Supplemental Information

Brain network dynamics associated with intentional weight loss in older adults

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Distributions of BMI

Here we present the distribution of BMI for each weight-loss group (successful versus unsuccessful) separately.

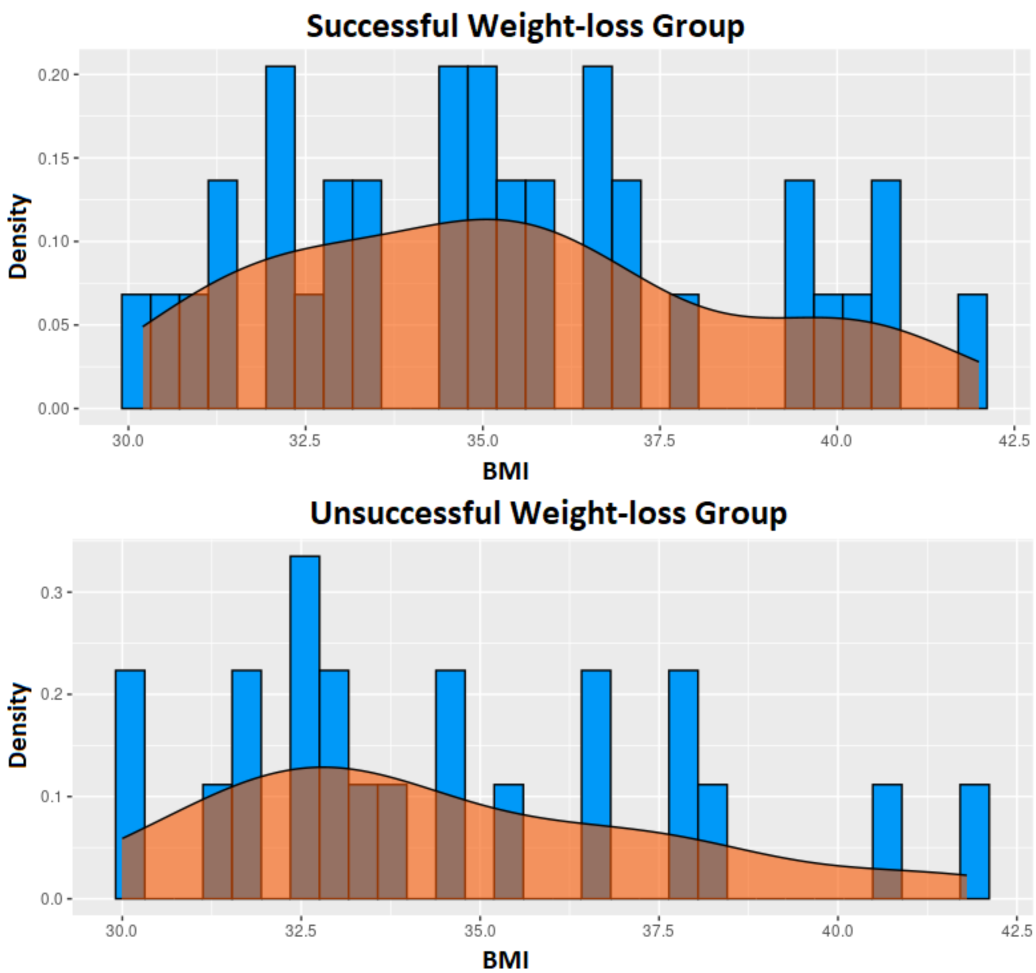

Figure 1: BMI Distributions for each weight-loss group.

Shen Atlas Regions in FN1 and FN2

On the following page is a list of Shen atlas regions (by atlas region number) included in our analyses. In bolded text are regions that belong to both FNs. Please note they are only included in our analysis one time, however.

