman correlation. Each subject will then be assigned to one of the canonical brain states using a winner-take-all approach, creating group-level assignments. We will then determine if these groups show differences in their accuracy or reaction time on the WM 2-back task condition. Next, we will calculate the dwell time that each subject spends in their preferred canonical brain state and determine if this dwell time corresponds with task performance.

**Anticipated results:** We hypothesize that subjects whose inter-block brain state looks the most like the resting-state principal functional gradient will exhibit better performance (higher accuracy rate and lower reaction time) on 2-back block conditions for WM. The alternative hypothesis is that individuals whose inter-block brain state looks more like a task-activated WM brain state will exhibit better performance, suggesting effective anticipatory engagement.

**Anticipated outcomes:** Conducting these analyses will help determine whether subjects tend to engage specific brain states and whether this preference influences their task performance.

Timeline/Pipeline:

Step 1: Using the 60 minutes of resting state fMRI & block/event specific time series

* Identify 4 group-level brain states (i.e. cortical maps, 360x1)
* Potential methods: apply PCA to timeseries or FC, HMM, dynamic FC and k means
* Step 1b. Apply best method to WM fMRI and extract task-activated states
* Step 1c: correlate task-activated states with resting states to see which overlap/are similar, keep only unique task-activated states
* Output: multiple vectors of 360 brain regions (a cortical map), each vector is a unique brain state for us

Step 2: Calculate percent time subject spent in each brain state by referring back labeled time points to the inter-task interval (Dwell time)

* You would correlate each column of the task time series data (each TR) against each brain state vector. For a given TR, it will be labeled as a certain state based on which brain state vector it has the highest correlation (similarity) to
* A subject will be assigned to a brain state based on which state they spent the most time in

Step 3: Model dwell time in each state to behavioral performance

* Linear fit with betas, use LASSO to determine which betas are most important
* Now with the labeled task time series data, correlate it to behavioral performance to create a model that can predict it? (Perhaps simple regression)

Final Draft of Abstract

Second Draft of Abstract:

**Title:** Evaluating whether resting state brain activity or task-specific brain activity can more accurately and precisely predict behavioral performance on fMRI data

**Context & What is known in the field, why our experiment/question is important and novel:**

**What is the Phenomena:**

**Why is this important to know:**

**What is the key scientific question:**

**What was our hypothesis:**

**How does our modeling work?**

**What do we expect to find?**

**Research Question:**

Overall question: during cognitive tasks, to what extent do individuals reuse resting-state functional connectivity patterns (the four groups) vs novel task-specific states, and which better explain differences in behavioral performance?

Sub-question 1: What are the dynamic functional connectivity states observed throughout the task? How similar are these to the four rest groups? (i.e. states that are similar to resting are called ‘resting’ and everything else is deemed a ‘unique task-specific brain state)

* Input: Sliding-window connectivity matrices from rest and task, do PCA to reduce dimensions
* Model: k-means clustering to define canonical rest states while all else is defined as unique task-specific brain state
* Output: rest-state centroids, labels for time windows as rest-reused time window or task-specific time window
* Alternative - HMM to identify latent states for event-based tasks (not block-design tasks like working memory or gambling)

Sub-question 2: To what extent are resting-state connectivity patterns reused during tasks, and do individuals exhibit consistent or unique state trajectories?

* Input: task windows with labels
* Model: calculate % dwell time of the total time series for rest-reused and task-specific
  + Optional: transition probabilities between states (Markov chains)
* Output: heatmaps of state reuse by task (i.e. working memory reuses rest states more than gambling), subject-level consistency (do high performers reuse specific states more?)

Sub-question 3: Does dwell time in rest-reused states or unique task-specific states more strongly predict individual behavioral performance?

* Input: Dwell time in rest-reused vs novel states
* Behavioral metrics (i.e. 2-back accuracy, gambling reward rate, etc.)
* Model: fit R^2, or which model explains more variance in performance?
* Output: \*"Dwell time in rest-reused states predicts 20% more variance in memory performance than novel states (ΔAIC = -5.2)."\*

First Draft of Abstract

**Context & What is known in the field, why our experiment/question is important and novel:**

**Research Question:**

Are the dynamic functional connectivity states observed during various cognitive tasks re-engaged or do they change throughout the task (i.e. unique or not the same states), and to what extent does the duration of these states predict individual behavioral outcomes?

