Supplementary Material

Additional details regarding revised analytic approach

An overview of our revised data analytic approach is presented in the main text of this manuscript. Additional details are included here. Our main aim was to examine the dynamic relationships between SAD-MDD comorbidity-related factors using ecological momentary assessment (EMA). To model the direct relationship between EMA items, we used network analyses to examine the contemporaneous (i.e., partial associations) and temporal (i.e., Lag 1 partial regressions) estimates. We also were interested in examining the role of certain items within the network; that is, which items were the most influential (*expected influence* centrality), as well as the predictability of each node by other nodes in the network. We sought to determine the extent to which there were idiographic differences both between and within individuals over time in terms of network structure, as well as expected influence. Finally, we were interested in examining the extent to which these individual-level estimates generated from the multilevel model differed from the estimates generated from the person-specific models.

Prior to all study analyses, each participant's data was visually inspected and cleaned to remove extraneous variables (e.g., timestamps) and to specify missing data. Linear trends of time were accounted for by regressing the EMA items onto the time variable and the residuals from this preliminary model were used in the following analyses. Network analyses largely consist of partial correlations and regressions; thus we calculated first order correlations to determine the extent to which high overlap or correlations between EMA items may pose a concern for multicollinearity within the model (Fried & Cramer, 2017). There were three items that were highly correlated – feeling down, feeling happy, and feeling pleased, ($|r|$s = .57 - .59). To reduce

the effects of multicollinearity, we reverse scored feeling happy and feeling pleased and created an average composite between these three items to represent depressed mood. This average composite was used in the rest of the network analyses.

We used two different network analytic packages to examine partial relationships between EMA variables. To model group-level relationships, we used multilevel vector autoregression (ML-VAR) (Epskamp et al., 2018). ML-VAR is a network analytic method that sequentially calculates univariate multilevel associative and lagged (i.e., regressive) effects for one variable at a time. That is, a multilevel model is constructed for each variable in which that variable is treated as the outcome variable and is predicted by the other variables in the model. Residuals from these preliminary multilevel models are then used to predict the residuals of other variables from the same (i.e., contemporaneous) or following (i.e., lagged) time points. We specified orthogonal (i.e., uncorrelated) random effects to reduce the number of random effects being modeled, as recommended by Epskamp and colleagues (2018). A regularization procedure, LASSO, is used to prune paths that may be spurious in the model (Epskamp et al., 2018). ML-VAR outputs two multilevel models. The first model demonstrates the contemporaneous or partial associations between variables. The second model demonstrates the temporal or partial regressive Lag 1 relationships (e.g., values from the previous time point) predicting values at the next time point. In this study, lagged or temporal effects represent the partial regressive relationships across three hours. The estimates from the contemporaneous and temporal models reflect the effect sizes of these relationships.

ML-VAR models are estimated using information borrowed from the group. That is, one of the assumptions of multilevel modeling is that each individual is part of the same group; the multilevel model borrows information from other participants when estimating the effects for

specific individuals. Previous researchers have demonstrated that group-level models may not adequately reflect individual-level effects (see Molenaar, 2004), thus, we sought to construct idiographic networks for each individual. These person-specific networks do not borrow information from the other participants. We constructed person-specific, vector autoregressive (VAR) network models for each participant using the graphicalVAR package (Epskamp, 2018). This package calculates multivariate correlations to output the contemporaneous model, which illustrates the partial associations over time. The graphicalVAR package also calculates multivariate regressions in the temporal model, illustrating the partial regressions from one time point to the next (i.e., over three hours). Similar to ML-VAR, the LASSO regularization method is used to shrink potentially spurious paths (Epskamp et al., 2018) and the estimates reflect the effect sizes of these relationships.

The role and influence of individual EMA variables within the network was characterized further by examining network centrality statistics. We calculated the one-step expected influence for each variable in the contemporaneous models to determine the impact that each variable has on the rest of the network (Bringmann et al., 2019; Robinaugh et al., 2016). The one-step expected influence represents the sum of the paths between a given variable and the rest of the network accounting for both the valence and magnitude of these pathways (Robinaugh et al., 2016). Thus, a variable that is more connected (i.e., has more pathways to other nodes) will have a larger expected influence. For the temporal ML-VAR network, we calculated both the outward expected influence, which is the sum of the pathways between one node predicting other nodes in the network, as well as the inward expected influence, which is the sum of pathways that predict a given node. The expected influence value can be either positive or negative depending on the valence of the pathways in the network and the magnitude can range in size, with the

largest possible value being the total number of potential pathways between that node and the rest of the model. We also calculated the predictability of each node by other nodes in the contemporaneous individual-level networks. To do this, we calculated the R2 for each node using mixed graphical modeling via the mgm package (Haslbeck & Waldorp, 2020). Notably, due to constraints within the analytic procedure for mixed graphical modeling, we were not able to model the effects of time (i.e., model the within-day associations). Thus, these models represent the within-person associations between EMA items. Additionally, to facilitate the estimation of mixed graphical models, we imputed missing observations within an individual's data using random forest imputation methods (i.e., missForest package; Stekhoven, 2013). Overall, there were no clear patterns in node-level predictability across the group; individual-level differences in node-level predictability can be found in Table S4.

To further test the extent to which individuals differed from the group, we sought to compare the individual-level estimates derived from the ML-VAR models to the individual-level estimates derived from the person-specific VAR models.[1] This comparison illustrates the extent to which individual-level effects differ as a function of the model estimation process (e.g., borrowing information from the group). A high correlation between these estimates would suggest that the multilevel model uses assumptions that reflect the underlying group structure.

Rationale for revised analytic plan

We aimed to construct person-specific (i.e., idiographic) networks of SAD-MDD comorbidity-related factors as assessed via EMA. We sought to compare how the inter-item relationships differed across individuals in the group and within individuals over time. Our

[1]We calculated unregularized person-specific VAR models and compared the estimates from these models with the individual-level estimates from the mlVAR model as the individual-level estimates from mlVAR are not regularized.

original analytic plan focused primarily on examining the temporal, Lag 1 and Lag 2, effects between items over time. However, new information regarding our statistical analyses prompted us to reconsider our analytic plan and revise our statistical approach. Here we discuss our rationale for our revised analytic plan, and, in the interest of full transparency, we present a brief overview of our original analytic plan along with the original findings. We conclude with a brief comparison of our current results with our previous findings.

When beginning our original analyses, we were primarily concerned with potential violations of stationarity (see Hamaker, 2012 for one example of discussion of issues with stationarity in time-series data) and so we decided to use dynamic structural equation modeling (DSEM; Asparouhov et al., 2018; Muthén & Muthén, 2017) to construct both multilevel and person-specific models of SAD-MDD comorbidity-related factors. DSEM uses a structural equation modeling approach with Bayesian estimation to model direct inter-item relationships, as well as latent variables. Importantly, DSEM is able to directly model linear effects of time by adding these pathways to the structural equation model. Furthermore, to address our concerns regarding stationarity, Mplus notifies the user of the number of iterations in a DSEM analysis that may contain some violations to stationarity, which assists the user in determining whether the individual's data meets the assumptions of our time series analyses. For example, if many of the iterations in a DSEM analysis returned violations to stationarity, we may conclude that a different analytic approach would be needed to account for non-linear time trends.

Following the analytic plan presented below, we constructed Lag 1 and Lag 2 DSEM and multilevel DSEM (ML-DSEM) models. Notably, in our review of Mplus iteration output, we did not encounter significant issues with stationarity (i.e., very few iterations across models returned violations to stationarity). However, after further communication with lead research groups using

these methods, we learned that our Lag 1 and Lag 2 models were likely significantly underpowered. Given the number of variables and lagged effects included in our models, we believe that we would need several hundred observations to achieve adequate statistical power (instead of approximately 150 observations). Thus, we decided to revise our analytic plan to focus primarily on modeling the contemporaneous (i.e., partial association) and temporal (i.e., Lag 1) models instead of the Lag 1 and Lag 2 models. Recent evidence from simulation studies of idiographic networks suggests that the temporal effects may be especially difficult to model in datasets with fewer observations (such as the number of time points available in our study) and with numerous nodes (Mansueto et al., 2020). This information reinforced our decision to shift our focus to contemporaneous and Lag 1 effects only.

Notably, we decided to conduct our revised analyses working exclusively within the network analytic framework. It is important to explain that we could have conducted our revised analyses using DSEM (Bringmann & Eronen, 2018) and would likely have achieved similar findings as will be discussed below due to similarities in the estimation procedure. However, there are two key reasons to use the network approach in our revised analyses: 1) accessibility of the software for replicating future analyses and 2) the use of the LASSO regularization procedure to shrink potentially spurious effects that occur when running multiple tests (i.e., when constructing a network using more than a few nodes). We briefly expand upon these reasons below.

Currently all documentation for DSEM has been written for Mplus software, which is not open-source. Thus, the first author had limited access to conducting the revised analyses in Mplus, as would many interested readers, which we believed would limit the replicability and

transparency of these findings.[2] Secondly, the two network analytic packages used in our revised approach use a regularization procedure – LASSO – to prune or shrink paths that are sufficiently small to zero. Thus, when interpreting results, only the pathways that are likely to be meaningful (e.g., not sufficiently small) and statistically significant are retained and presented in the model output. In the interest of transparency regarding our original methods, we briefly describe our original analytic plan below and summarize a comparison between the findings using DSEM and our current findings.

Original analytic plan using DSEM

Before beginning DSEM analyses, we planned to use exploratory factor analyses (EFA) to determine whether latent variables should be modeled using DSEM. A model specifying up to five factors was constructed and output from each model was examined. Output from parallel analyses and cutoffs for standard fit indices were used to determine whether a simple factor structure existed.[3] Notably, there were no clear factor structures for participants. We also originally planned to construct DSEM models that included all possible pathways of inter-item EMA and between EMA items and time variables (i.e., day number and survey number); however, as these models included more pathways than observations, a simpler model was constructed that included the effects of EMA items on time, as well as a regression path between all EMA items predicting *feeling down* or feelings of sadness. This model was chosen because sadness (i.e., depressed mood) was the primary EMA item of interest.

To construct person-specific DSEM models, an open model was run without specifying

[2] Notably, it is possible to construct structural equation models using open-source software, such as R. However, we suspect that this procedure would be sufficiently difficult for readers who need more structured guides for conducting time series analyses, given the limited documentation for conducting dynamic structural equation modeling in R at the time of this writing.

[3] A simple factor structure refers to a model structure in which there are a sufficient number of indicators loading onto each factor with low cross-loadings on the other factors (as described in Yang, 2005).

iterations. After the model converged, successive models were run with twice as many iterations and the proportional scale reduction (PSR) factor was evaluated (Muthén, 2010). The model was considered to be final when at least two models converged with low, stable PSR (a cutoff of 1.01 was used). When necessary, commands to prune iterations (Asparouhov, 2014) and weak priors (L. Muthén, personal communication, 12/13/2017) and recoding of categorical response options were used to achieve model convergence.

To model group-level relationships, ML-DSEM was used (Hamaker et al., 2018). Results from the ML-DSEM model demonstrated the autoregressive and cross-lagged relationships that are significant at the group-level. We constructed a model[4] that included the random within-level auto-regressive and cross-lagged effects between all EMA items predicting feelings of sadness, as well as regressing all EMA items on time variables and random error terms. Means and variance of each parameter from the within level were included on the between-level. ML-DSEM also generates individual-level estimates for each pathway using information obtained in the generation of the group-level model. These estimates were used in comparison with the individual-level estimates generated from each person-specific DSEM (see below for further discussion). Mplus, version 8.2 (Muthén & Muthén, 2017) was used to conduct the EFA and DSEM analyses.

To compare overlap in the individual-level estimates generated from the person-specific and multilevel models, we compared the number of pathways that were demonstrated in the multilevel model that were represented in the person-specific models and calculated the percentage of person-specific pathways that were shared with the multilevel model. To assist

[4]We first specified two initial models that were too complex to result in convergence (due to the large number of pathways). These models included all random within-level effects, as well as all random effects excluding random covariances between the error and variances of the covariance.

with data visualization, we constructed density plots of the standardized individual-level estimates computed by the multilevel model compared with the standardized estimates produced in each person-specific model for each pathway predicting daily sadness. These graphs served to visualize whether the individual-level estimates from ML-DSEM versus person-specific DSEM models reflected similar distributions. Plots were generated using R, including the Mplus Automation package, version 0.7-3 (Hallquist & Wiley, 2018) and the ggplot2 package, version 3.1.0 (Wickham, 2016). Code for these original analyses is available from the first author. These final analyses are somewhat comparable to our Aim 3 analyses presented in the main manuscript in which we compared the individual-level autoregressive estimates generated from ML-VAR to the autoregressive estimates generated in the person-specific graphicalVAR models.

Results from original DSEM models

Lag 1 ML-DSEM model

The ML-DSEM model converged with stable, low PSR across successive models with increasing iterations. Overall, there were significant effects of time, such that feeling down increased over the month. Additionally, there was a significant autoregressive effect of feeling down, such that feeling down at one time point predicted feeling more down three hours later. Feeling lonely, avoiding social situations, and more physical activity since the last assessment were all risk factors for feeling more down three hours later; whereas, feeling calm was a protective factor for feeling down. Multilevel effects can be found in Table S5 and those effects with a 95% credible interval that did not include 0 can be seen in Figure S6.

Person-specific Models

Examining each woman's person-specific DSEM model revealed considerable variability. Only a minority of women (n = 14, 56.00%) had models that demonstrated at least one

statistically significant autoregressive or cross-Lagged effect. Of these fourteen individuals, two women (IDs 14 and 20) demonstrated models that reflected one directed effect, such that for these two women, their feelings of sadness increased over the month. Likewise, there were two women (IDs 13 and 22) whose models reflected one significant effect – an autoregressive effect of down – suggesting that for these two individuals, their feelings of sadness were predicted by higher levels of sadness at the previous time point. The remaining ten women exhibited varying pathways. Individual-level effects with a 95% credible interval that did not include 0 can be seen in Figure S6.

Lag 2 Multilevel and Person-specific DSEM Models

As some EMA items may have changed on a longer timescale than every three hours, we also constructed multilevel and person-specific DSEM models at Lag 2 (every six hours). The Lag 2 multilevel and all DSEM models converged with stable, low PSR across successive models with increasing iterations. Overall, there was an autoregressive effect of feeling down at Lag 1 and 2, such that feeling down at one time point predicted feeling more down both at three and six hours later. Consistent with the Lag 1 multilevel model, feeling lonely predicted feeling more down three hours later, whereas, feeling calm predicted feeling less down later on.

Similar to the Lag 1 models, there was considerable variability to the number of significant directed pathways demonstrated at Lag 2 for each woman. There were nine (25.71%) women whose model demonstrated at least one significant directed Lag 2 pathway and three of these women demonstrated a significant Lag 2 autoregressive effect. Interestingly, two out of the three women's autoregressive pathways were incongruent in valence from the multilevel model. That is, for these two women when they were feeling down, they were less likely to feel down six hours later. Multilevel effects from the Lag 2 model can be found in Table S6 and those effects

with a 95% credible interval that did not include 0 can be seen in Figure S7.

Comparison of original DSEM and revised VAR findings

We believe that our revised approach using network analyses focusing on contemporaneous and Lag 1 effects resulted in a more parsimonious approach given the concerns with statistical power in calculating Lag 1 and Lag 2 DSEM models. Notably, direct comparisons between Lag 1 DSEM and Lag 1 (i.e., temporal) ML-VAR and graphicalVAR models are limited due to our creation of an average composite variable for depressed mood, which was created to reduce concerns with multicollinearity in the network analyses. However, when comparable, the results for Lag 1 models across DSEM and VAR approaches were largely similar. That is, there were relatively few statistically significant cross-regressive pathways between EMA items predicting within-day symptoms of depression (i.e., *feeling down* in the ML-DSEM model; average composite of *depressed mood* in the VAR models). For example, there were statistically significant autoregressive effects for feeling down across both models. Additionally, feeling lonely and avoiding social situations both predicted feeling down at the next time point across both models. However, the ML-DSEM model also suggested that feeling calm and physical activity both statistically significantly predicted feeling down at the next time point; these effects were not demonstrated in the ML-VAR model. Moreover, the person-specific temporal models using DSEM and graphicalVAR remained sparse with few women demonstrating more than one Lag 1 effect. For example, the autoregressive effects remained the most common pathways demonstrated in these person-specific models.

Finally, the comparison of individual-level estimates generated from the multilevel model to the individual-level estimates generated from the person-specific models revealed a similar pattern of findings. With few exceptions, the spread of the distributions for the estimates from

the person-specific models were larger than the individual-level estimates generated from the multilevel model, suggesting that the idiographic models may contain more error or noise compared to the multilevel model. Regardless, there was relatively large correlation between the individual-level estimates generated from the multilevel and idiographic models. Overall, these results suggest that on average, there were large correlations between the individual-level estimates; however, given the spread of the distribution, there may be considerable discrepancy suggesting that the multilevel model may be making different, potentially less accurate, assumptions about the individual.

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Table S1

Contemporaneous estimates from the ML-VAR model

	DHP	Calm	Irritated	Anxious	Lonely	Accomp	Hungry	PhysAct	Avoid	Drowsy	Restless	Focused
DHP												
Calm	-0.15**											
Irritated	0.32**	-0.11**										
Anxious	0.21**	-0.25**	0.09**									
Lonely	0.34**	0.07*	0.00	0.02								
Accomp	-0.27**	0.04	-0.05*	-0.003	0.001							
Hungry	0.03	0.002	0.01	0.01	0.01	0.03						
PhysAct	-0.06*	-0.05*	0.04*	-0.01	0.02	0.13**	0.001					
Avoid	0.06*	0.04	0.07*	0.03	0.19**	-0.02	0.01	-0.02				
Drowsy	0.15**	0.06*	-0.06*	-0.03	0.05*	-0.05*	0.01	-0.07*	0.06*			
Restless	0.02	-0.19**	0.09*	0.13**	0.02	0.01	0.03	-0.01	-0.002	0.004		
Focused	-0.08*	0.09**	0.03	0.06*	-0.01	0.26**	0.01	0.01	0.00	-0.15**	-0.03	

Note. The contemporaneous estimates included here are the partial correlations from the multilevel VAR model. DHP = average composite of Down, Happy (reverse scored), and Pleased (reverse scored); Accomp = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations.

* $p < .05$; ** $p < .001$.