FN1	**FN2**
15	13
23	14
25	34
35	**37**
36	48
37	52
40	53
61	**61**
78	68
83	72
84	82
100	92
102	95
111	146
124	149
158	164
159	**169**
161	**170**
163	**180**
168	182
169	185
170	188
173	198
180	205
181	207
212	228
218	231
219	235
221	254
241	
247	
248	
253	
261	

Additional Information on the Hidden Semi-Markov Model (HSMM)

The complete data log-likelihood of the HSMM for one participant, given there are K unique network states, can be written as:

$$\begin{aligned}
\ell^*(\mu_{1:\,K}, \Sigma_{1:\,K}, P, \pi, d_{1:K}(u)) &= \log f(\tilde{s}, \tilde{y}) \\
&= \log f(\tilde{y}|\tilde{s}) + \log f(\tilde{s}) \\
&= \sum_{t=1}^{T} \log f(y_t|s_t) + \sum_{r=2}^{R-1} \log(f(s_r|s_{r-1}) d_{s_r}(u_r)) \\
&+ \log(f(s_R|s_{R-1}) D_{s_R}(u_R)) + \log(f(s_1) d_{s_1}(u_1)),
\end{aligned} \tag{1}$$

where s_r is the r^{th} visited state, u_r is the number of consecutive time points spent in that state, and $d_{s_1}(u_1)$ is the sojourn distribution for the first entered state.

The first term is based on the conditional distribution of the observed BOLD signal vector given the underlying k^{th} hidden network. This term takes on a Gaussian distribution:

$$f(y_t|s_t = k) \sim \mathcal{N}(\mu_k,\, \Sigma_k). \tag{2}$$

The second section of the equation is comprised of two parts. The first is a transition probability matrix, denoted P, where the probability at the i^{th} row and j^{th} column represents the probability of transitioning from network state i to state j (i.e., $p_{ij} = P(S_t = j|S_{t-1} = i)$). The second, $d_{s_r}(u_r)$, represents the sojourn distribution.

The third term section accounts for the last state a participant enters. Note that:

$$D_i(u) = \sum_{v>=u} d_i(v)$$

is the survivor function and pertains only to the sojourn time in the final state. It allows ones to not assume that the process is leaving the final state immediately after time T.

The fourth term is the distribution of the network state at the first time point, multiplied by the distribution of how long a participant will remain in that state.

Minimum State Distance Plot

For our main analysis, we fit one set of network states using the data across all individuals in our sample. The number of states one can fit must be specified a-priori and is heavily dependent on the number of participants, number of timepoints, and number of ROIs. As the number of states increases, the number of parameters will similarly increase, as well. Given our sample size, we found that five states produced stable parameter estimates over multiple fittings of the model. Moreover, based on extensive simulations, what we have found is that an inaccurate specification of the number of states can lead to the identification of spurious or merged states. Our solution to this problem involves running the model with different numbers of states and examining the Euclidean distance between the states. The distance between the states should indicate how similar or dissimilar the states are. Genuine brain states are very distinct from each other, while the structure of spurious states is very similar to genuine brain states. Therefore, we executed the model with varying numbers of states and subsequently assessed the minimum distance between the identified states in each run. The run exhibiting the highest minimum distance was the 5 state run, indicating that it had the highest distinctiveness in the estimated states. The figure below shows the minimum distance for each run of the model.

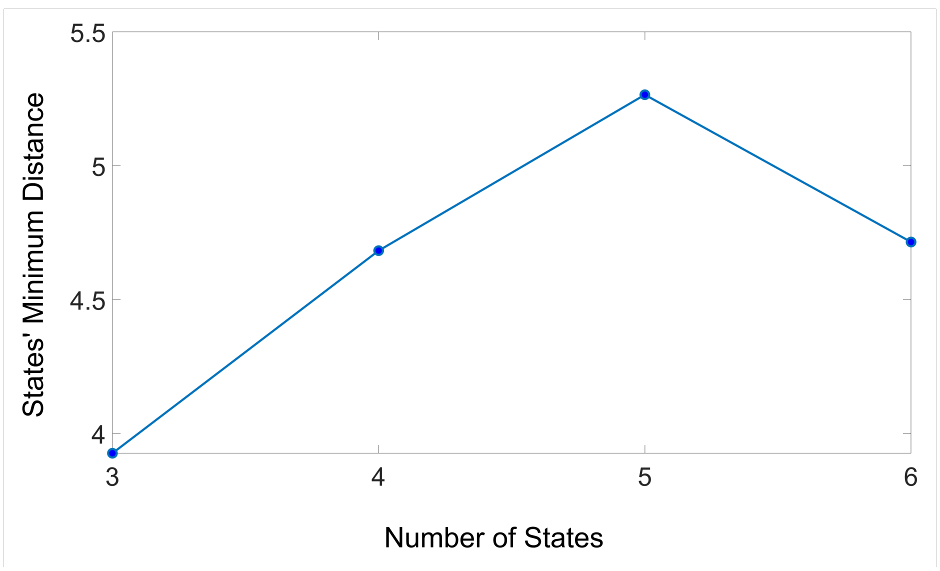

Figure 2: Plot of minimum distance between state pairs in each run. The run with the highest minimum distance between the pairs specifies the optimal number of states. Here we found 5 states to be the optimal number.