Sub-question 1: what are the dynamic functional connectivity states present throughout the task for individuals? (i.e. what components or parameters are identifiable and significantly related to the task or rest)

Sub-question 2: which dynamic functional connectivity states are repeated/reused throughout the task or are unique/do not recur? (how similar are the states to each other over time?)

Are high performers those who reuse optimal rest states during tasks? (Test if reuse of rest states correlates with performance)

Amber:

Start with rest-derived states (from HCP resting data) and test if they reappear during tasks (Sub-Q2). Then: Compare how well rest-reused states vs. novel task-only states predict behavior (Sub-Q3.1).

Example: If subjects reuse a rest-like "frontoparietal control" state during working memory tasks, does dwell time in this state correlate with 2-back accuracy?

If a novel "task-only" state emerges, is it linked to better/worse performance?

Sub-question 3.1: Does state dwell time or trajectory predict their task performance? Does this correlate with their behavioral performance such that ‘high’ or ‘low’ performers could be identified by the parameters or characteristics of their brain state?

Amber: Key question: Which state type (rest-reused or novel) explains more variance in performance?

**Hypotheses:**

**Methods We Will Use (Include Inputs and Outputs of each model):**

Sub-question 1:

* Perform k-means clustering on sliding-window connectivity matrices, calculate gap statistic, the clusters would therefore be similar brain states
* Try Hidden Markov Models if k-means fails

Sub-question 2:

* Do k-means & sliding window for all subjects, compute cosine similarity between task states and rest states
* Define ‘reuse’ as similarity >0.8 (empirical threshold)

Sub-question 3:

* For dwell time: mixed-effects regression (statsmodels format), random intercepts per subject to account for baseline differences, plot partial regression slopes to show how dwell time predict performance

**Anticipated Results:**

Brainstorming for Project Proposal

**Keywords** → brain states, dynamic functional connectivity, HCP data set, brain-cognition relationship, cognitive state transformation model, task-specific subsystems

**Comments & Thoughts from Previous Literature, context, etc.:**

Operating from a “all models are wrong, but some are useful labels” perspective:

* Brain states are ambiguously defined as necessary for each research paper, but the basic idea is that the brain’s function is different in regard to specific conditions/tasks of the experiment, and that these functional differences are detectable
* Specifically, when using sliding window techniques, the proper timeframe for a window should be the length of time of an expected block or task, or perhaps slightly less than the duration of a task to account for switches in brain states and exclude that from a window
* Pragata: when training a model, averaging the data across subjects was too noisy due to each person having a different baseline, so keeping within-subject data will be better for training a model

Other papers

* [Similar paper](https://pmc.ncbi.nlm.nih.gov/articles/PMC10928152/#:~:text=These%20results%20reveal%20a%20shared%20latent%20brain,dynamic%20brain%20processes%20across%20multiple%20cognitive%20tasks) to our current direction
* “During a task, BOLD signal changes take 6–12 s to reach maximum intensity, where it remains relatively constant for sustained long periods of activity, and 8–20 s to return to baseline values after the task is finished” <https://doi.org/10.1016/j.neuroimage.2010.06.052>
* “The data vectors (time series, spectrum and spectrogram) for all pixels wereusedasinputforclusteranalysis. In this analysis we useda modified k-means clustering algorithm. The k-mean algorithm was run 10 times for each number of clusters (k). The clustering analysis was repeated for different k from k=3 to k=45 (in steps of 1). The clusters were evaluated using a squared Euclidean distance index between the values of the data vectors of each pixel (i.e. the time series or spectrum or spectrogram data).” <https://doi.org/10.1016/j.neuroimage.2008.12.015>
* A high-level summary of the key steps for capturing whole-brain, data-driven, time-varying connectivity is presented in Figure 1(b). Input to the analysis can consist of timecourses from regions or from networks (e.g., component timecourses). Next, timecourse pairs can be analyzed using a fixed-window or adaptive windowing approach [23], [30] or a time-frequency approach [21], [31]. The next step involves estimating the states, which can be done a number of ways, for example, by k-means clustering [30], principal component analysis (PCA) [26], [32], or independent component analysis (ICA) [33], [34]. Finally, the summary measure of the states can be done for each state separately, for example, by dwell time or connectivity within each state matrix [29], [35] or across all states, such as in a metastate approach [33], [34]. <https://doi.org/10.1109/MSP.2015.2478915>
* there are double-dimension reduction stages using PCA where the first step is to perform a subject-level PCA, and after vertical concatenation of dimension-reduced subject data, a second-level PCA is applied at the group level to estimate a common group subspace [48] <https://doi.org/10.1109/MSP.2015.2478915>