Table S2

Temporal estimates from the ML-VAR model

	DHP	Calm	Irritated	Anxious	Lonely	Accomp
DHP	0.22** [0.14, 0.29]	-0.04 [-0.09, 0.01]	0.03 [-0.02, 0.07]	0.03 [-0.02, 0.08]	0.04* [0.003, 0.09]	-0.04 [-0.09, 0.002]
Calm	-0.06 [-0.12, 0.01]	0.07* [0.01, 0.12]	-0.03 [-0.08, 0.03]	-0.08* [-0.13, -0.02]	-0.02 [-0.07, 0.03]	0.003 [-0.05, 0.06]
Irritated	0.06* [0.002, 0.12]	-0.01 [-0.05, 0.03]	0.12** [0.06, 0.18]	0.04 [-0.01, 0.08]	0.001 [-0.04, 0.04]	-0.03 [-0.08, 0.03]
Anxious	0.04 [0.02, 0.10]	-0.07* [-0.12, -0.02]	0.05* [0.01, 0.09]	0.17** [0.12, 0.22]	0.04 [-0.002, 0.09]	-0.02 [-0.08, 0.03]
Lonely	0.02[-0.05, 0.08]	-0.04* [-0.09, -0.001]	0.02 [-0.03, 0.06]	0.04 [-0.002, 0.09]	0.19** [0.14, 0.25]	-0.01 [-0.05, 0.04]
Accomp	-0.06* [-0.12, -0.004]	-0.01 [-0.06, 0.03]	0.01 [-0.03, 0.05]	-0.01 [-0.07, 0.04]	-0.05* [-0.09, -0.01]	0.16** [0.09, 0.22]
Hungry	0.04 [-0.02, 0.10]	0.001 [-0.04, 0.05]	-0.004 [-0.05, 0.04]	-0.01 [-0.05, 0.04]	0.02 [-0.02, 0.07]	0.02 [-0.02, 0.07]
PhysAct	-0.10* [-0.15, -0.04]	0.01 [-0.04, 0.05]	0.02 [-0.03, 0.07]	0.05* [0.005, 0.10]	-0.03 [-0.08, 0.01]	0.02 [-0.03, 0.07]
Avoid	-0.01 [-0.07, 0.05]	-0.01 [-0.06, 0.04]	0.03 [-0.02, 0.08]	0.04 [-0.02, 0.10]	0.09* [0.04, 0.14]	0.01 [-0.04, 0.07]
Drowsy	0.05 [-0.01, 0.10]	-0.04 [-0.08, 0.01]	0.00 [-0.05, 0.05]	-0.02 [-0.06, 0.03]	0.04 [-0.003, 0.10]	0.04 [-0.01, 0.08]
Restless	0.01 [-0.05, .08]	-0.01 [-0.06, 0.04]	0.04 [-0.001, 0.09]	0.10** [0.05, 0.14]	0.01 [-0.04, 0.06]	0.03 [-0.01, 0.07]
Focused	-0.09* [-.15, -.03]	0.02 [-0.03, 0.06]	0.002 [-0.04, 0.05]	0.04 [-0.007, 0.09]	0.01 [-0.04, 0.06]	-0.03 [-0.08, 0.03]
	Hungry	PhysAct	Avoid	Drowsy	Restless	Focused
DHP	0.01 [-0.03, 0.04]	0.03 [-0.01, 0.06]	0.05* [0.01, 0.09]	-0.004 [-0.04, 0.03]	0.001 [-0.05, 0.05]	0.01 [-0.04, 0.05]
Calm	0.03 [-0.01, 0.07]	0.01 [-0.02, 0.05]	0.01 [-0.04, 0.05]	0.03 [-0.01, 0.07]	-0.02 [-0.06, 0.04]	-0.01 [0.01, 0.04]
Irritated	0.001 [-0.03, 0.04]	0.02 [-0.01, 0.06]	0.02 [-0.02, 0.06]	0.01 [-0.03, 0.05]	0.03 [-0.01, 0.06]	0.01 [0.12, 0.06]
Anxious	-0.02 [-0.07, 0.02]	-0.03 [-0.08, 0.02]	0.001 [-0.05, 0.05]	-0.01 [-0.05, 0.03]	-0.01 [-0.06, 0.07]	0.02 [0.10, 0.07]
Lonely	0.02 [-0.01, 0.05]	0.01 [-0.03, 0.04]	0.04 [-0.004, 0.09]	0.01 [-0.03, 0.05]	0.01 [-0.04, 0.02]	-0.02 [0.08, 0.02]
Accomp	0.00 [-0.05, 0.05]	0.001 [-0.04, 0.04]	0.003 [-0.04, 0.04]	0.01 [-0.03, 0.05]	0.02 [-0.02, 0.15]	0.10** [-0.005, 0.15]
Hungry	-0.04 [-0.08, 0.01]	0.02 [-0.03, 0.06]	0.01 [-0.03, 0.05]	0.01 [-0.03, 0.05]	0.04 [-0.01, 0.07]	0.03 [0.10, 0.07]
PhysAct	-0.02 [-0.06, 0.01]	0.12** [0.09, 0.16]	-0.03 [-0.07, 0.01]	-0.02 [-0.06, 0.03]	0.05* [0.01, 0.05]	0.01 [-0.04, 0.05]
Avoid	0.02 [-0.03, 0.07]	-0.004 [-0.04, 0.03]	0.19** [0.13, 0.25]	0.04 [0.00, 0.08]	0.01 [-0.04, 0.03]	-0.01 [0.05, 0.03]
Drowsy	0.07** [0.03, 0.11]	0.06* [0.02, 0.09]	-0.01 [-0.05, 0.03]	0.18** [0.13, 0.23]	0.04 [-0.00, 0.05	0.01 [0.10, 0.05]
Restless	-0.01 [-0.04, 0.03]	-0.01 [-0.05, 0.04]	0.01 [-0.05, 0.03]	0.02 [-0.03, 0.06]	0.10 [0.05, 0.03	-0.01 [0.08, 0.03]
Focused	0.01 [-0.04, 0.06]	-0.003 [-0.04, 0.04]	-0.01 [-0.05, 0.03]	0.003 [-0.04, 0.04]	-0.02** [-0.06, 0.15]	0.09** [-0.03, 0.15]

Note. Values represent the pathway between the column predicting the row at the next time point; values on the diagonal represent the autoregressive estimates. Values in brackets represent the 95% confidence interval around the fixed partial regression estimate. DHP = average composite of Down, Happy (reverse scored), and Pleased (reverse scored); Accomp = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations. * $p < .05$; ** $p < .001$.

Table S3

Contemporaneous estimates from three exemplar person-specific VAR models

ID 001	DHP	Calm	Irritated	Anxious	Lonely	Accomp	Hungry	PhysAct	Avoid	Drowsy	Restless	Focused
DHP												
Calm	0.00											
Irritated	0.00	0.00										
Anxious	0.00	-0.04*	0.00									
Lonely	0.21*	0.00	0.00	0.00								
Accomp	-0.16*	0.00	0.00	0.00	0.00							
Hungry	-0.02*	0.00	0.00	0.00	0.00	0.00						
PhysAct	0.00	0.00	0.00	0.00	0.00	0.00	0.00					
Avoid	0.00	0.00	0.00	0.00	0.09*	-0.02*	0.00	0.00				
Drowsy	0.00	0.00	0.00	0.00	0.00	-0.02*	0.00	0.00	0.04*			
Restless	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03*		
Focused	0.00	0.00	0.00	0.00	0.00	0.27*	0.00	0.00	0.00	0.00	0.00	

ID 002	DHP	Calm	Irritated	Anxious	Lonely	Accomp	Hungry	PhysAct	Avoid	Drowsy	Restless	Focused
DHP												
Calm	-0.05*											
Irritated	0.12*	-0.21*										
Anxious	0.30*	-0.38*	0.04*									
Lonely	0.20*	0.00	0.00	0.00								
Accomp	-0.02*	0.00	0.00	-0.05*	0.00							
Hungry	0.00	0.00	0.00	0.00	0.00	0.00						
PhysAct	0.00	0.00	0.00	0.00	0.00	0.02*	0.00					
Avoid	0.00	0.00	0.00	0.00	0.02*	0.00	0.00	0.00				
Drowsy	0.00	0.00	0.00	0.00	0.03*	0.00	0.00	-0.09*	0.00			

Restless	0.00	-0.08*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03*	
Focused	0.00	0.00	0.00	0.00	0.00	0.15*	0.00	0.00	0.00	0.00	0.00

ID 003	DHP	Calm	Irritated	Anxious	Lonely	Accomp	Hungry	PhysAct	Avoid	Drowsy	Restless	Focused
DHP												
Calm	0.00											
Irritated	0.16*	0.00										
Anxious	0.00	-0.15*	0.00									
Lonely	0.00	0.00	0.00	0.00								
Accomp	-0.004*	0.00	0.00	0.00	0.00							
Hungry	0.00	0.00	0.00	0.00	0.00	0.00						
PhysAct	0.00	0.00	0.00	0.00	0.00	0.00	0.00					
Avoid	0.00	0.11*	0.00	-0.15*	0.00	0.00	0.00	0.00				
Drowsy	0.09*	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
Restless	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		
Focused	0.00	0.00	-0.09*	0.00	0.00	0.00	0.00	0.00	0.00	-0.03*	0.00	

Note. The contemporaneous estimates included here are the partial correlations from the graphical VAR model. DHP = average composite of Down, Happy (reverse scored), and Pleased (reverse scored); Accomp = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations. IDs correspond to the presentation in main text and do not correspond to actual participant IDs.

* $p < .05$.

Table S4.

Node predictability estimates from contemporaneous person-specific VAR models

ID	DHP	Calm	Irritated	Anxious	Lonely	Accomp	Hungry	PhysAct	Avoid	Drowsy	Restless	Focused
001	0.47	0.23	0.26	0.22	0.18	0.07	0.00	0.24	0.32	0.57	0.59	0.50
002	0.00	0.80	0.17	0.39	0.19	0.46	0.00	0.00	0.18	0.35	0.45	0.13
003	0.43	0.49	0.69	0.11	0.00	0.27	0.14	0.00	0.00	0.46	0.54	0.53
004	0.26	0.30	0.38	0.48	0.00	0.56	0.10	0.36	0.12	0.00	0.53	0.22
005	0.09	0.27	0.36	0.47	0.53	0.16	0.47	0.00	0.15	0.22	0.00	0.30
006	0.26	0.61	0.36	0.33	0.54	0.76	0.24	0.22	0.00	0.10	0.15	0.00
007	0.18	0.58	0.26	0.43	0.56	0.73	0.55	0.18	0.05	0.21	0.40	0.08
008	0.28	0.08	0.27	0.14	0.58	0.49	0.20	0.75	0.11	0.20	0.28	0.10
009	0.05	0.21	0.00	0.38	0.41	0.74	0.53	0.51	0.55	0.18	0.13	0.00
010	0.00	0.22	0.14	0.00	0.46	0.30	0.19	0.51	0.22	0.63	0.09	0.35
011	0.22	0.32	0.43	0.00	0.00	0.59	0.31	0.67	0.04	0.48	0.57	0.30
012	0.00	0.00	0.16	0.55	0.16	0.00	0.17	0.55	0.26	0.00	0.61	0.71
013	0.61	0.52	0.63	0.46	0.33	0.00	0.00	0.59	0.34	0.47	0.54	0.38
014	0.40	0.35	0.56	0.00	0.39	0.17	0.00	0.00	0.48	0.38	0.47	0.30
015	0.11	0.30	0.35	0.34	0.51	0.04	0.04	0.00	0.00	0.49	0.32	0.32
016	0.52	0.27	0.36	0.78	0.36	0.59	0.08	0.26	0.11	0.00	0.51	0.34
017	0.38	0.30	0.29	0.55	0.53	0.46	0.12	0.00	0.19	0.09	0.00	0.39
018	0.39	0.00	0.12	0.49	0.28	0.63	0.10	0.34	0.37	0.12	0.00	0.00
019	0.04	0.07	0.00	0.61	0.21	0.24	0.51	0.34	0.23	0.25	0.05	0.16
020	0.00	0.00	0.29	0.61	0.09	0.11	0.42	0.59	0.38	0.30	0.00	0.07
021	0.15	0.00	0.00	0.50	0.10	0.52	0.25	0.00	0.30	0.20	0.35	0.05
022	0.00	0.00	0.03	0.00	0.34	0.47	0.25	0.13	0.00	0.57	0.32	0.24
023	0.00	0.00	0.00	0.00	0.00	0.43	0.27	0.37	0.00	0.37	0.61	0.23
024	0.10	0.35	0.38	0.26	0.19	0.00	0.33	0.50	0.23	0.26	0.26	0.68

025	0.70	0.00	0.59	0.41	0.40	0.00	0.00	0.26	0.37	0.39	0.51	0.30
026	0.25	0.42	0.42	0.54	0.00	0.27	0.04	0.08	0.00	0.22	0.47	0.45
027	0.42	0.39	0.76	0.42	0.00	0.00	0.24	0.00	0.00	0.22	0.42	0.26
028	0.34	0.12	0.31	0.52	0.00	0.36	0.29	0.18	0.00	0.00	0.48	0.40
029	0.18	0.21	0.48	0.28	0.74	0.29	0.13	0.20	0.36	0.00	0.00	0.43
030	0.30	0.10	0.31	0.44	0.30	0.66	0.15	0.00	0.11	0.00	0.28	0.00
031	0.00	0.42	0.46	0.21	0.51	0.46	0.70	0.00	0.10	0.19	0.26	0.00
032	0.00	0.07	0.28	0.37	0.44	0.48	0.44	0.49	0.06	0.04	0.33	0.13
033	0.00	0.21	0.00	0.28	0.55	0.40	0.39	0.26	0.62	0.08	0.29	0.05
034	0.09	0.10	0.00	0.00	0.44	0.36	0.49	0.16	0.63	0.68	0.22	0.08
035	0.07	0.12	0.36	0.39	0.00	0.32	0.38	0.34	0.40	0.54	0.62	0.23

Note. Predictability estimates were calculated from individual-level mixed graphical models. DHP = average composite of Down, Happy (reverse scored), and Pleased (reverse scored); Accomp = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations.

Table S5

Estimates from the Lag 1 ML-DSEM model

Path	Estimate	Posterior S.D.	95% Credible interval, Lower bound	95% Credible interval, Upper bound
Day	0.04*	0.02	0.01	0.07
Survey	0.02	0.03	-0.04	0.08
Down &1	0.18*	0.02	0.13	0.23
Happy &1	-0.04	0.07	-0.09	0.01
Calm &1	-0.04*	0.02	-0.08	0.00
Irritable &1	0.02	0.02	-0.02	0.06
Anxious &1	0.04	0.02	-0.01	0.08
Lonely &1	0.06*	0.02	0.02	0.11
Accomplished &1	-0.02	0.02	-0.07	0.02
Hungry &1	-0.02	0.02	-0.05	0.02
Physical Activity &1	0.04*	0.02	0.002	0.07
Social Avoidance &1	0.04*	0.02	0.01	0.08
Drowsy &1	0.01	0.02	-0.03	0.05
Pleased &1	-0.002	0.03	-0.05	0.05
Restless &1	0.01	0.02	-0.03	0.05
Focused &1	-0.003	0.02	-0.04	0.04

Note. * denotes a 95% credible interval that does not include 0, suggesting statistical significance. &1 refers to Lag 1 variables.

Table S6

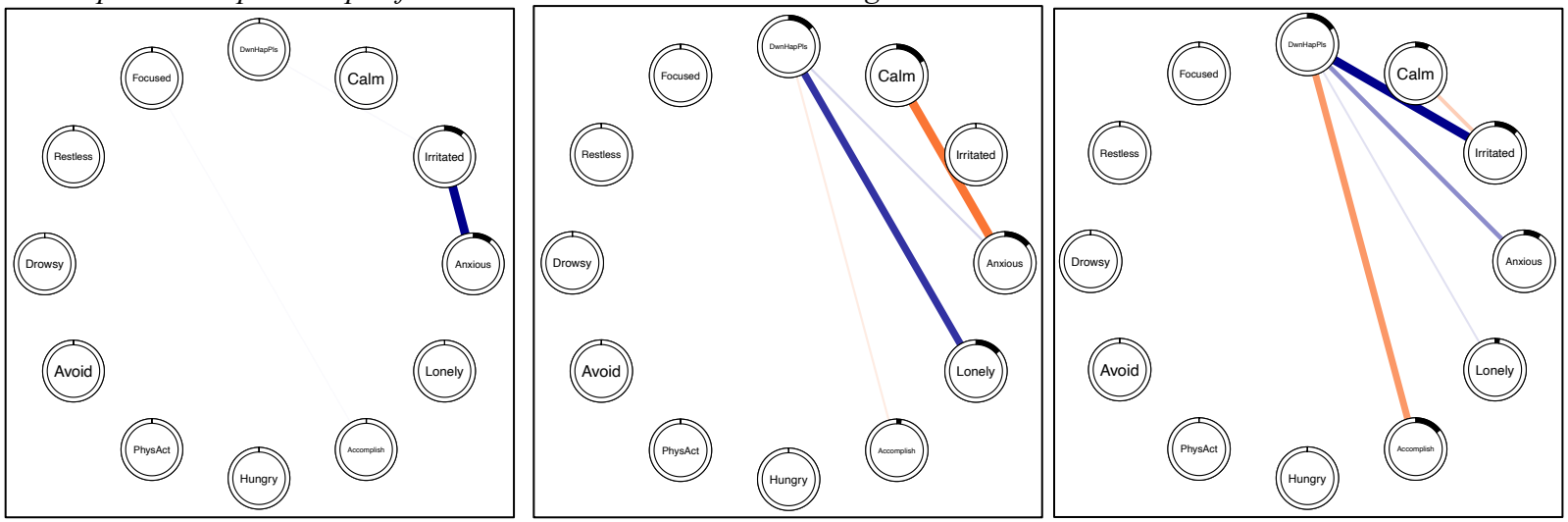
Estimates from the Lag 2 ML-DSEM model

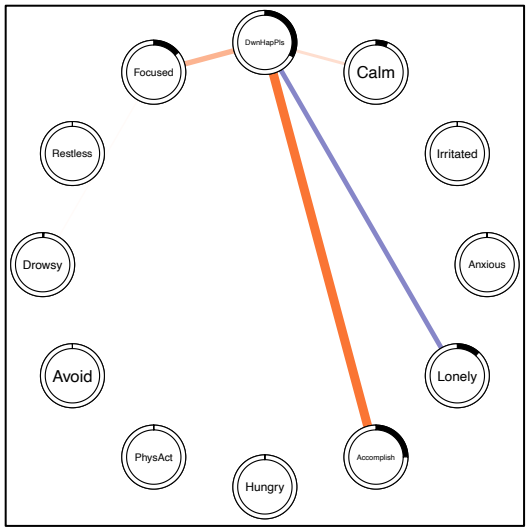
Path	Std. Estimate	Posterior S.D.	95% Credible interval, Lower bound	95% Credible interval, Upper bound
Day	0.03	0.02	-0.01	0.06
Survey	0.02	0.03	-0.04	0.09
Lag 1 variables				
Down	0.18*	0.02	0.13	0.22
Happy	-0.04	0.02	-0.09	0.01
Calm	-0.05*	0.02	-0.08	-0.002
Irritable	0.01	0.02	-0.03	0.05
Anxious	0.03	0.02	-0.01	0.07
Lonely	0.05*	0.02	0.01	0.09
Accomplished	-0.03	0.02	-0.07	0.02
Hungry	-0.02	0.02	-0.05	0.01
Physical activity	0.03	0.02	-0.01	0.07
Social avoidance	0.03	0.02	-0.01	0.07
Drowsy	0.000	0.02	-0.04	0.04
Pleased	0.005	0.02	-0.04	0.05
Restless	0.0001	0.02	-0.04	0.04
Focused	0.001	0.02	-0.04	0.04
Lag 2 variables				
Down	0.08*	0.03	0.04	0.14
Happy	0.004	0.03	-0.05	0.06
Calm	-0.01	0.03	-0.06	0.04
Irritable	0.02	0.02	-0.03	0.07
Anxious	0.03	0.03	-0.02	0.08
Lonely	0.02	0.02	-0.03	0.06
Accomplished	-0.02	0.03	-0.06	0.04
Hungry	0.03	0.02	-0.003	0.07
Physical activity	0.03	0.02	-0.01	0.07
Social avoidance	0.003	0.02	-0.04	0.05
Drowsy	0.03	0.02	-0.01	0.08
Pleased	0.04	0.03	-0.02	0.10
Restless	0.04	0.02	-0.01	0.08
Focused	0.03	0.02	-0.01	0.07

Note. * denotes a 95% credible interval that does not include 0, suggesting statistical significance.

Figure S1.