Dwell Time Distributions (Group Comparisons on Separate Plots)

Here we present dwell time distributions for the successful vs. unsuccessful weight-loss groups, for each state separately, to facilitate viewing between-group differences.

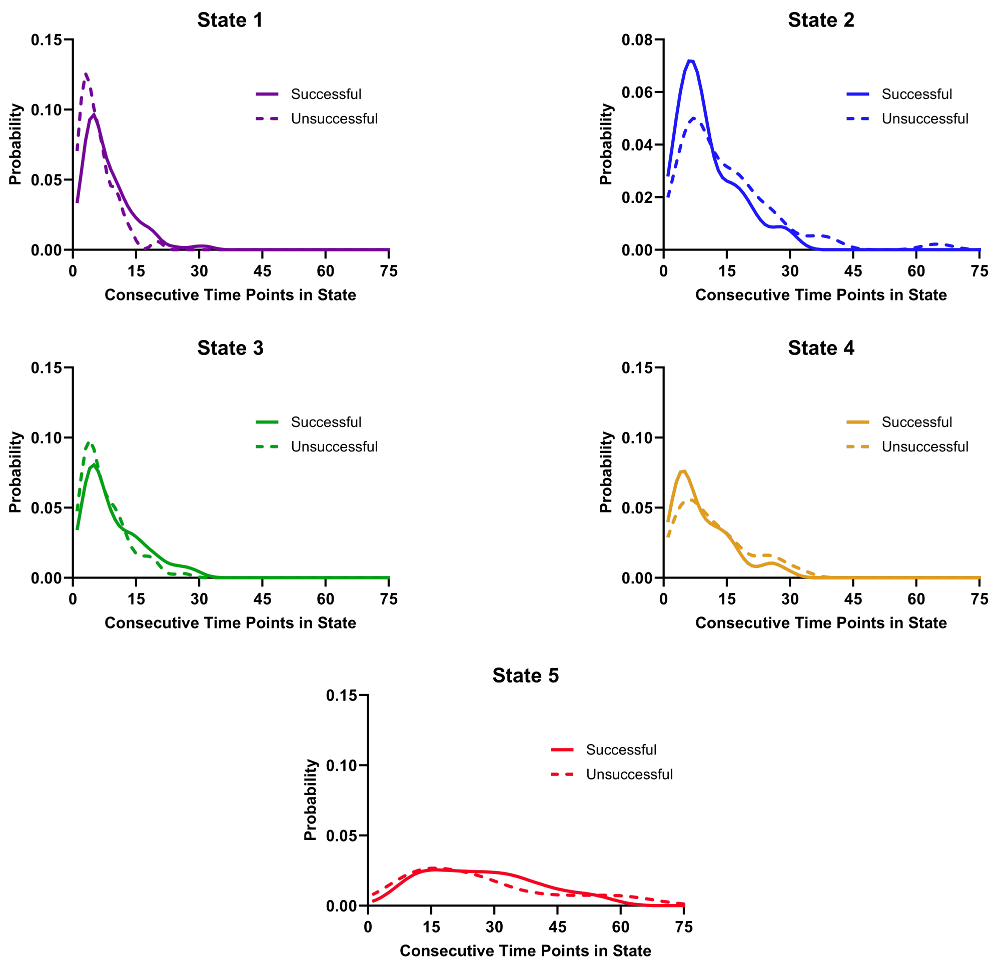

Figure 3: Estimated empirical sojourn distributions for each state for the successful and unsuccessful weight loss groups, indicating that successful weight loss participants spent less time in states 2 and 4 (p-values = 0.038, 0.046, respectively) and more time in state 1 (p-value = 0.033) than unsuccessful weight-loss participants before switching to another state.