*Why this matters:*

*Standard fMRI analyses average brain signals over long periods, hiding rapid network reconfigurations that may drive moment‑to‑moment cognition. If task performance hinges on how long a person lingers in particular connectivity states, dynamic state metrics could outperform traditional static contrasts and point toward state‑targeted neurofeedback or stimulation to improve memory and attention.*

*What is already known, and the gap*

*• Rest: Sliding‑window and hidden‑Markov approaches consistently reveal four recurring “rest states” (e.g., Allen 2014; Vidaurre 2017).*

*• Task: Task‑based studies report fronto‑parietal increases but rarely relate them to the established rest‑state repertoire.*

*Gap: No large study has yet tested whether the same individuals reuse rest states during cognitive load and whether state dwell time explains behavioral variance. This project fills that gap.*

*Novelty*

*1. Cross‑condition mapping within subjects (rest → task).*

*2. Individual‑level prediction of behavior rather than group averages.*

*3. Large, open Human Connectome Project dataset (N ≈ 100) for power and reproducibility.*

*Type of question*

*Descriptive: Which connectivity states appear during the task, and how do they overlap with rest states?*

*Predictive: Does state dwell time explain performance beyond age, sex, and motion*

**Research Questions:**

Overall question:How consistent or different are brain states across tasks and across subjects(?)

*Can we predict brain states at other time points given a current brain state?*

*Lucas: When healthy adults perform a two‑back working‑memory task, do they enter the same four connectivity states seen at rest or recruit additional task‑specific states, and does the time spent in each state predict their accuracy and reaction time?*

*Everything in italics is brainstorming*

Comparing subject to subject (across subjects) vs comparing task to task

* In all sub-questions, at minimum we are using all subjects’ data for the purpose of sample size, but this is not asking questions about differences between individuals, rather it is acknowledging that individuals have differences and accounting for it in the models (i.e. the questions aren’t asking why individuals have differences, just that they do and the model shouldn’t be trained such that it overfits to one person’s brain activity)
* ***As for a question that does ask why or how subjects differ which we may or may not answer: Can also look at: high performer’s brain state may be different from low performer’s***
* In sub-question 3, we are asking about task-to-task where we are looking at brain states related to tasks and their differences

Sub-question 1: What is a brain state? How are we defining a brain state?

* Input:  *A cortical area by (subject x time) matrix input into PCA to get the 3 principal components*
* Parameters/model: K-means or PCA or t-SNE (W1D4 dimensionality reduction, monkey planning arm trajectory)
* *Somehow how the group’s brain state changes over time*
* Output: all subjects’ brain states over time, correlating how similar the brain states are to each other
* Meaning/purpose: this would suggest that different people’s brain states are similar when doing the same task, implying there are distinct brain states for a task.

Transition between sub-question 1 & 2: We’d expect that: for a given task, there is distinct/unique activity related to that task and not other tasks, such that a model could be given test data and with some degree of accuracy predict correctly what the task was

Sub-question 2: How do brain states relate to the performance or structure of the task? (Within task)

* Can you decode what the task was given an individual’s brain state?
* If you can decode what the task was given an individual’s brain state, then presumably this arises because there are recurring, consistent/stable patterns of activity between tasks or task vs rest
* *What kinds of recurring patterns of connectivity exist in task vs rest?*
* *Can we identify metastable regimes that align with behavioral or task features?*
* *Input: raw time series or sliding window (dynamic functional connectivity) or trajectories(?), k-means? A cortical area by (subject x time) matrix input into PCA to get the 3 principal components*
* *Parameters/model: predictive, GLM, CNN/Deep learning,*
* *Outputs: probability of the task state, binary (could be categorical if saying task-win, task-loss, rest, etc. or watching video relational, video unsure, video no, so use Poisson)*
* *Evaluation: did the model get decoding the time series data right? Accuracy of prediction/correctness of prediction?*

*How do brain states relate to each other?*

*I.e. Does winning right beforehand cause any losses to ‘feel worse’? Does a win after a series of losses feel more exciting? (Too hard to answer this example with the data we have)*

*MAIN: Do temporally prior neural states in the mentalizing network predict mean reaction times during a social cognition task?*

*SAMPLE: Predicting the difference in mean reaction times between mental and random blocks in a specific brain region (e.g., medial prefrontal cortex (mPFC), temporo-parietal junction (TPJ))*

Sub-question 3: (across tasks) what patterns of activity (specific brain regions) are common to all tasks and which ones are unique to a task?