Contemporaneous person-specific VAR models with linear detrending





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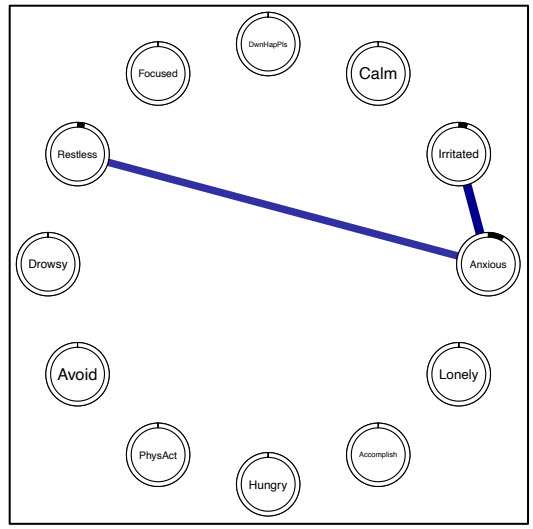

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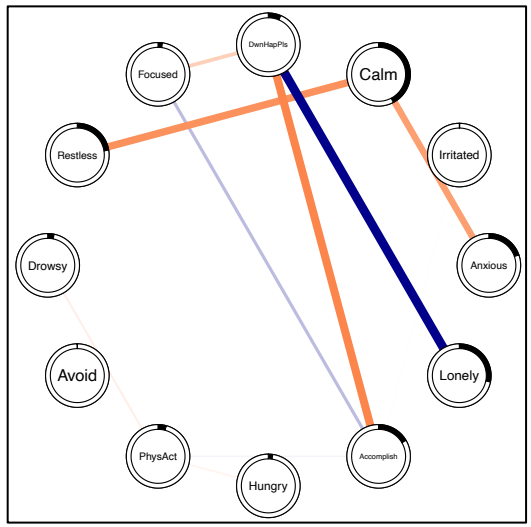

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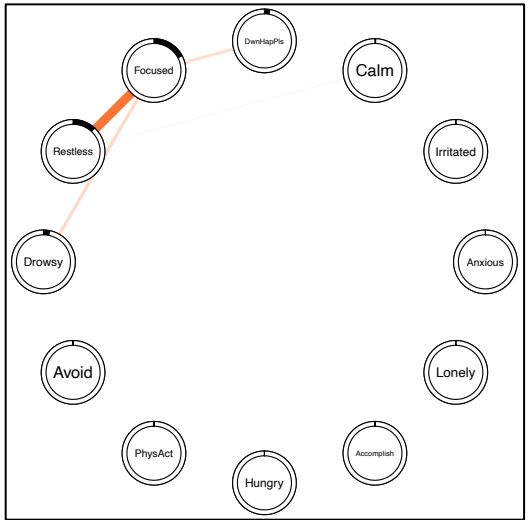

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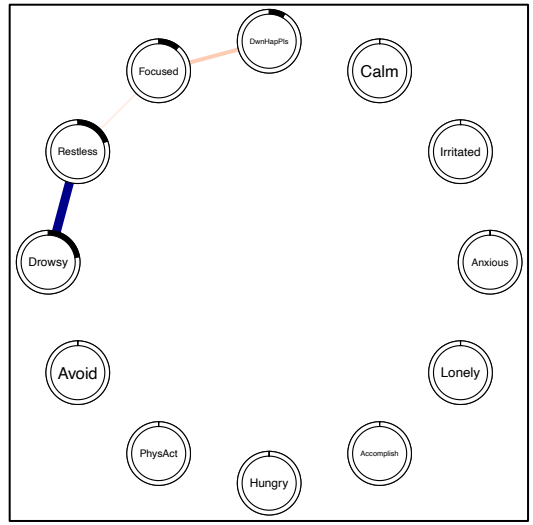

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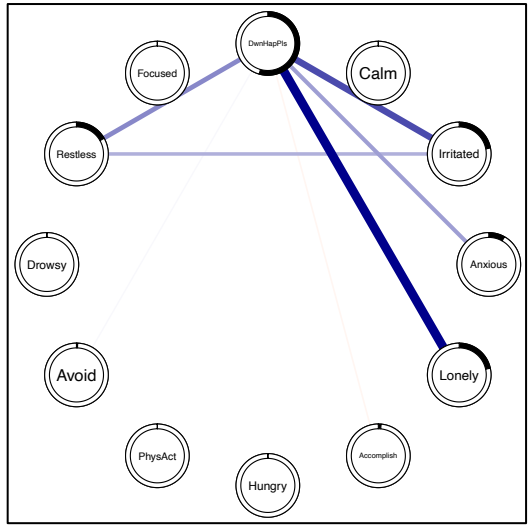

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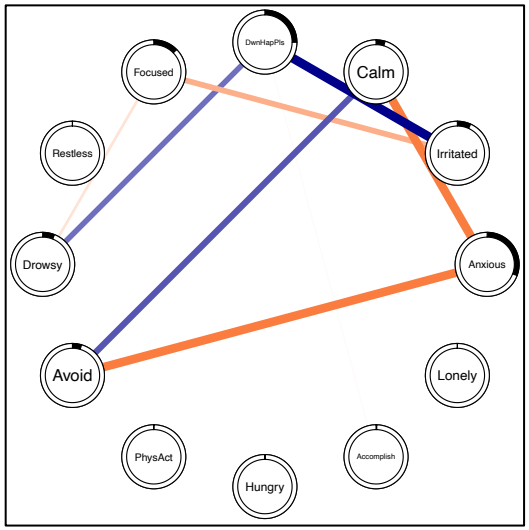

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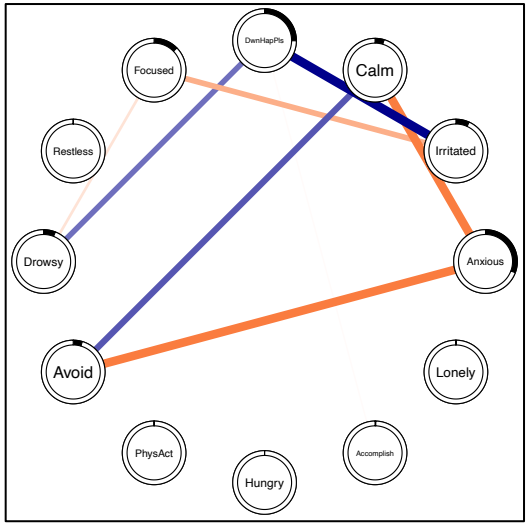

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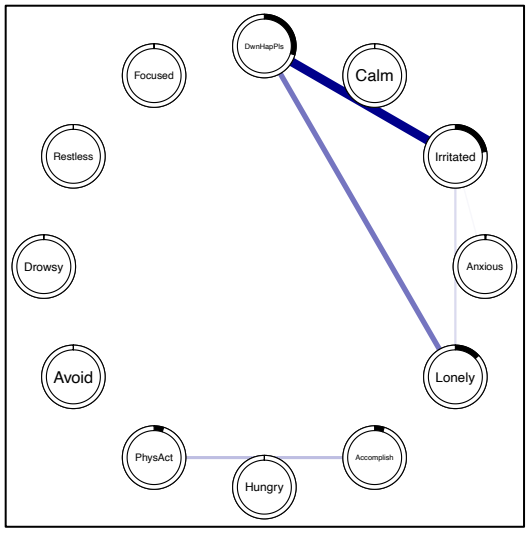

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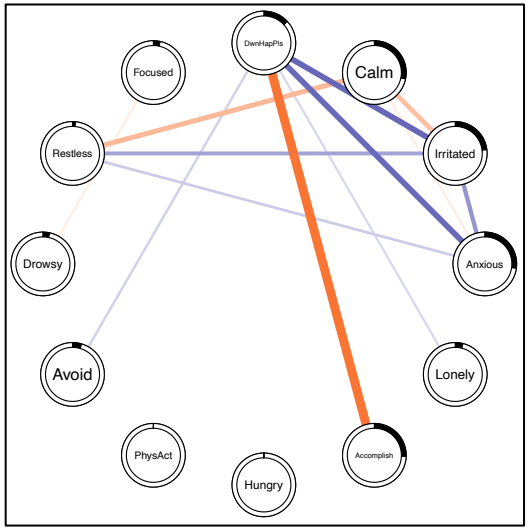

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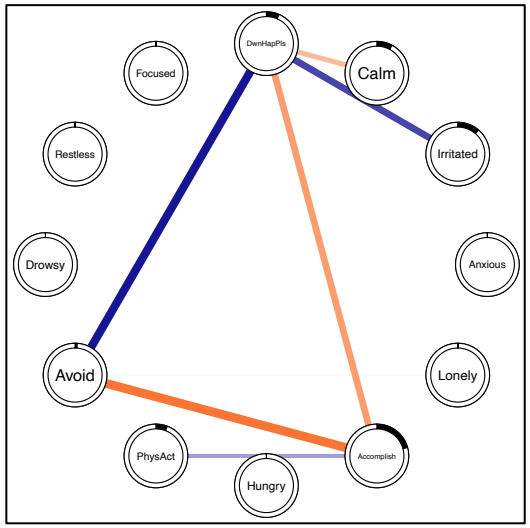

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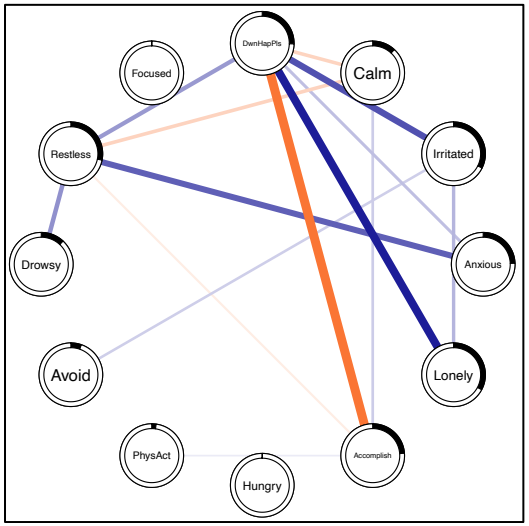

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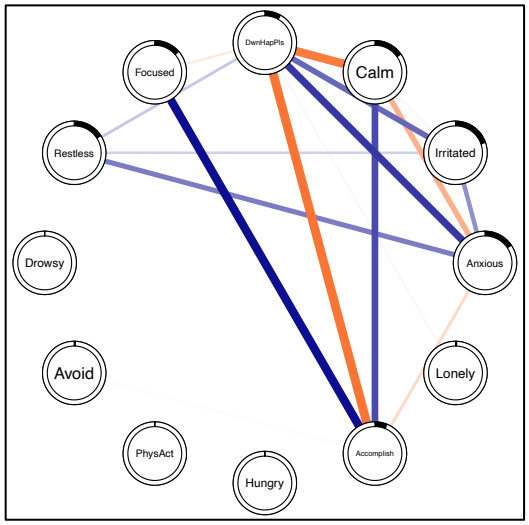

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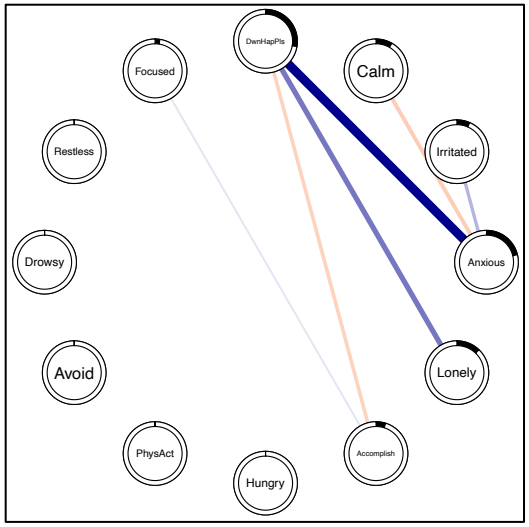

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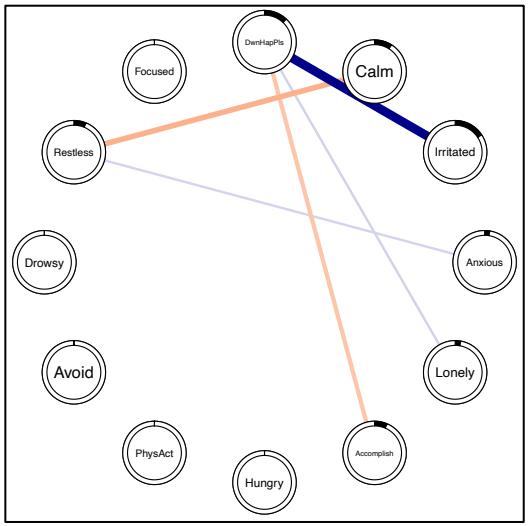

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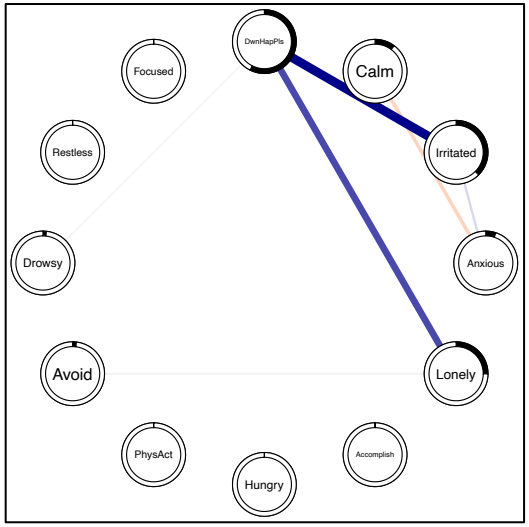

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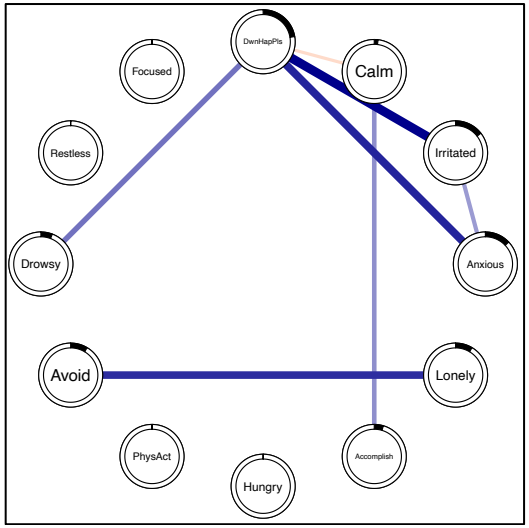

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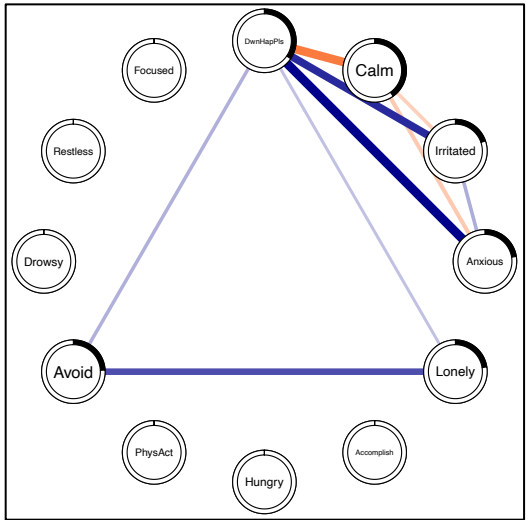

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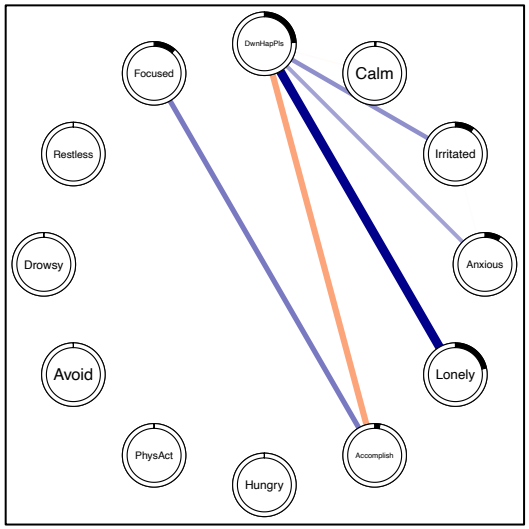

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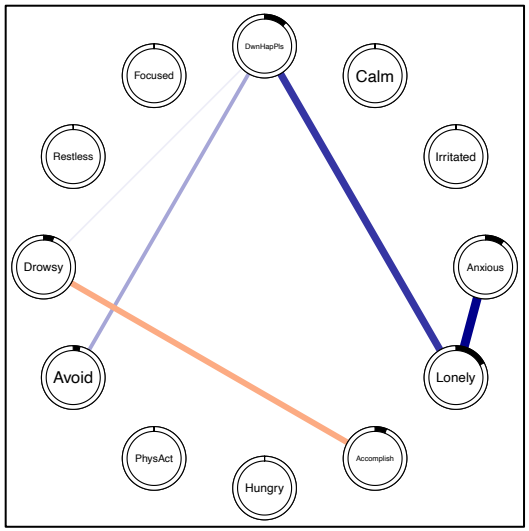

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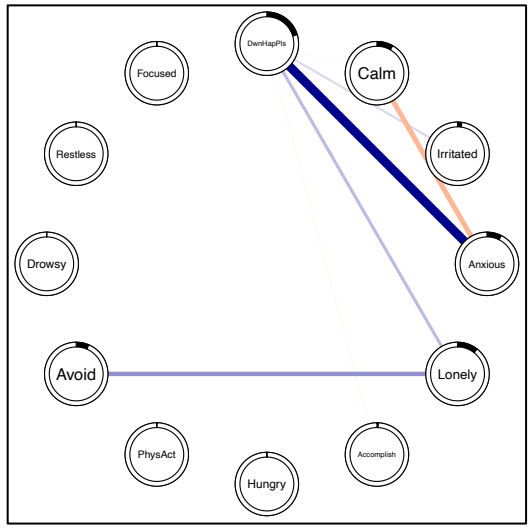

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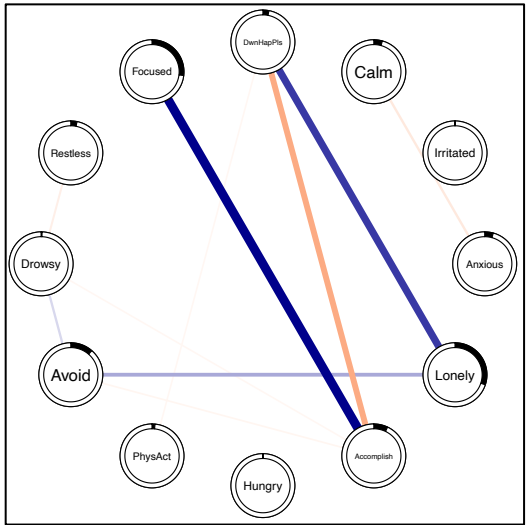

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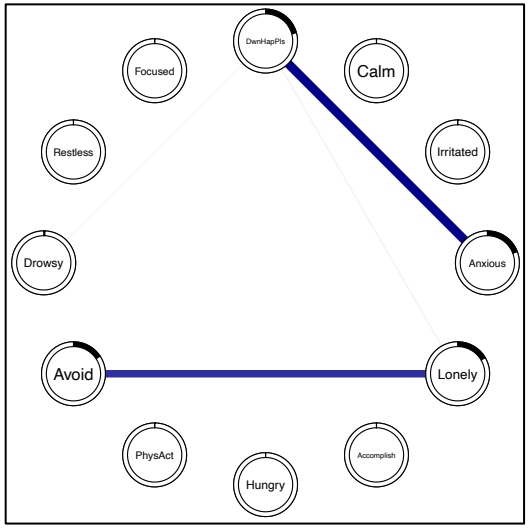

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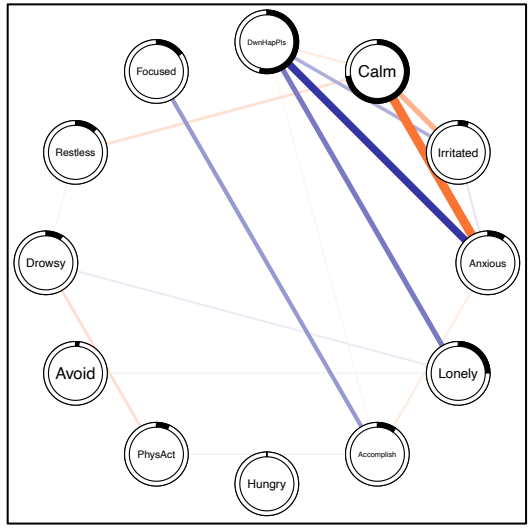

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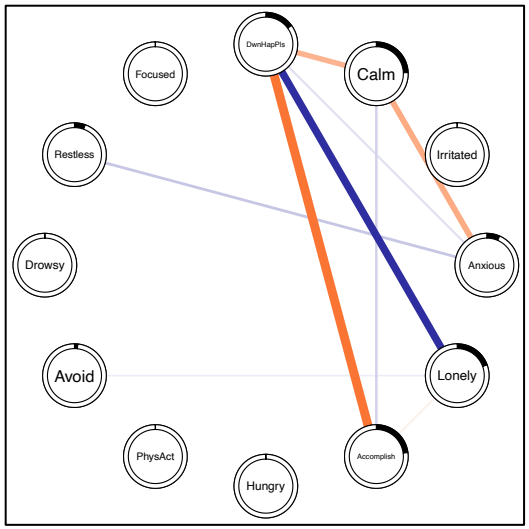

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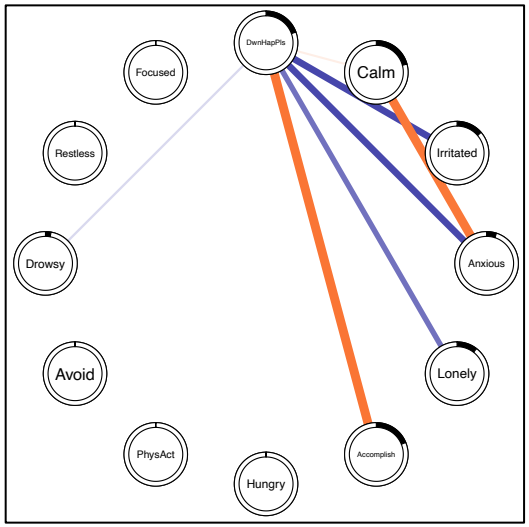

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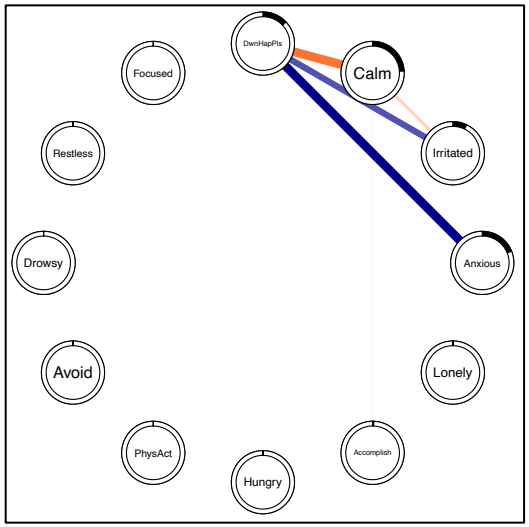