* Maybe ‘resting state’ activity is the same or similar across tasks or different across tasks
* Brain states that are common or unique across tasks?
  + Do these relate to individual performance on a task?
* *Input: how do you format the data*
* *Output: what should the output be that would allow you to compare brain states across tasks?*
* K-means → Brain states for every single task, compare them to see if they are unique or comparable → individual level info (e.g., trajectory of dimensional brain states)
  + What brain tasks are common for all tasks vs. unique to a task in HCP data set? And then see if these explain individual performance on task
* How many times did a person enter this brain state, how long did they spend in this brain state? Is that related to their performance?
* Brain states for every single subject for every single task

*Why might the brain states be related like so?*

* *Does the recurrence or entropy of task-related brain states carry predictive or explanatory weight?*

**Hypotheses:**

* H1: What we expect/how we think it works:
* H0: Null, neutral, contrasting alternative

**Experimental Methods/Design:**

* What techniques are we using?
* How are we going to validate our models and show that they are appropriate?
* How are we going to design models that may explain something about how the brain works?

**Parameters**

* Outputs: what do we want our models to show, demonstrate/output?
* Inputs: what data do we have? How is it structured? What parameters are relevant for our models? How are we going to feed our data into the models?

**Anticipated Results:**

**Significance/Impact/Implications for future research:**

**AI Buddy Prompt:**

Functional neuroimaging studies often collapse brain activity across time, which results in loss of important individual-level information regarding how the brain changes in response to task demands. Additionally, previous work has shown that individuals transition between 4-5 brain states, or whole-brain patterns of neural activation, during rest. However, it's unclear if these brain states also exist during tasks and if they relate to individual cognitive performance. Using resting-state and task fMRI from healthy adults from the Human Connectome Project, our goal is to determine if there are common brain states that individuals occupy across rest and task, or if there are unique brain states for different tasks. Additionally, we want to know if which brain states an individual occupies is associated with performance on a cognitive task. Identifying the relationship between individual-level brain state dynamics and behavior can help us understand how the brain flexibly reorganizes to accommodate different task demands.