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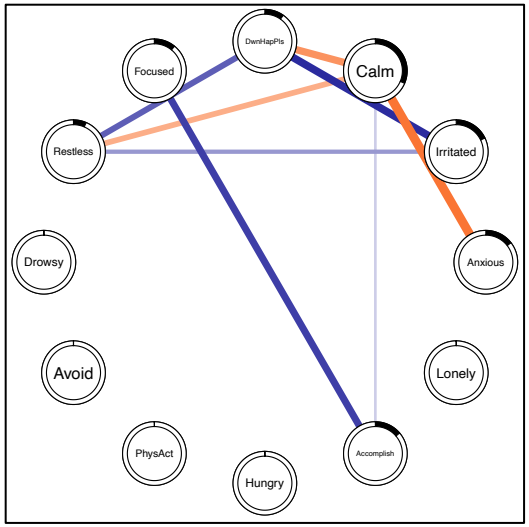

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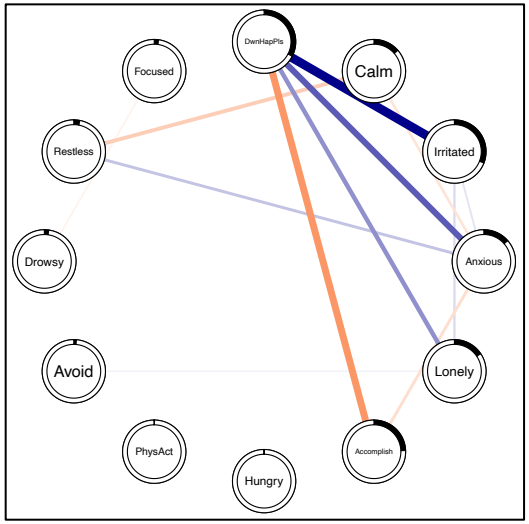

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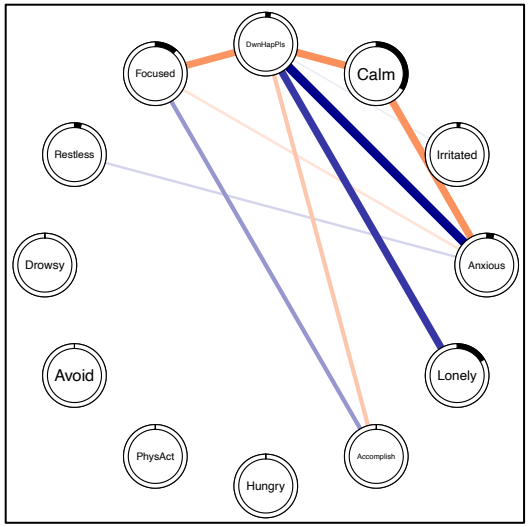

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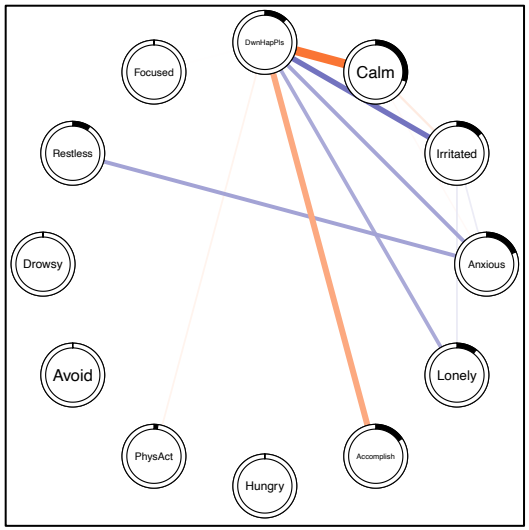

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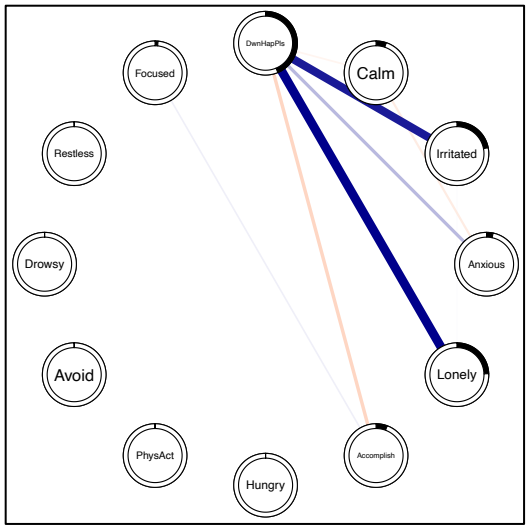
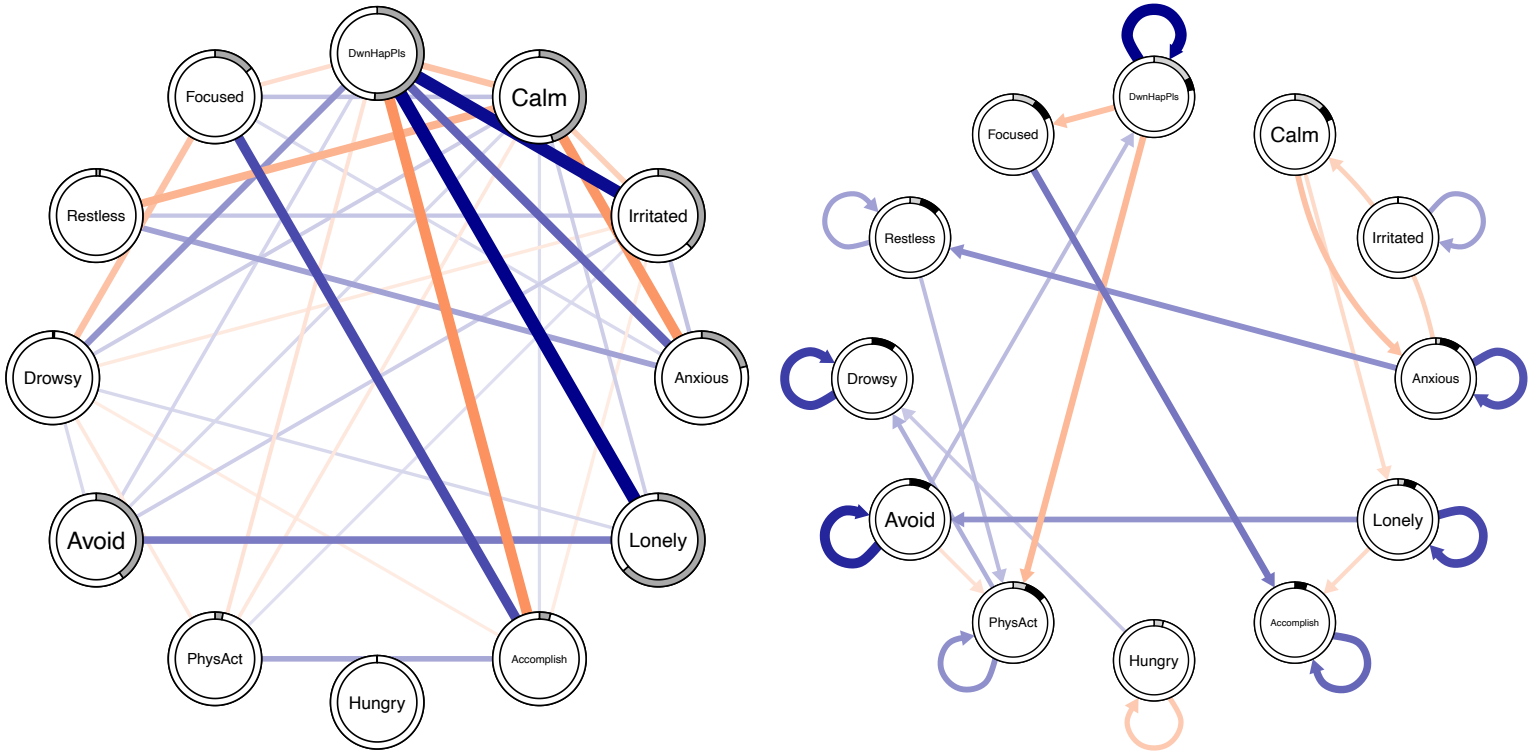


035

Note. These models demonstrate the partial associations for each participant (participant number displayed below the model) with linear trends of time removed. Orange pathways represent negative relationships; dark blue pathways represent positive relationships; the width of the line corresponds to the magnitude of the relationship. The extent to which the ring around each node is solid reflects the absolute magnitiude of the expected influence for each node –nodes with larger expected influnce on the network have more a greater proportion of the ring shaded. DwnHapPls = average composite of Down, Happy, and Pleased; Accomplish = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations.

Figure S2.

Contemporaneous and temporal ML-VAR networks with nonlinear smoothing

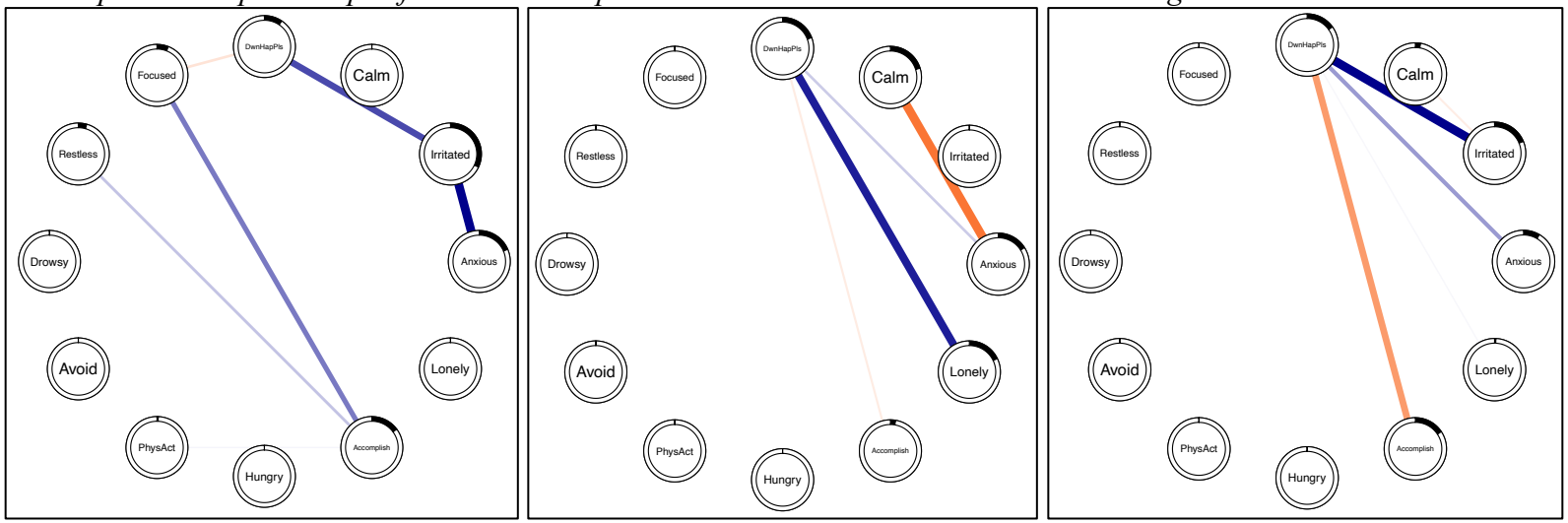


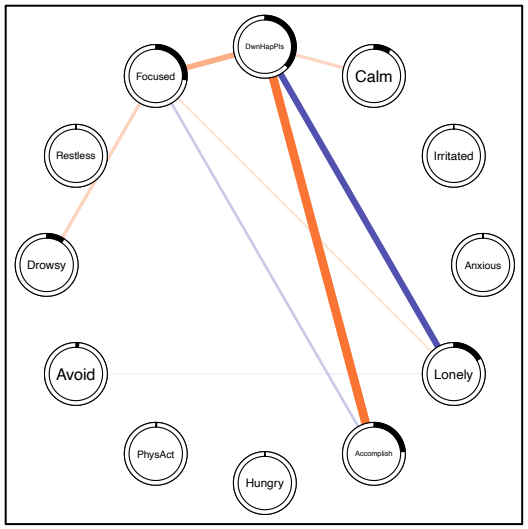
Note. These models demonstrate the partial associations for each participant (participant number displayed below the model) using nonlinear smoothing via a loess model. Orange pathways represent negative relationships; dark blue pathways represent positive relationships; the width of the line corresponds to the magnitude of the relationship. The extent to which the ring around each node is

solid reflects the absolute magnitiude of the expected influence for each node –nodes with larger expected influnce on the network have more a greater proportion of the ring shaded. DwnHapPls = average composite of Down, Happy, and Pleased; Accomplish = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations.

Figure S3.

Contemporaneous person-specific VAR contemporaneous networks with nonlinear smoothing





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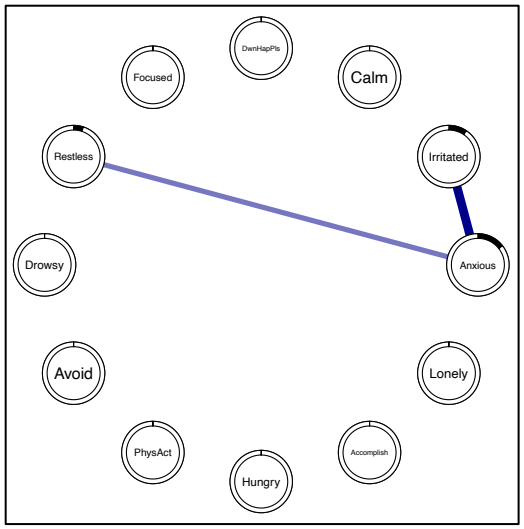

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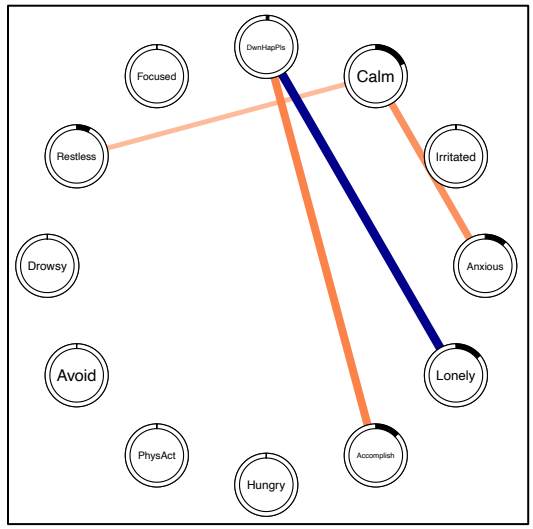

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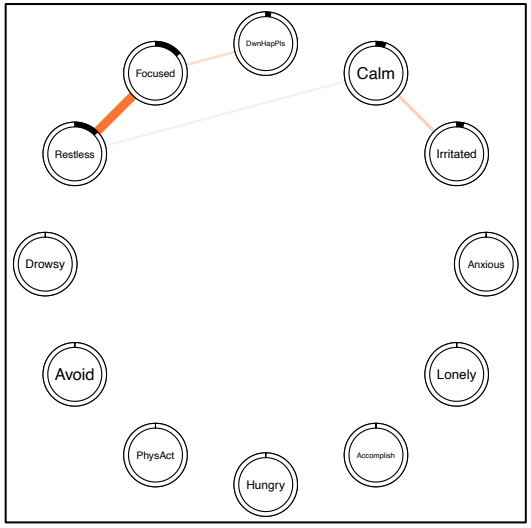

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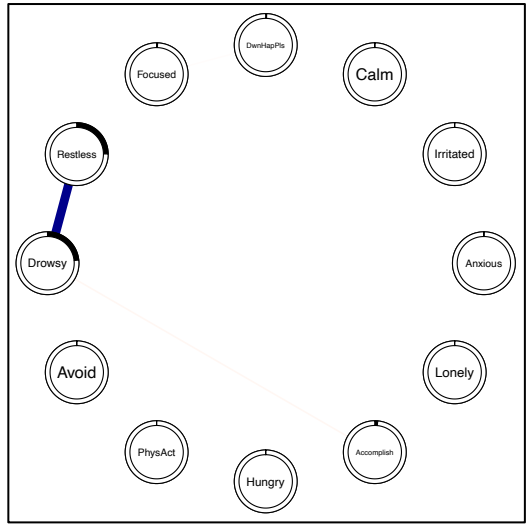

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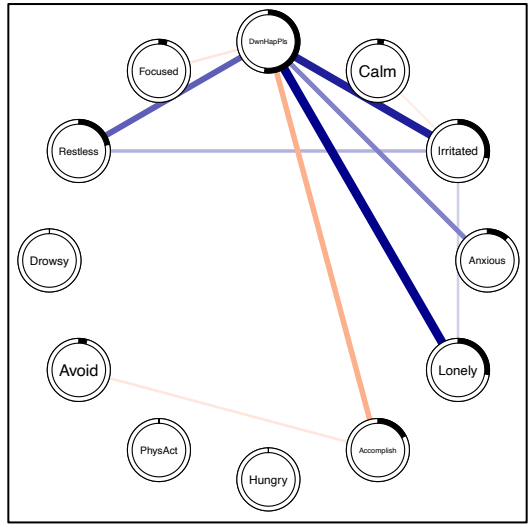

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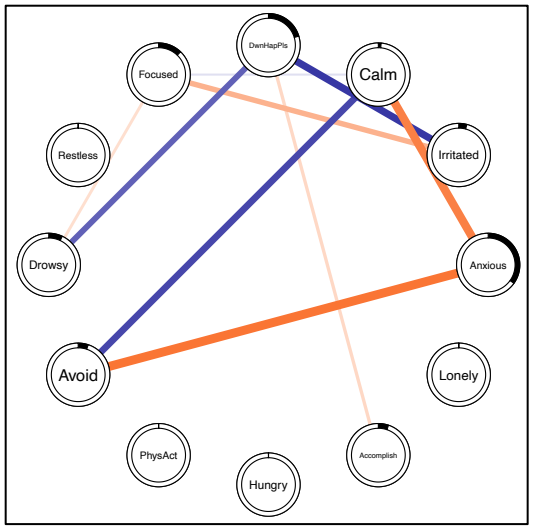

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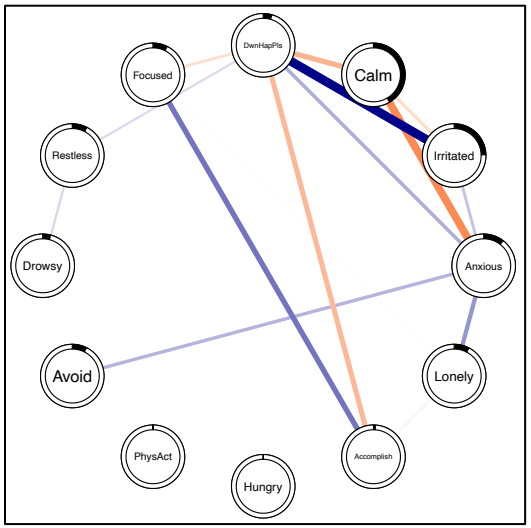

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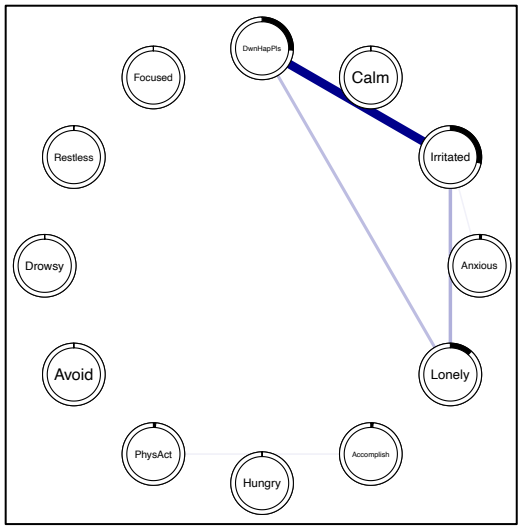

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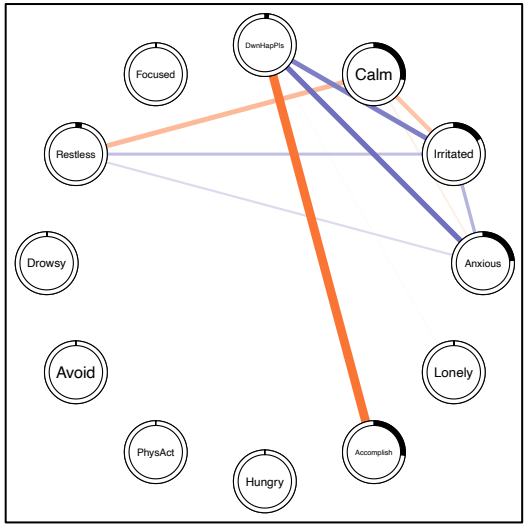