**Notes for 07/15/2025**

* [Paper 1:](https://pmc.ncbi.nlm.nih.gov/articles/PMC9307138/) Tasks better than non-tasks → working memory best task for predicting
* [Paper 2:](https://pdf.sciencedirectassets.com/272508/1-s2.0-S1053811921X00043/1-s2.0-S1053811921001245/main.pdf?X-Amz-Security-Token=IQoJb3JpZ2luX2VjEDIaCXVzLWVhc3QtMSJHMEUCIHIuy3zb5sic0ab6OarlxmHH2A3RWundD9Yu3CdeadgjAiEAtLx85IICXbAQ%2BZETd0bAOM5VXfSEEtWzTpZuavkKYrIqsgUISxAFGgwwNTkwMDM1NDY4NjUiDEFyhtt%2B%2Fxqiw4NHWCqPBTYOT%2BVntu8CFmmFzDfmphP5G7oUmi0aMF3PUwTzxtFp%2BtrxdqVLWN9rMT7y9Fjc%2BoN7Q5pFJ06LvXPX6W4AnegF%2Fb5FADPrQ61RFecbSEaPoA3BqwQjQ4Z3903%2BBEbpD76yVoMdKe%2FZwc0PbDU777m2FurOhUTwDvPjN2hiTEwX%2FKjxZBrDa44IzQOe7WpP2zu89SQ6VPbUMd65SvUdMCEHhnsWHo0Z8xim9elilU1cDCvwBpllYyswgKuRixtfzW0ExTI9tFljm2wRbqlPNFJB4xOyOSGpzckIMKjduVNzW1nP%2B7Pg%2BzBphiawaMT4XLTp4JP%2Bkbp68TLtqH7BB7UtuTtIBHyMNL41ehkSaBmOZihtte8QfuCPfi8j8nU9E4Lr1vxOI13w6FYgns3F8e4NEy9I1GZve7OiJau0z8yARIC6AplyZnh2Mon0De5eL43%2BS1ERH8EZ9ZKHcHVc97k60u3AhZ2ri0tA7Antk9kW2iMwJ%2FdZtAvpkBNv9pmT27nPOHgx9twUF1V6QAo4Iz6mY81roia4i2%2FiNx2K9U%2FYld0B0Yx8RONxop%2ByJ5AJ6Dhvi91DLhKyMdGlms%2BpqiHBOWXz5eD6XujLoEw3y3hBL0uQ61ZfSXuqqis8eW4YESIWLqWAeIT6LvuNm8igztjRzDyRIJRpl7%2BqYtJ1S2u%2BgOzscokGSiHExmgy5snbELqVvPQs0dyI2M2iMJgg5qo1f%2FTg4aIcEThBUojitIOOVCMFu%2BAKix6gbabEDX47SrWgDOf1xtqHTAAlWpImwlTbH5lsXSTeeVQGiVsO78j4vb4NNzST9Vr8qQqpxwTsqGCcRn1NAQcaSh12pFquXYSbIoYWk4xh9UFF8AZmk2cw8aTawwY6sQF0lJudF6mjNafBzTnxgRtkuHTfsDuPbB9RcsV4kzVnLnKzETIj4desAfBLGjq8plVsGRWr4X8d9BSr%2FLPU3po%2FdB8OOZz44T7fVkl1oeawTBgGZIkr449wZrtqbLOMqg9k62LSjXwuEmFRMSzym3nzrqjhxmS4dsiEpmh%2BMJiw0oi1DNfcv2tqW%2FsOKXikno6qnv8RsgujCqJpb431xYljex25ruoBB5cSpeCRaQldSBE%3D&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Date=20250715T191657Z&X-Amz-SignedHeaders=host&X-Amz-Expires=300&X-Amz-Credential=ASIAQ3PHCVTY4EKQAMSI%2F20250715%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Signature=a0a878730589da3b2604a0604a1a3964b31ea23e36185e725df6e8f99fad52de&hash=3079df673fd540a9ab7778f21c6afc6cb2c728e0ed08c759221f4a5da67ace90&host=68042c943591013ac2b2430a89b270f6af2c76d8dfd086a07176afe7c76c2c61&pii=S1053811921001245&tid=spdf-df3e724d-cd6e-42c9-9e88-918f5ac150d1&sid=077a39967f43664035984b71e0db3a4a719fgxrqa&type=client&tsoh=d3d3LnNjaWVuY2VkaXJlY3QuY29t&rh=d3d3LnNjaWVuY2VkaXJlY3QuY29t&ua=131d5b5107025c5f0b&rr=95fb98e42f54e995&cc=us&kca=eyJrZXkiOiJqQ24va3JsdGtQMXJnaXZDaUVJQXhQclhFRi8vREdYbHhxY1Vzd2F0bTNML1pZclBCbWcrcGc2TlFNN2xVTUJvY1dwckNxa3ZFWUNIbEFVMmlhV3kwQW9oRXlEUFdBSDlaZkxJN3NCNnUzdFJkSUFtNU1iMEpoOXNNc2I5QzZUZTVOYmpCTmVxSy9DemF4M2s1a0I5OWpqR2hOeXMyNnU0TnVCSVNZdjh6OUhjUjJ0OCIsIml2IjoiMmYyYTkxODVlNTgyZTgwZjJjZmM3YTJjMTgzY2FjMjEifQ==_1752607023621) Possible to predict brain states → But the simple linear model only generates a blurred image from the average prediction of each category. One possible solution to this problem is to use a multi-label decoding model based on GCN. Specifically, given a short-series of fMRI signals, the model predicts a set of cognitive states instead of one single task condition. Due to the delay effect of hemodynamic response that reaches plateau around 6s past stimulus, we can modify the label matrix by prolonging each event duration until 8s after the task onset and allow multiple labels assigned to the same time point.