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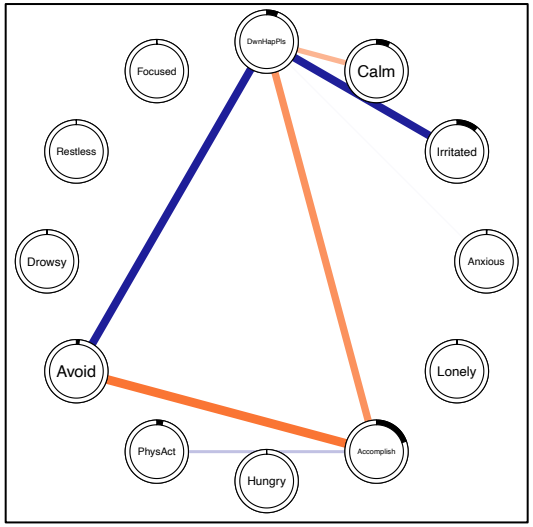

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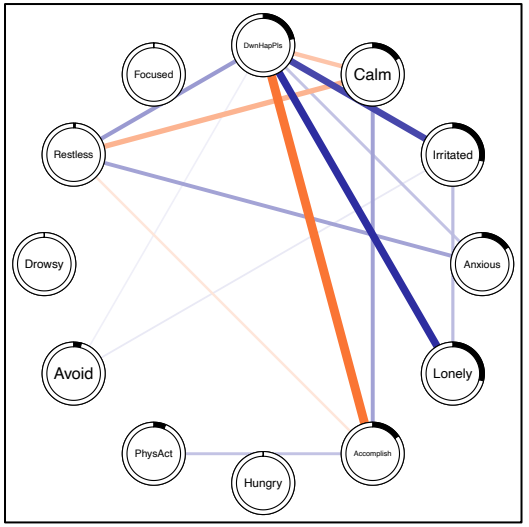

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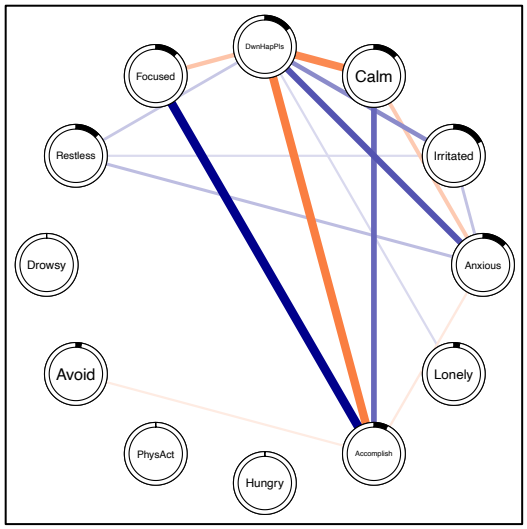

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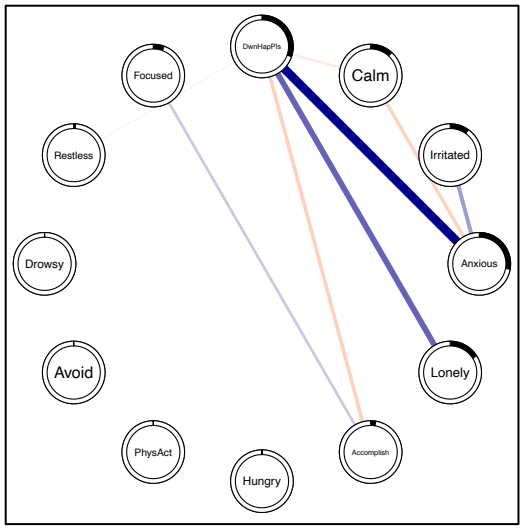

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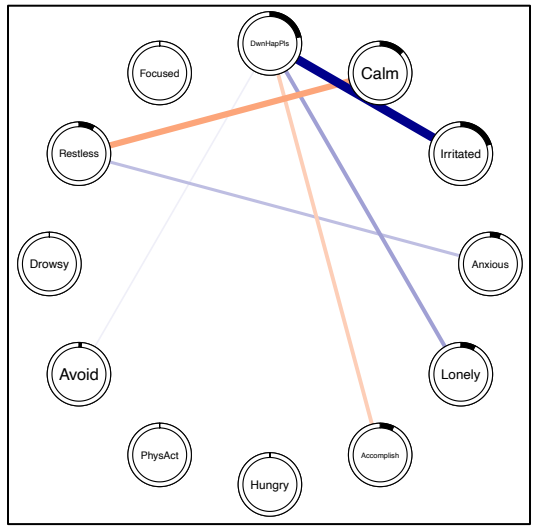

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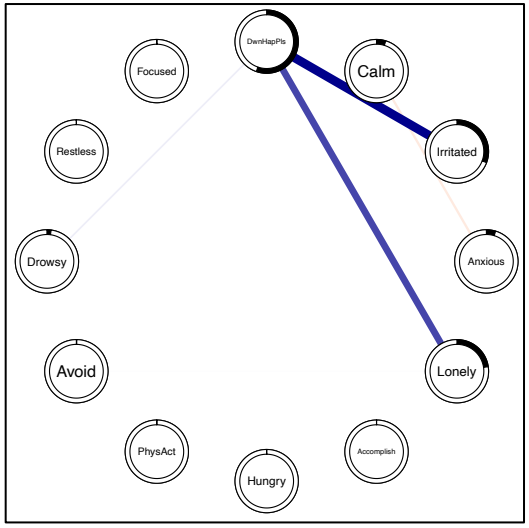

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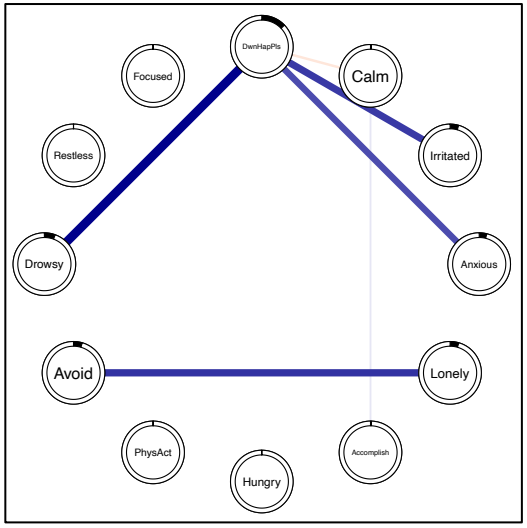

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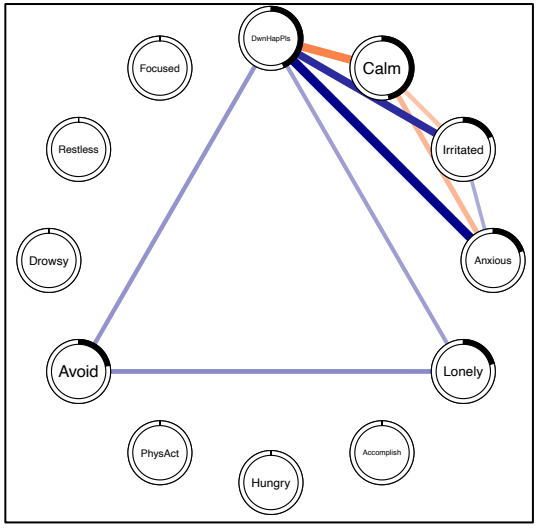

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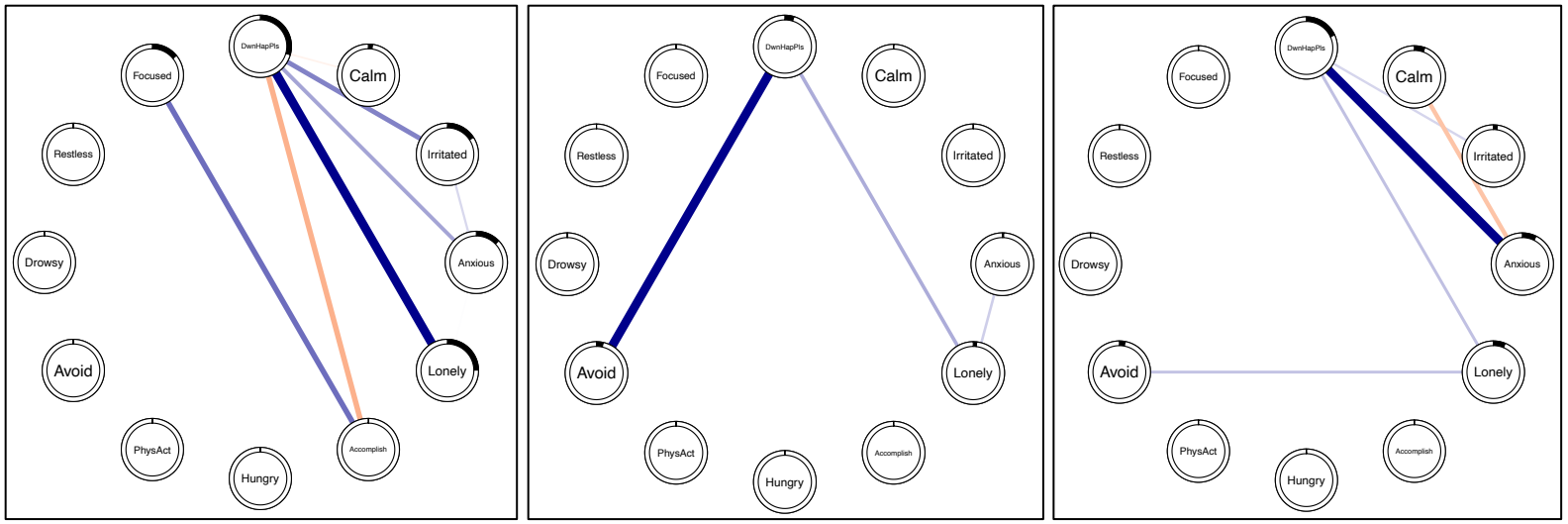

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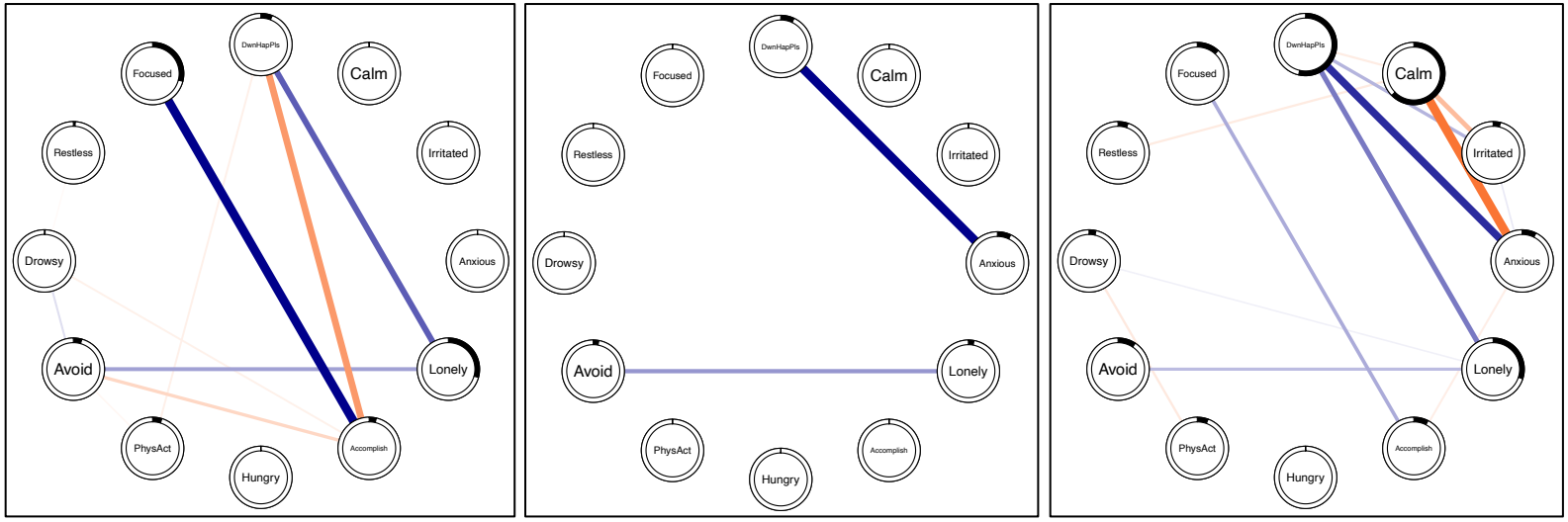

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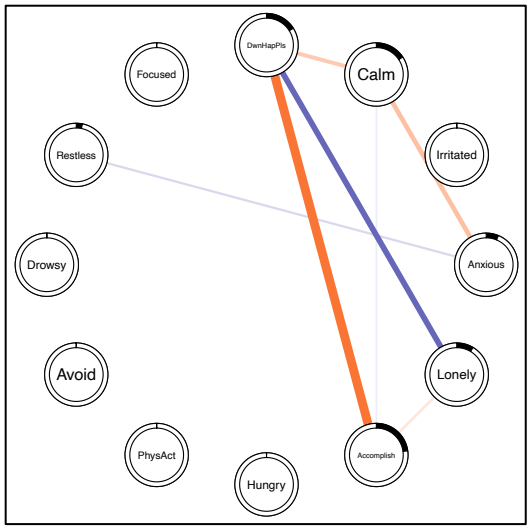

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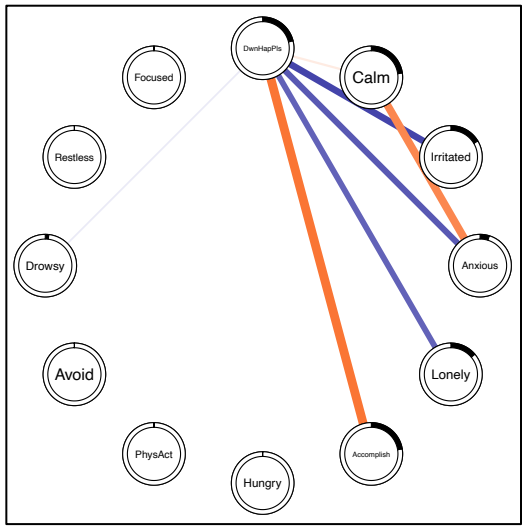

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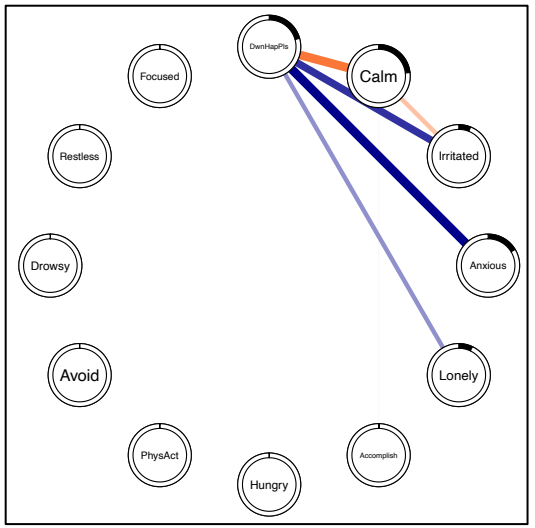

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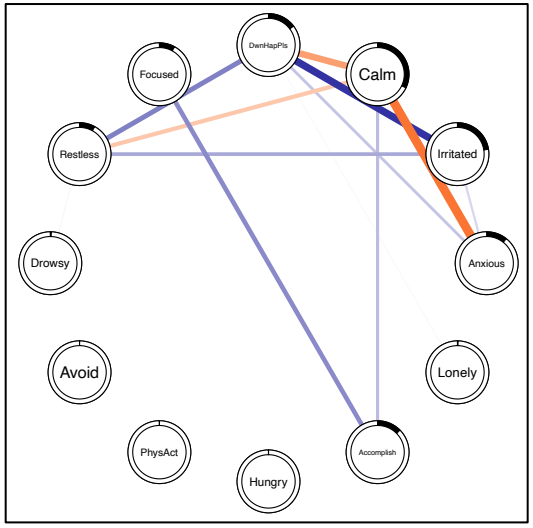

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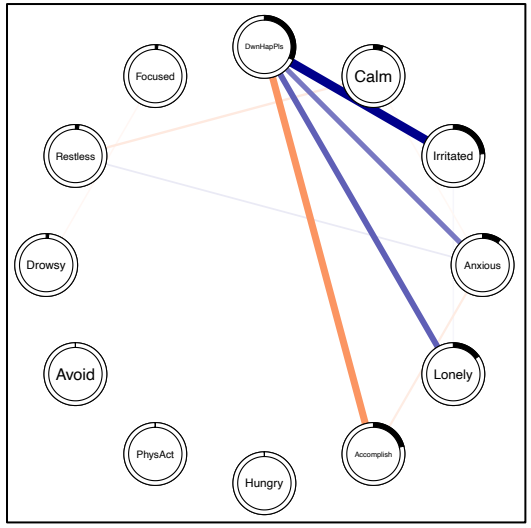

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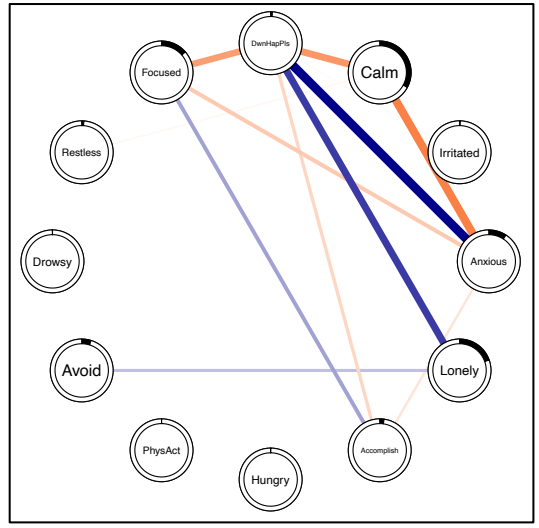

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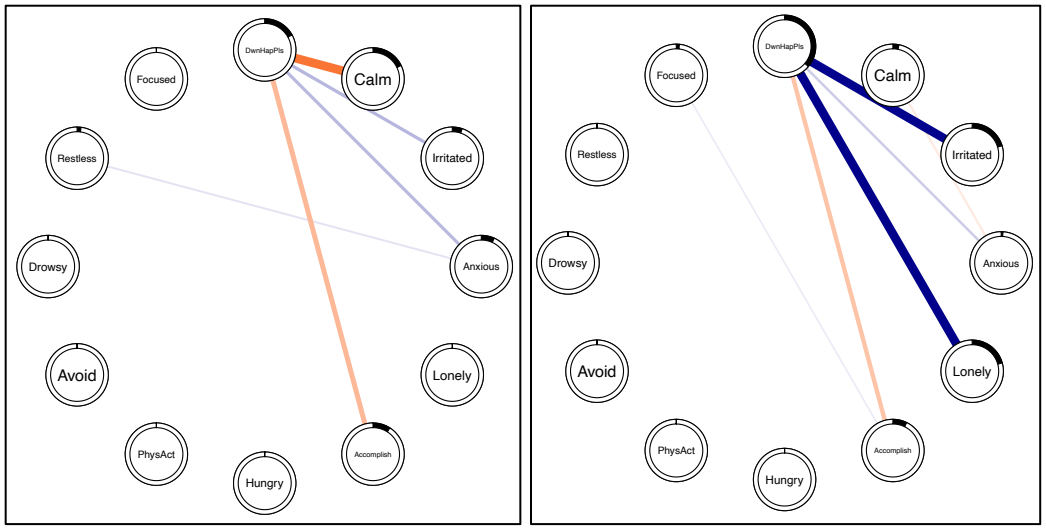
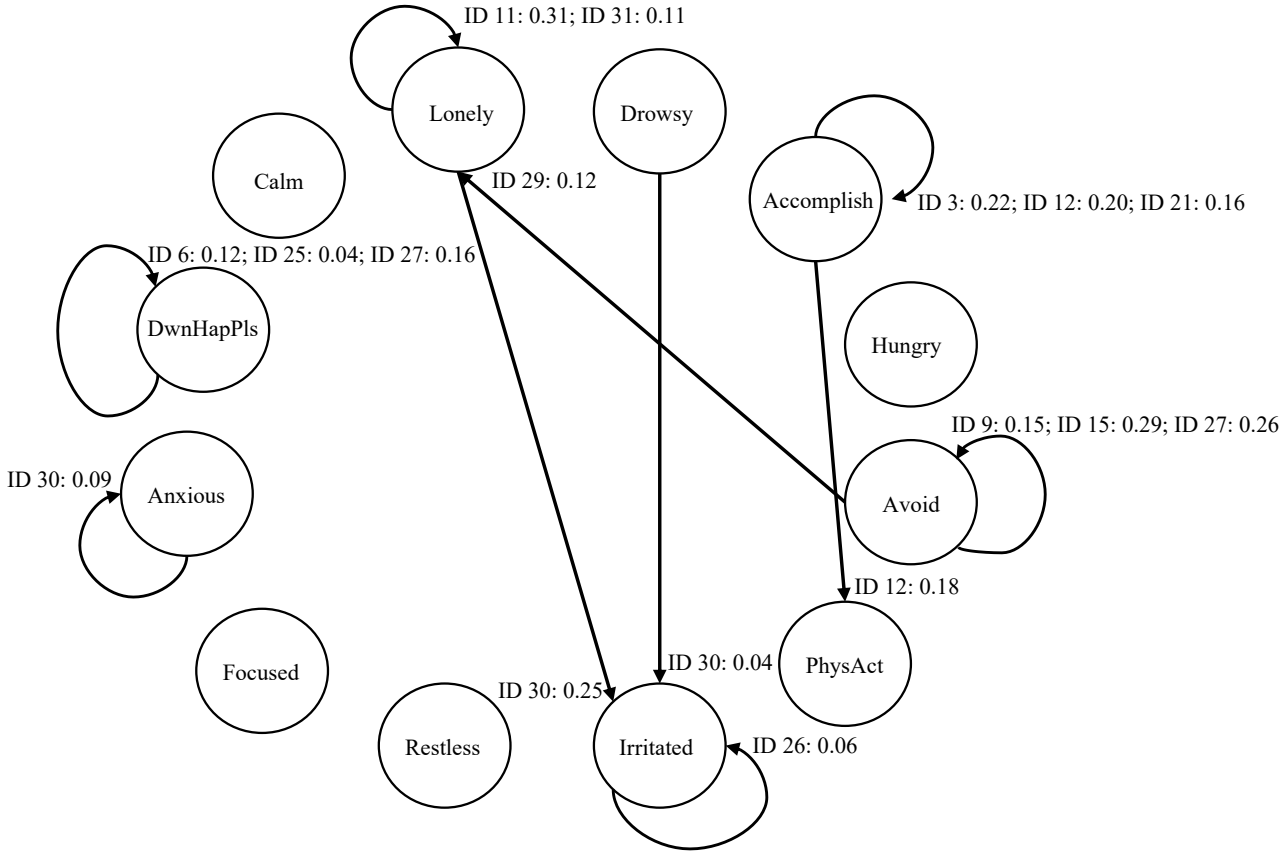


034 035

Note. These models demonstrate the partial associations for each participant (participant number displayed below the model) using nonlinear smoothing via a loess model. Orange pathways represent negative relationships; dark blue pathways represent positive relationships; the width of the line corresponds to the magnitude of the relationship. The extent to which the ring around each node is solid reflects the absolute magnitiude of the expected influence for each node –nodes with larger expected influnce on the network have more a greater proportion of the ring shaded. DwnHapPls = average composite of Down, Happy, and Pleased; Accomplish = Accomplished; PhysAct = Physical Activity; Avoid = Avoiding social situations.

Figure S4.

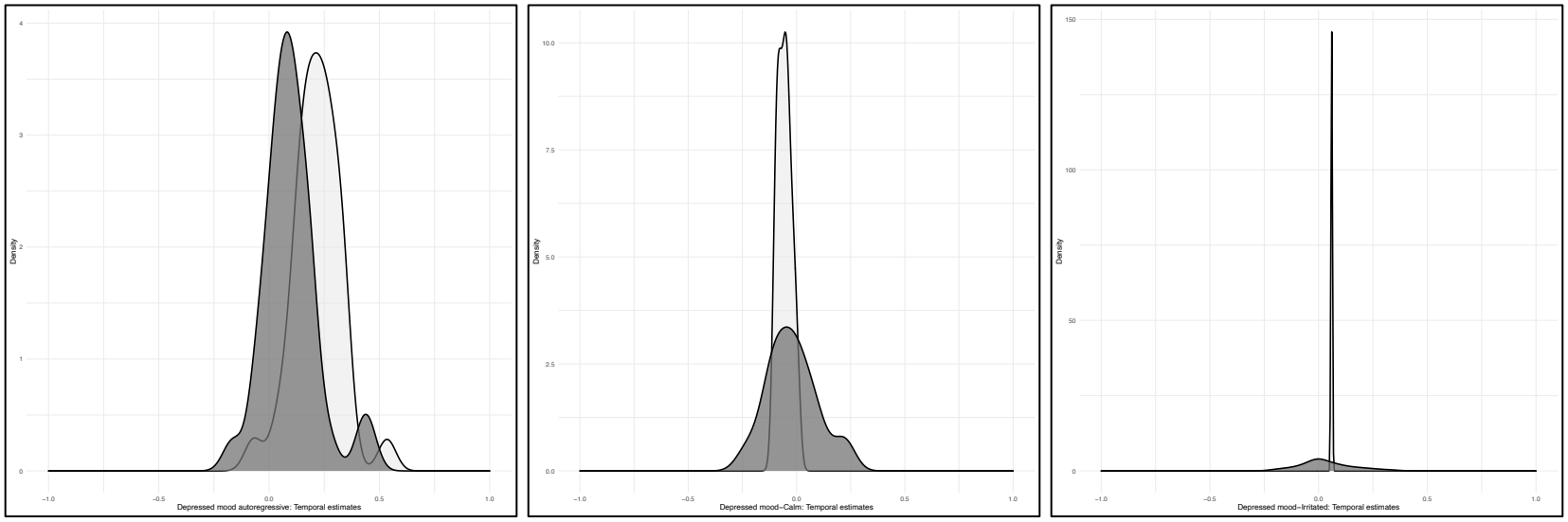
Temporal person-specific VAR models with linear detrending



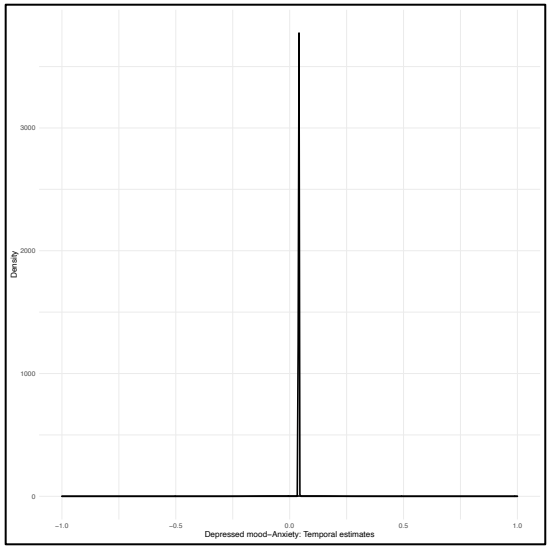
Note. The model shown here is a template of the temporal estimates from the person-specific VAR models with linear trends of time removed. Curved arrows represent autoregressive effects; solid arrow represent positive partial regressive effects. Participant estimates are listed to the side of the arrowhead for each effect. ID = Participant ID number.

Figure S5.

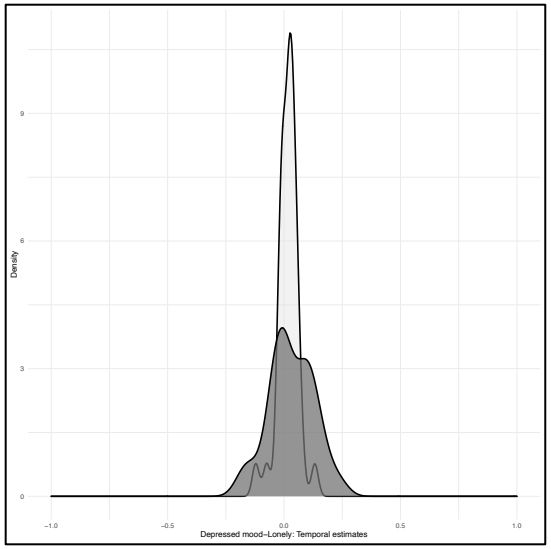
Density plot displaying the distribution of temporal individual-level estimates generated from the ML-VAR model and the distribution of temporal individual-level estimates generated from the person-specific VAR models



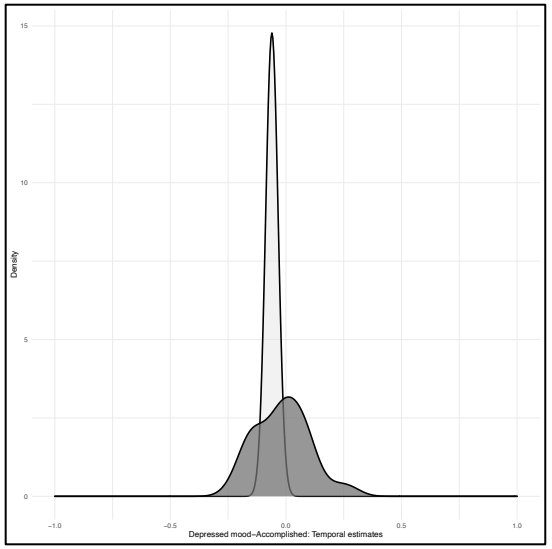
Depressed mood autoregressive | Depressed mood-Calm | Depressed mood – Irritated