* [Paper 3:](https://pdf.sciencedirectassets.com/272508/1-s2.0-S1053811922X00165/1-s2.0-S1053811922007030/main.pdf?X-Amz-Security-Token=IQoJb3JpZ2luX2VjEDMaCXVzLWVhc3QtMSJIMEYCIQDA8wf93OUqE%2BBFRsAopdY2ZNwqQ3SVEUrN6BjUhBYctQIhAMYt%2BoFli6s2UMsYi%2FhL%2BYn32x8ehGGY9tVz5Zhj2PyLKrIFCEsQBRoMMDU5MDAzNTQ2ODY1Igzn2bAoBkJPTTJaEXEqjwWhFwGahU0g0bOaYcXq%2FLEKVeSERTZIAAimJ4UvZZdxGm3JRM%2FMfRQVUMzAG%2FgMJEI3KLNppMC3C1ro5RvPwNvSGjMdb3kjUGmLwV0jMm8W37jqVI39Ys3m%2F7v123dSZkCxBHLzuobXZ%2FR77TQy10fT4065ZFsOAJF%2F2wajYVXj3b1OtnQBGwV3SVrd%2FcajL%2BYK%2BnzjXcLKdvzvzWkE%2FzHq6cnHYSIrr2FcIb18nfohk2O%2B9wa3sm%2B4Jik2eqyAZ60sA0sjc%2Bxl419oul%2F3hCGE15WbYivFml0AP2lbyIGCJa11K8RWQIgdCNjK4oGu0mB%2Bb2UPWNqLeLPTOZXTezrepDkygcOKa34Mxa7qCVaXgL8zyq8Hfy7OI%2B%2Bm6Lm3YK0ZcW0GIMu1mqlmXNYHVZO1G7dCTnS1RyZXJOZ34q3%2BeBlGgHhePRG%2BN%2B3mtbXUINbNzm0bLSdkv40XDAEoWJ9CrxUmQfGYqJeM4527Hm%2BNfi6wPWaJ613e3uAgy7sWVkg0tj7dciIue%2FBxbDF1EXKU%2BlSx0FYYi7YoXbCCfmz22vGbSBi37wPu78Sltf15zI1t1ECx7Kx4njKe0sQtQuDHnyP5XDAPBvW%2Fin8fLibL8ZuZtgAOZQUHz1XZewWo6iASKXINfJEQ10AHpS0JvV1BIiD6kuYG%2BIMERdtjfx7uw4gnEGfELfwyT7bxSUR65JzR3IEx1Lv1FNXleQ0bBri8BTfyeBM7CU5Imfs0%2B2rpOgMCOvgVel4eT%2F9YfbzhTo0Pa65tqWBI%2BUgQjnlTSAF1k7NbTJDhtXQZMqBrbF2jbYAVyPJoUsFNgb6pr3CQbW8HcIGA6L0ovO0U3bY0AiOZbsoCePk9P5C70aY42aTeMKe02sMGOrAByIbPIB%2BYyNiMWW2%2FM52%2FE3KiUhh1fRV4JBx55uhKKfyliiEtP1ByH7zFENM%2BdQzBdc72fTHFKPx91bjtM7bEcVe24cugIHx0SEB42FyCi6Pnxj7gdA2oAJyuuKXEZ7qm9bIYGvC%2FDba13KaL7RiD1kJp%2F%2FdBi3l3LmA%2BSi7EOXUltAcQhteoux3MiFwFRkOAlzfIPPcyVHieWgKARylhfSxlOYm50kPoBspOADcGcXg%3D&X-Amz-Algorithm=AWS4-HMAC-SHA256&X-Amz-Date=20250715T191718Z&X-Amz-SignedHeaders=host&X-Amz-Expires=300&X-Amz-Credential=ASIAQ3PHCVTY6WYTNAVY%2F20250715%2Fus-east-1%2Fs3%2Faws4_request&X-Amz-Signature=4c5aa285ba9b3f59b70e3ab959c646dde9690c9009b331f34f40dda098d7c0de&hash=33d07a8be1118236226c49e2eceb4603846f15765df3d1e67b2ae0688dcaf89a&host=68042c943591013ac2b2430a89b270f6af2c76d8dfd086a07176afe7c76c2c61&pii=S1053811922007030&tid=spdf-e254df99-4dd8-4e33-97ea-f0c570e49e08&sid=077a39967f43664035984b71e0db3a4a719fgxrqa&type=client&tsoh=d3d3LnNjaWVuY2VkaXJlY3QuY29t&rh=d3d3LnNjaWVuY2VkaXJlY3QuY29t&ua=131d5b5107025c5e58&rr=95fb9963cc31e27b&cc=us)
* [Paper 4:](https://pmc.ncbi.nlm.nih.gov/articles/PMC10928152/#:~:text=These%20results%20reveal%20a%20shared%20latent%20brain,dynamic%20brain%20processes%20across%20multiple%20cognitive%20tasks)

**Descriptive Stats for Social condition**

RT\_Mental RT\_Random

count 195.000000 195.000000

mean 1043.623077 1039.513675

std 414.984964 399.460399

min 457.666667 388.000000

25% 751.750000 724.750000

50% 926.333333 984.000000

75% 1241.500000 1253.333333

max 2670.000000 2716.000000