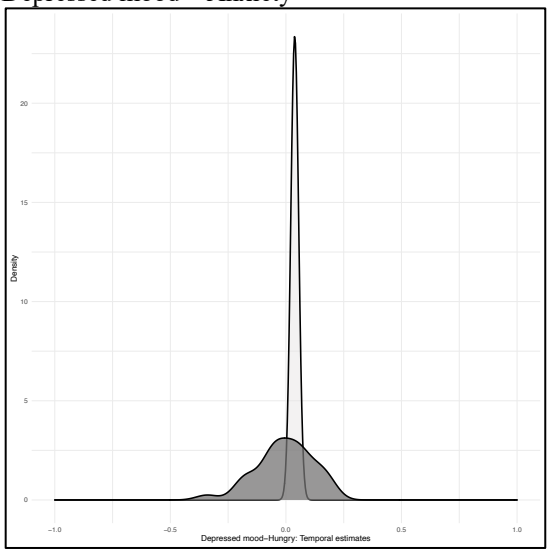
Depressed mood – Anxiety



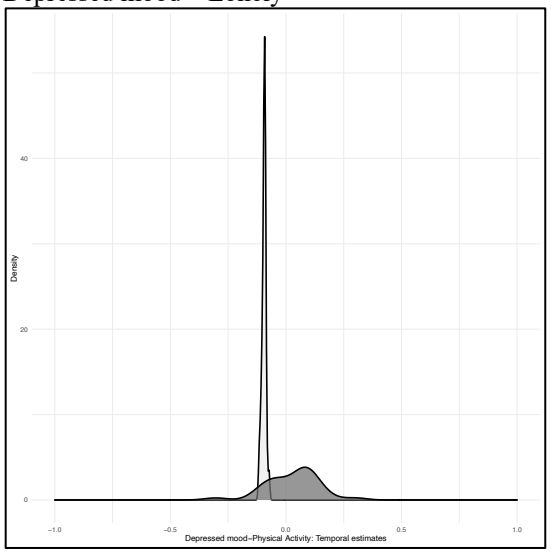
Depressed mood – Lonely



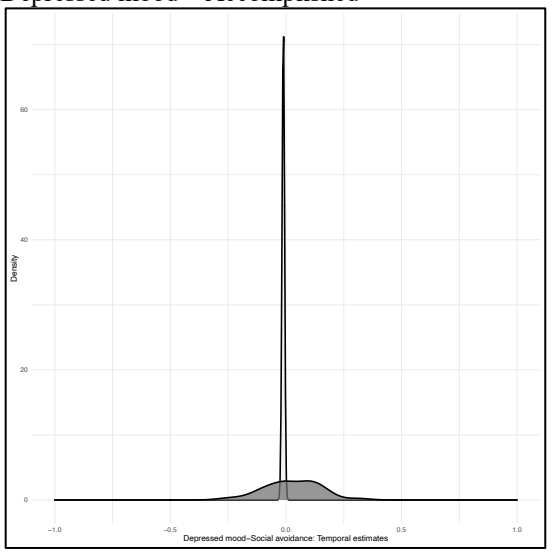
Depressed mood – Accomplished



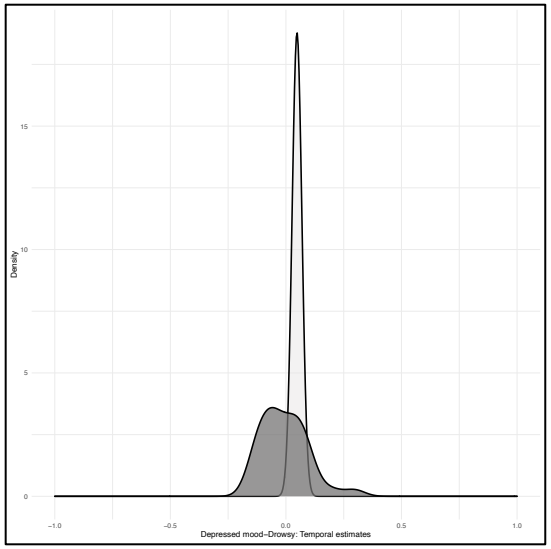
Depressed mood – Hungry



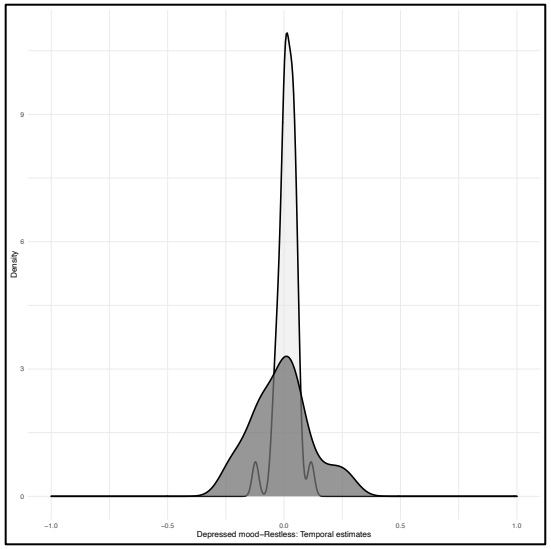
Depressed mood – Physical activity



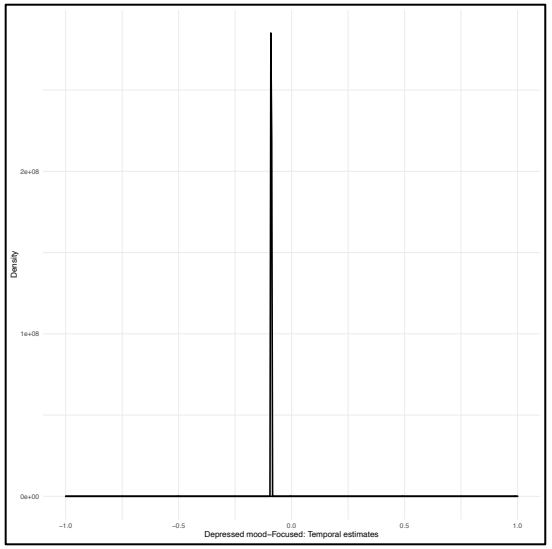
Depressed mood – Social avoidance



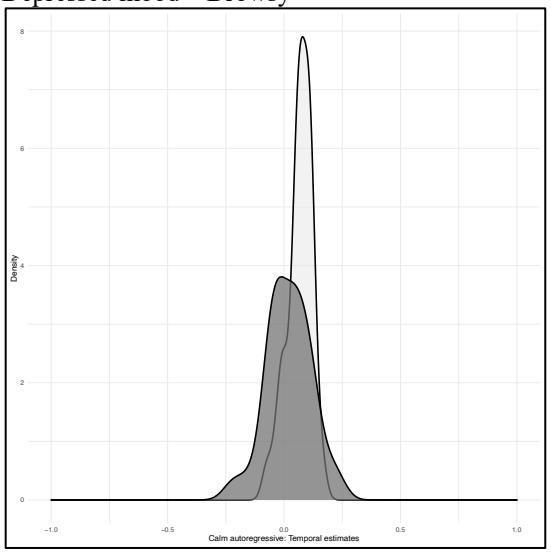
Depressed mood – Drowsy



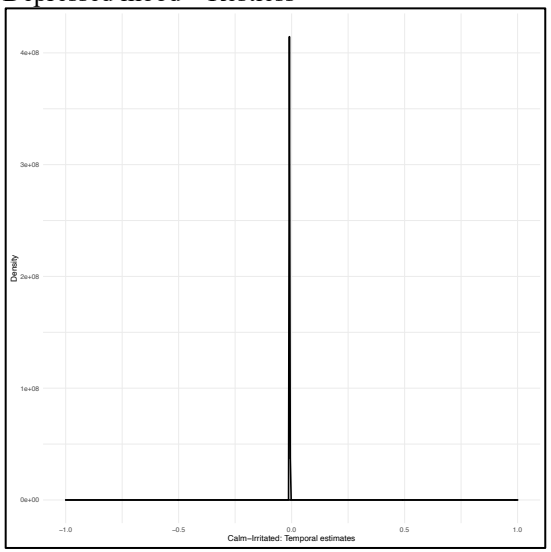
Depressed mood – Restless



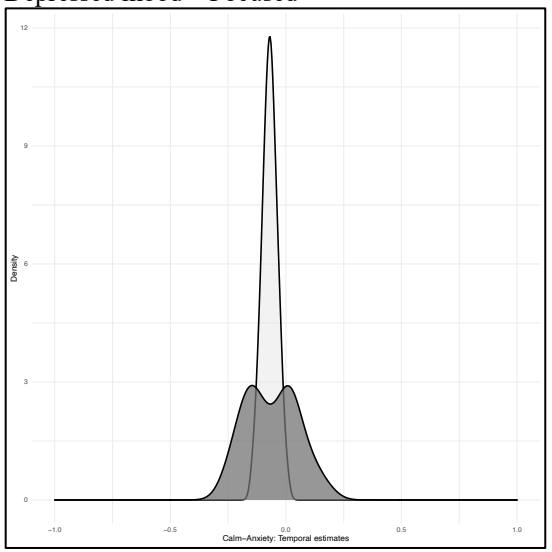
Depressed mood – Focused



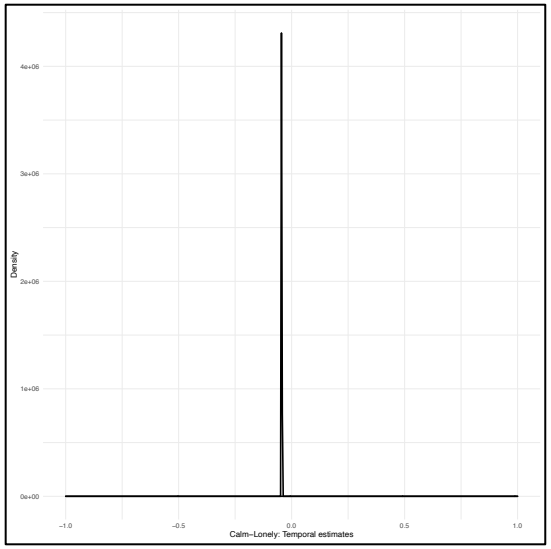
Calm autoregressive



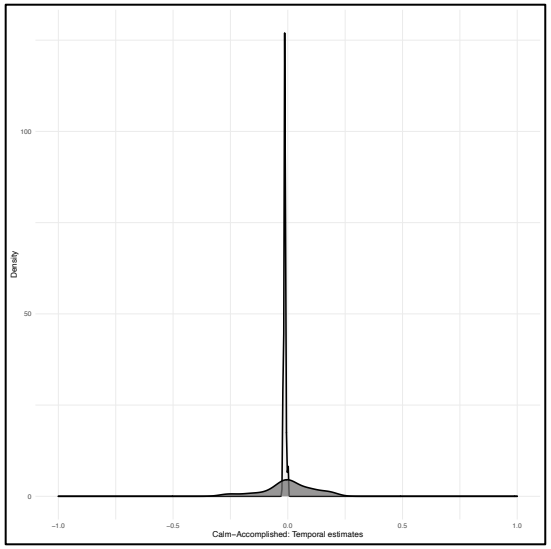
Calm – Irritated



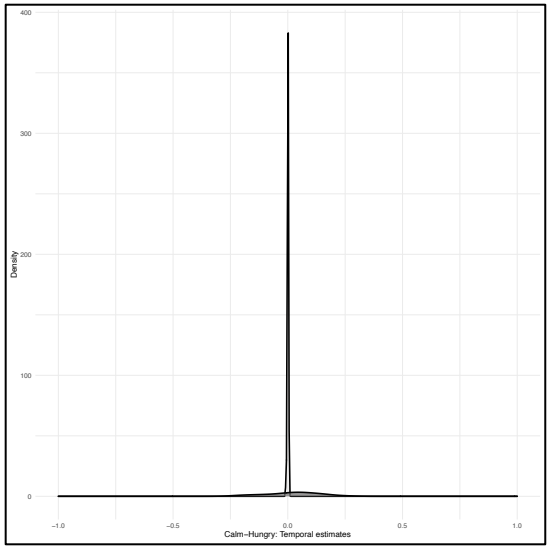
Calm - Anxiety



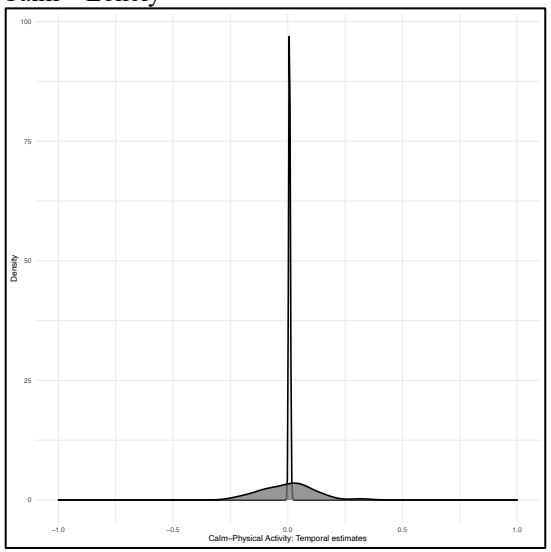
Calm – Lonely



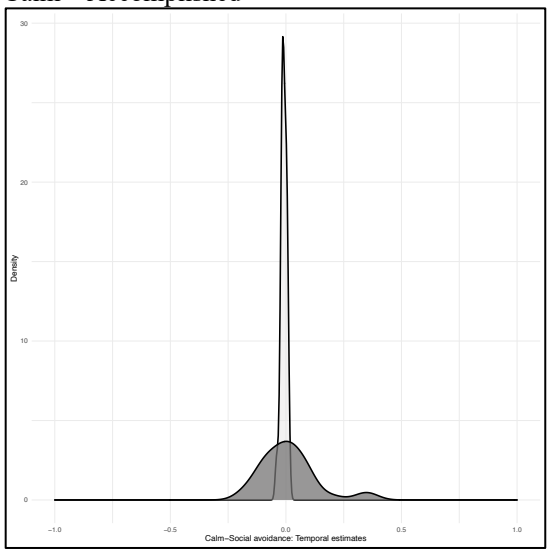
Calm – Accomplished



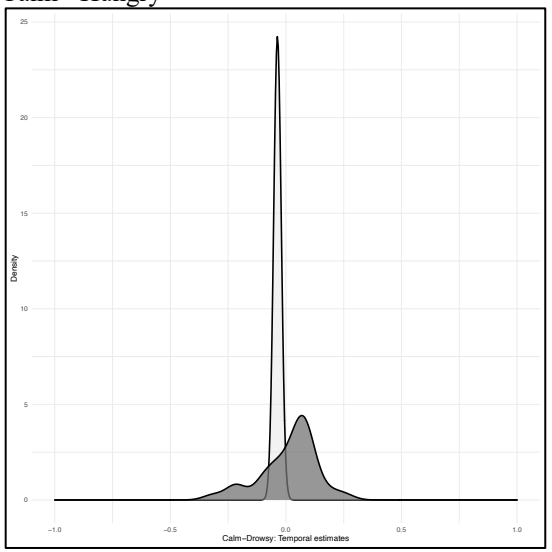
Calm - Hungry



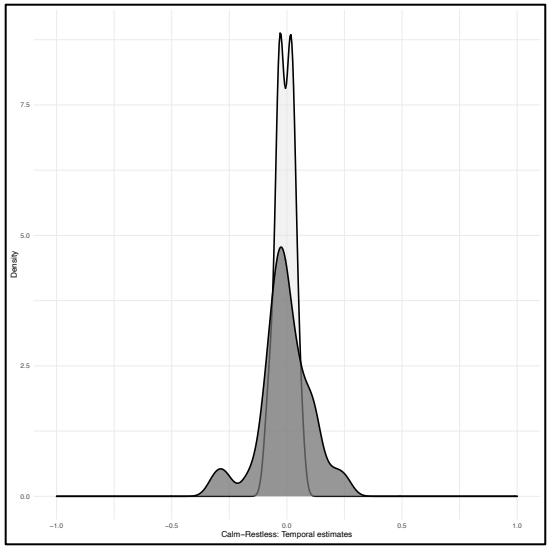
Calm – Physical activity



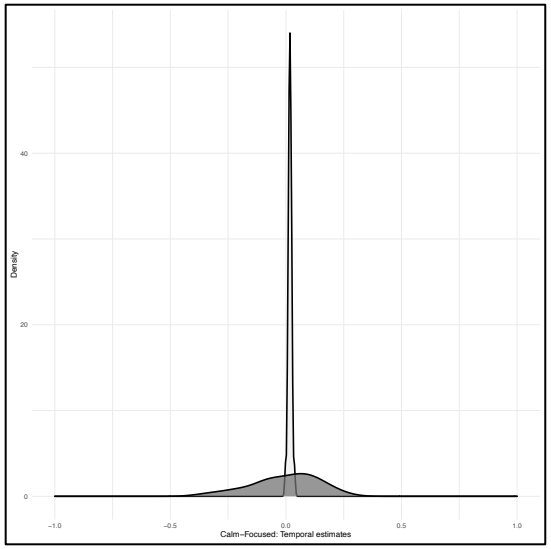
Calm – Social avoidance



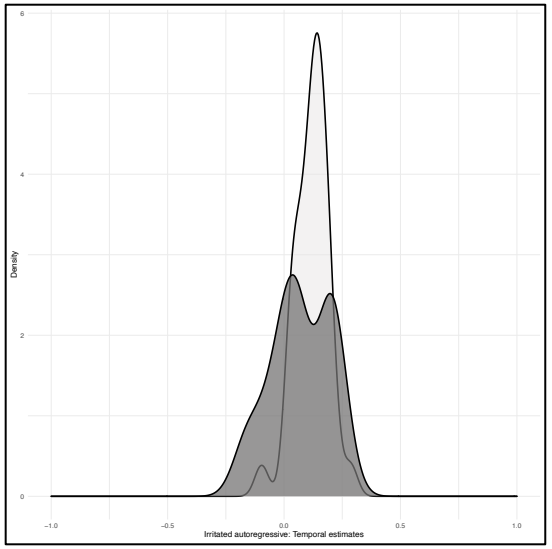
Calm – Drowsy



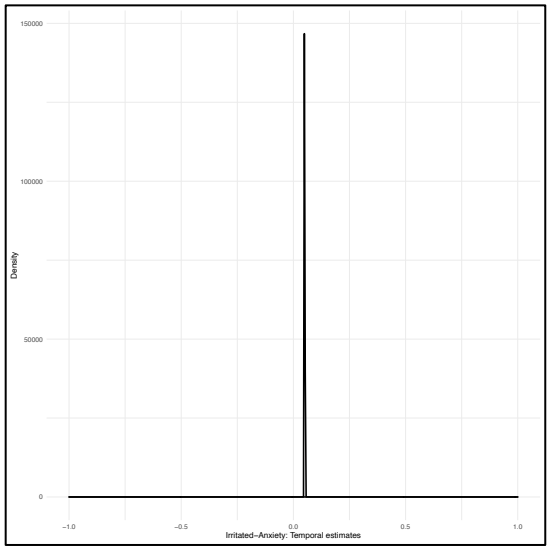
Calm – Restless



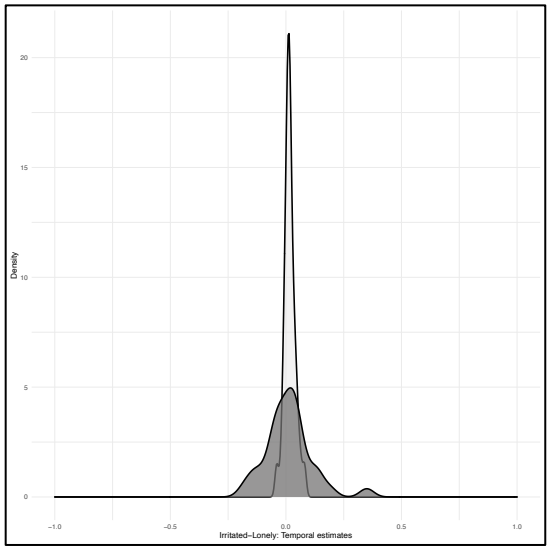
Calm – Focused



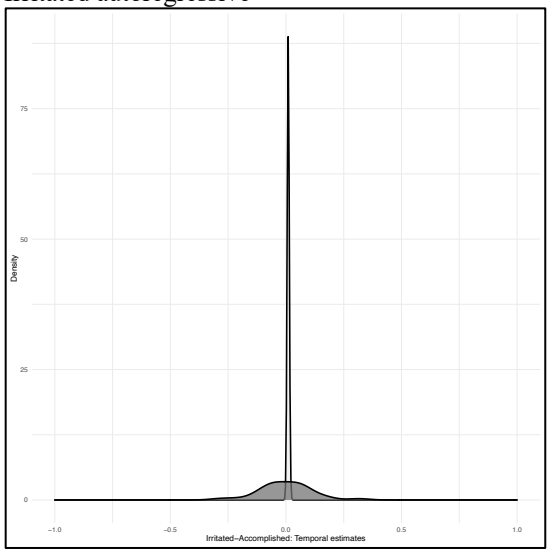
Irritated autoregressive



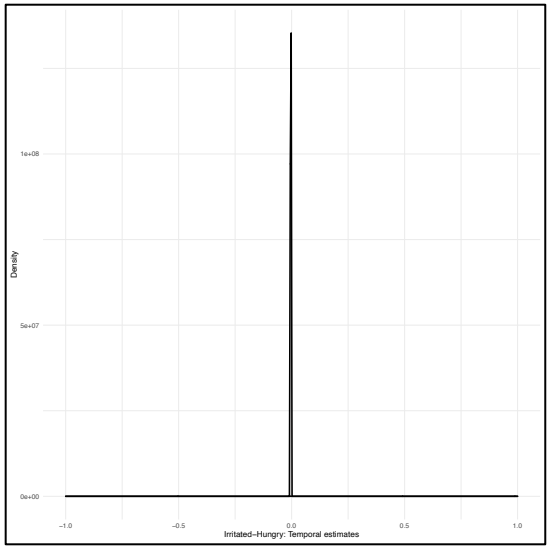
Irritated – Anxiety



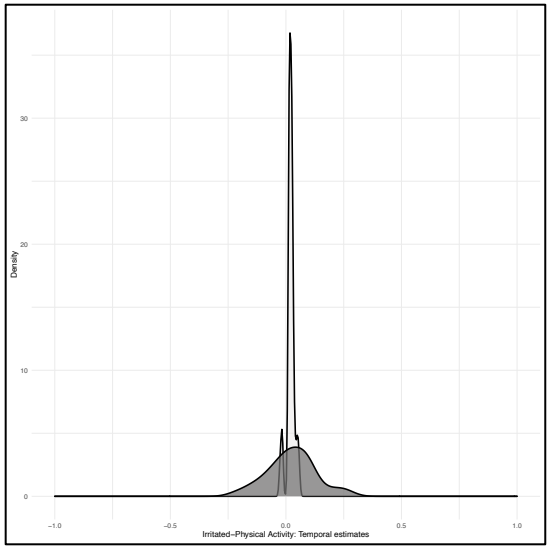
Irritated – Lonely



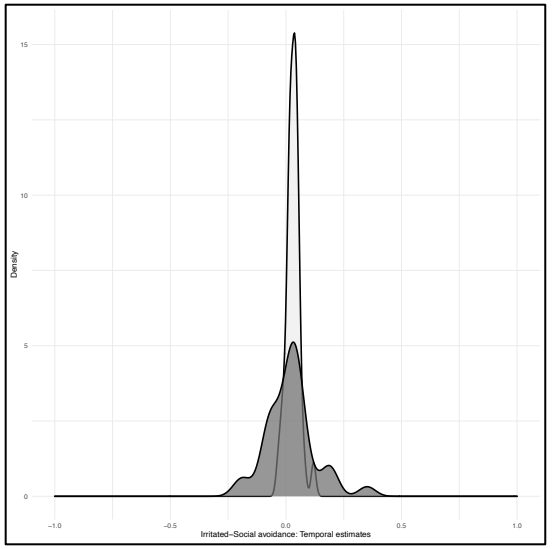
Irritated - Accomplished



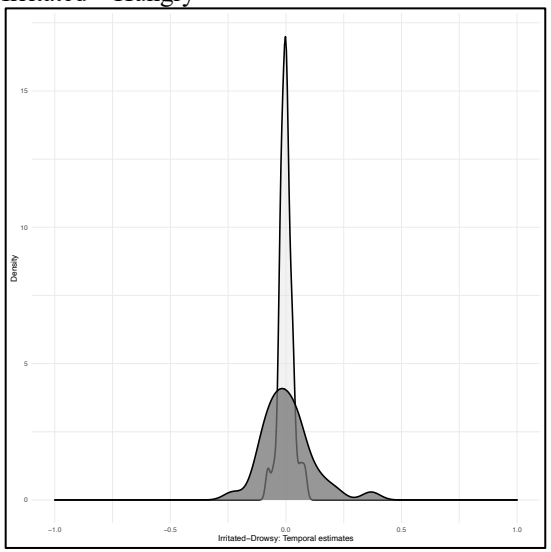
Irritated – Hungry



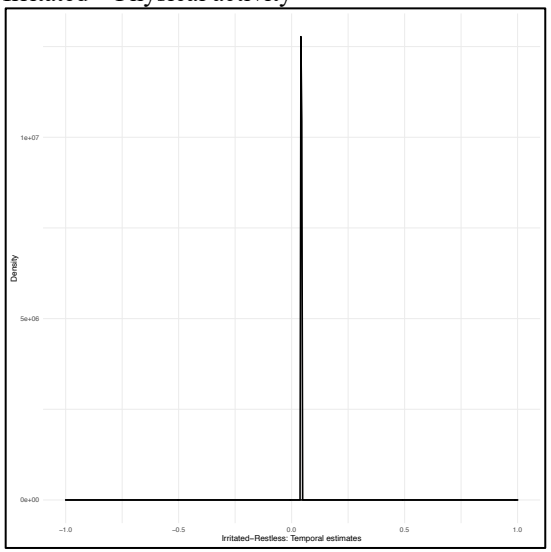
Irritated – Physical activity



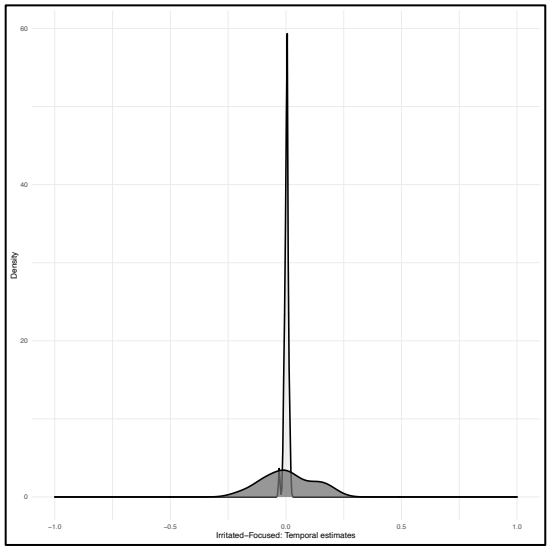
Irritated – Social avoidance



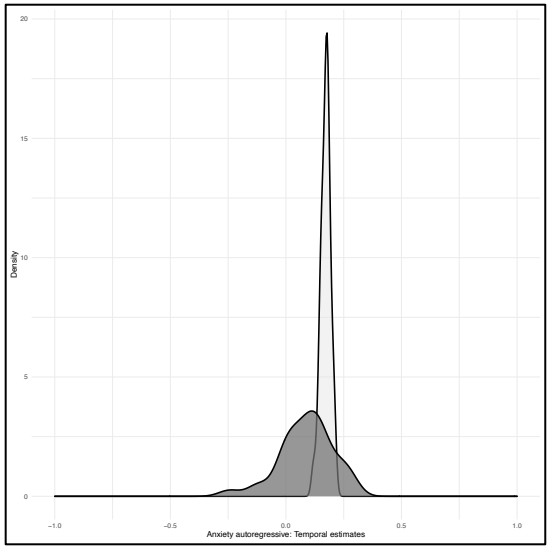
Irritated – Drowsy



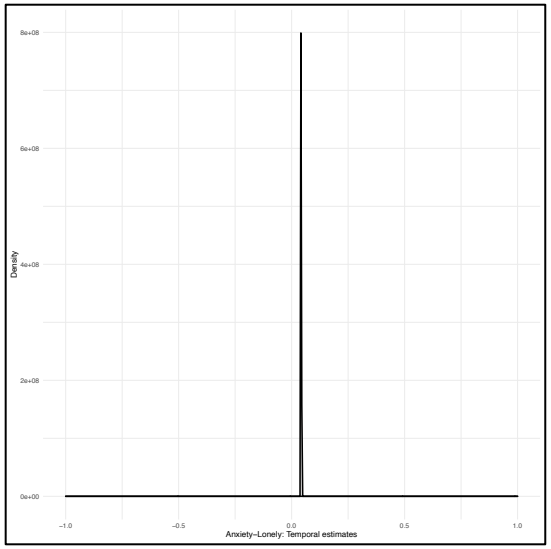
Irritated – Restless



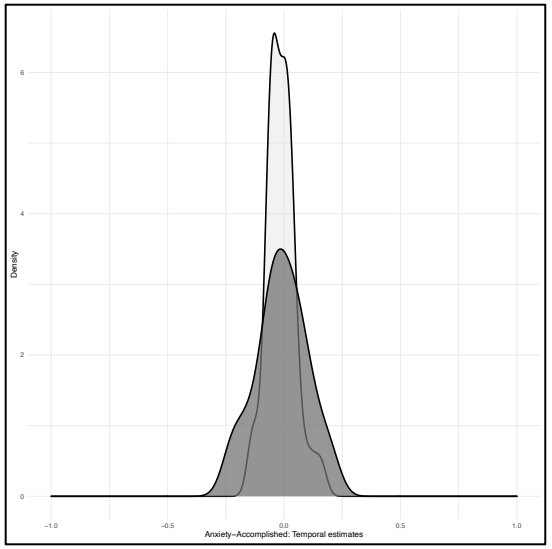
Irritated – Focused



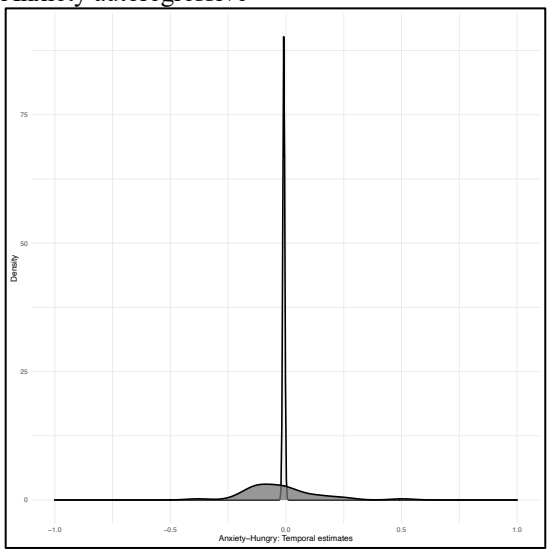
Anxiety autoregressive



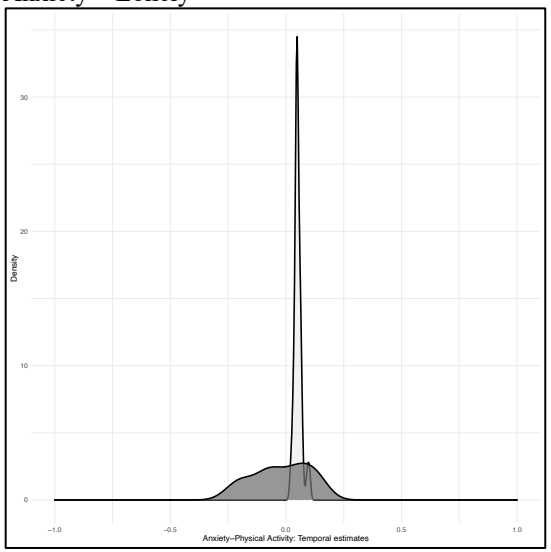
Anxiety – Lonely



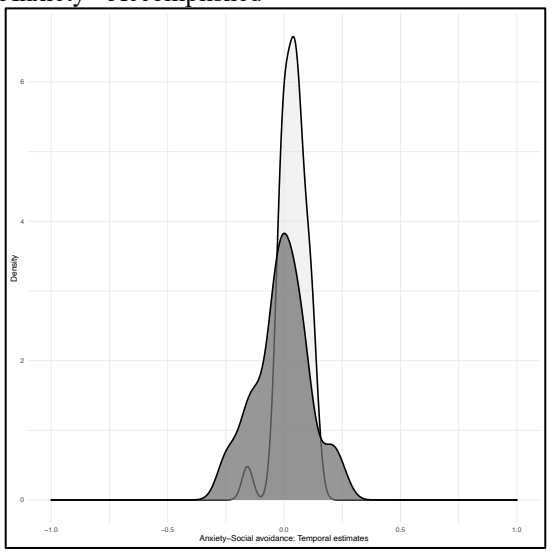
Anxiety - Accomplished



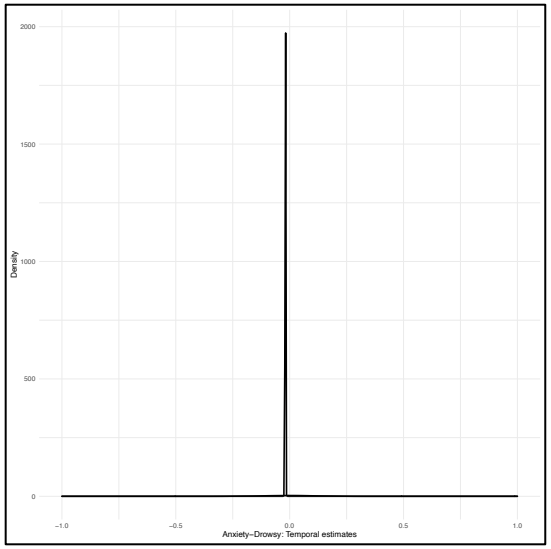
Anxiety – Hungry



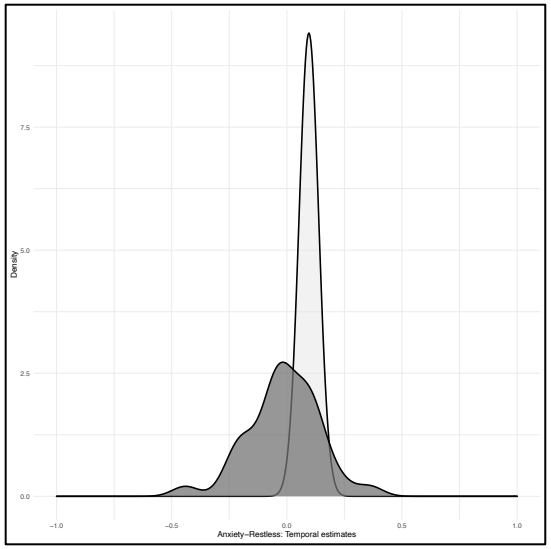
Anxiety – Physical activity



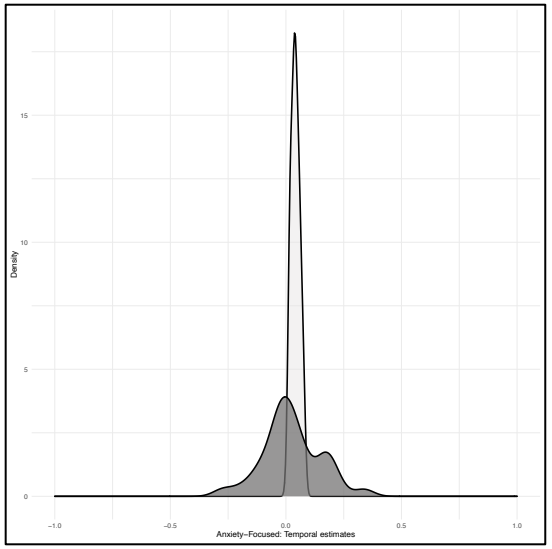
Anxiety – Social avoidance



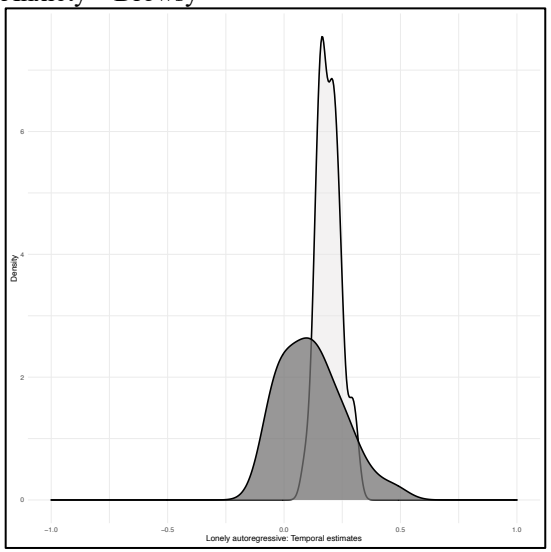
Anxiety – Drowsy



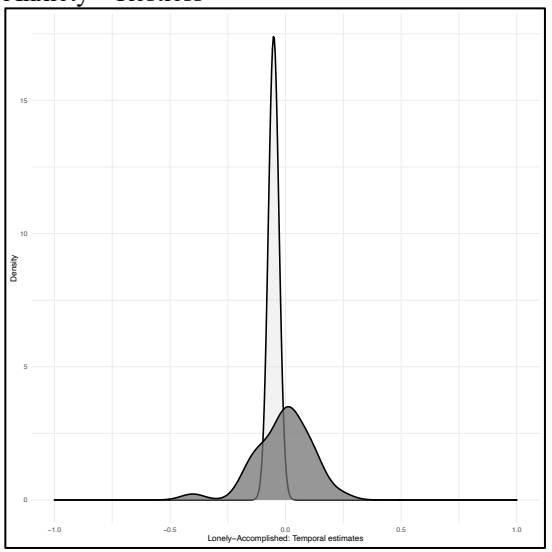
Anxiety – Restless



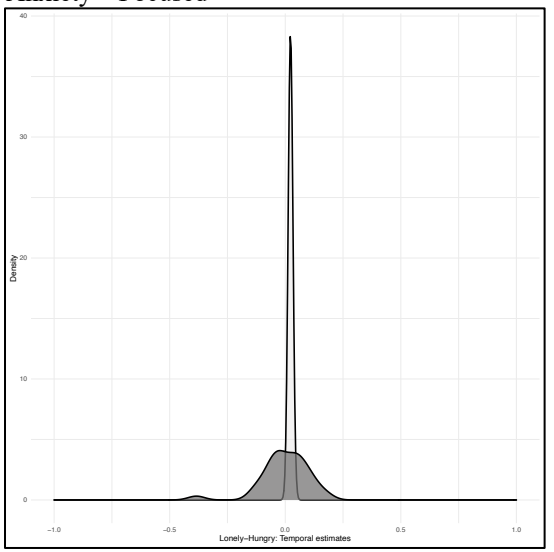
Anxiety – Focused



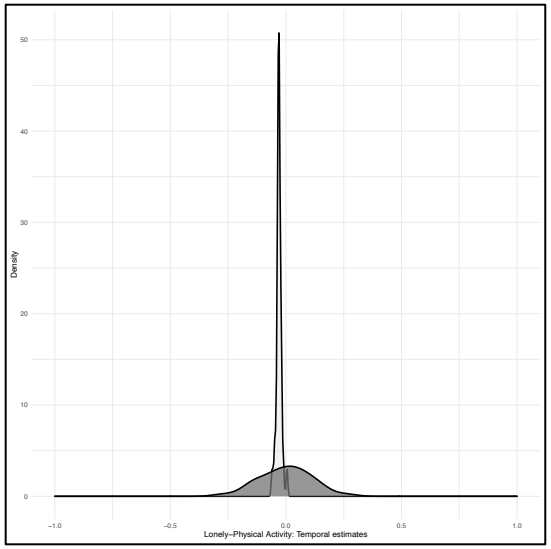
Lonely autoregressive



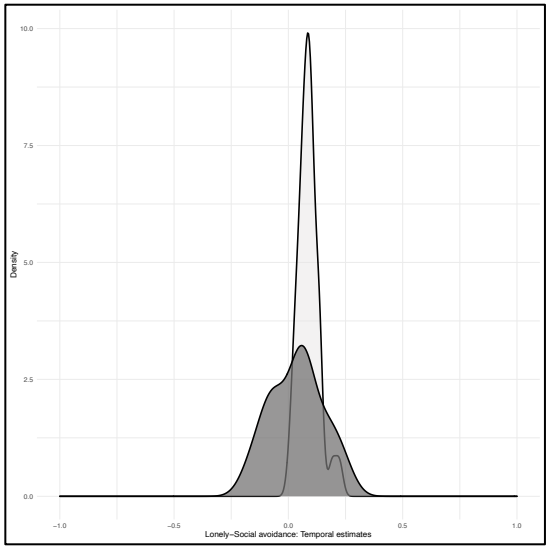
Lonely – Accomplished



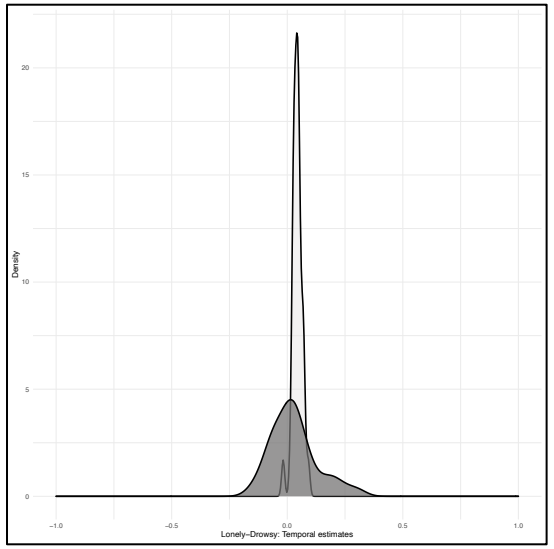
Lonely – Hungry



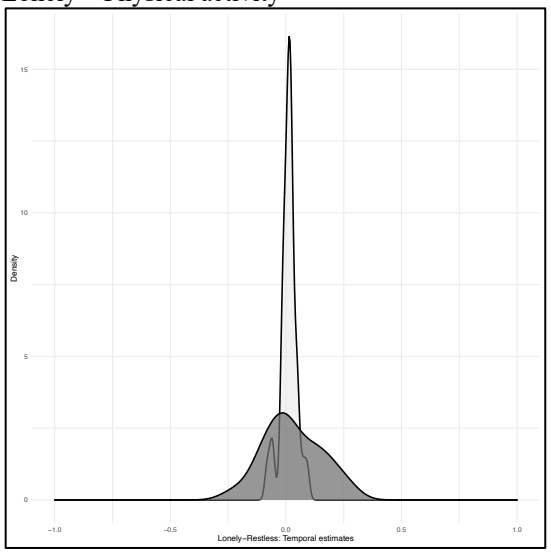
Lonely – Physical activity



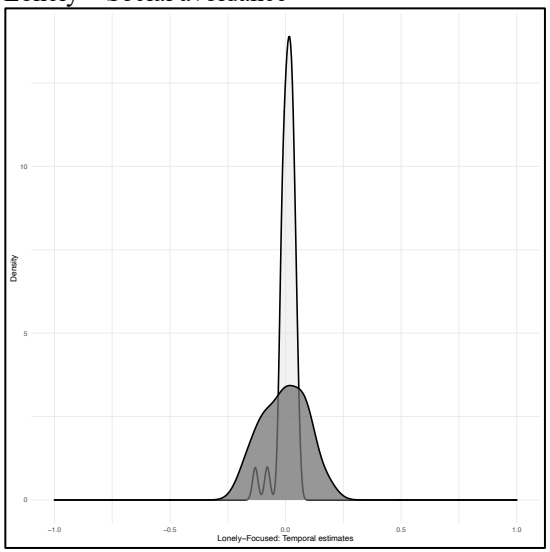
Lonely – Social avoidance



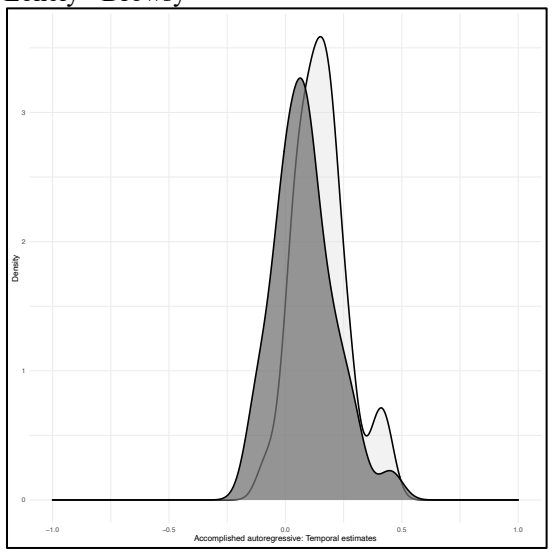
Lonely - Drowsy



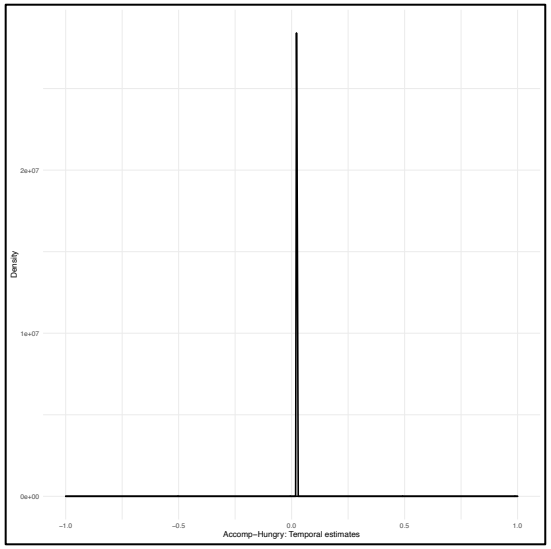
Lonely – Restless



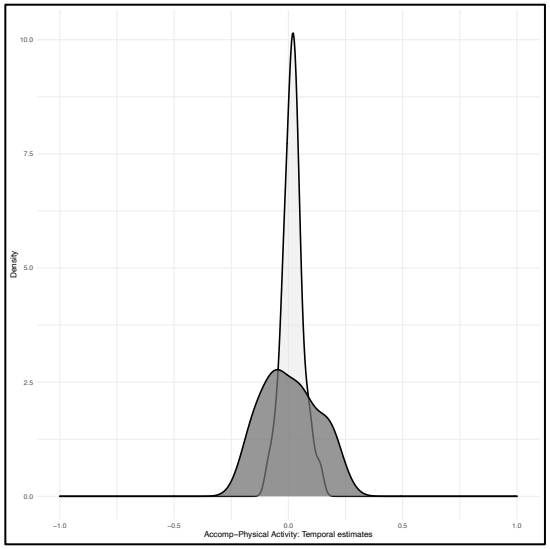
Lonely – Focused



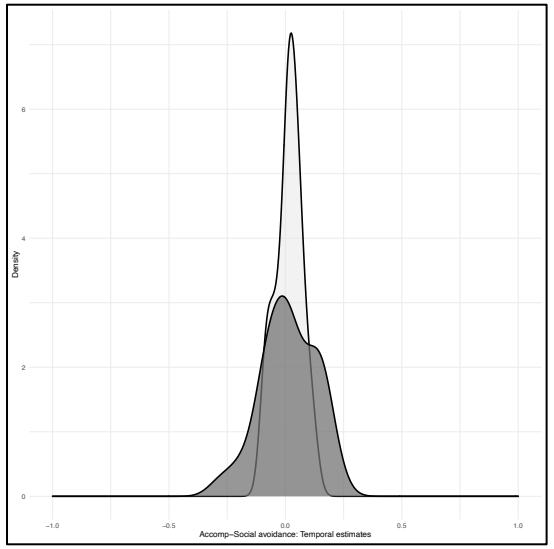
Accomplished autoregressive



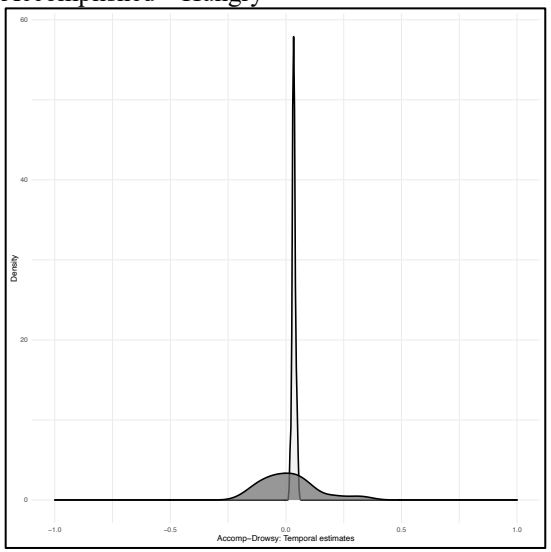
Accomplished – Hungry



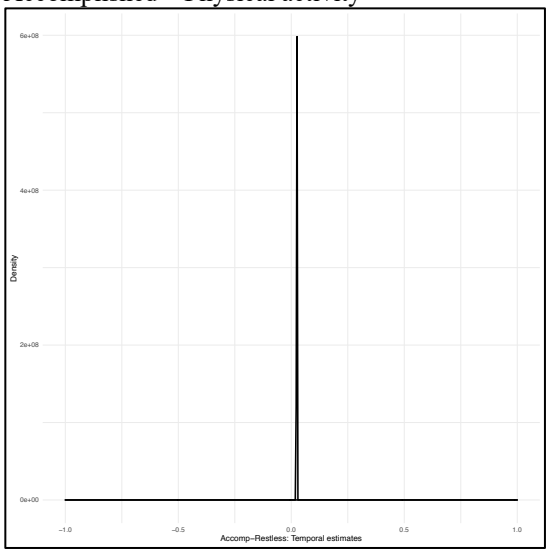
Accomplished – Physical activity



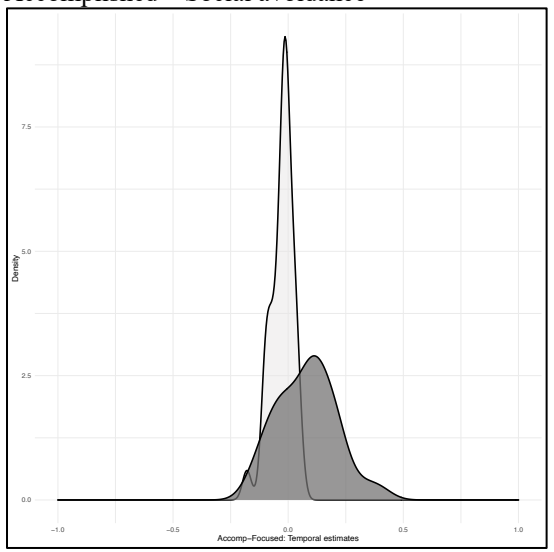
Accomplished – Social avoidance



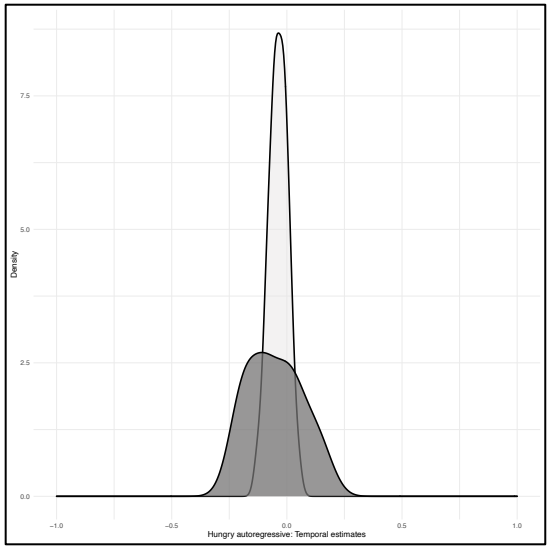
Accomplished – Drowsy



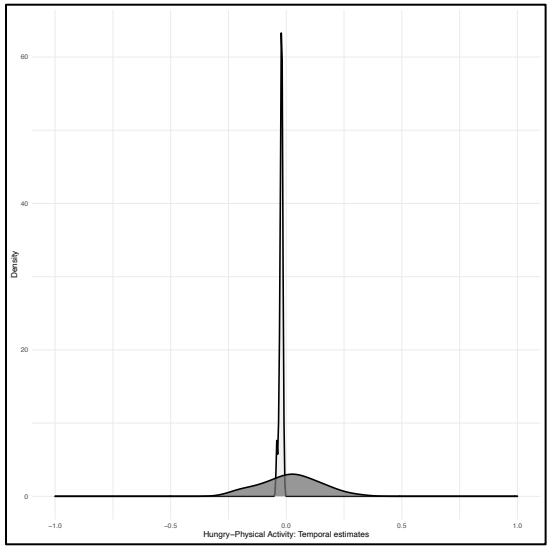
Accomplished – Restless



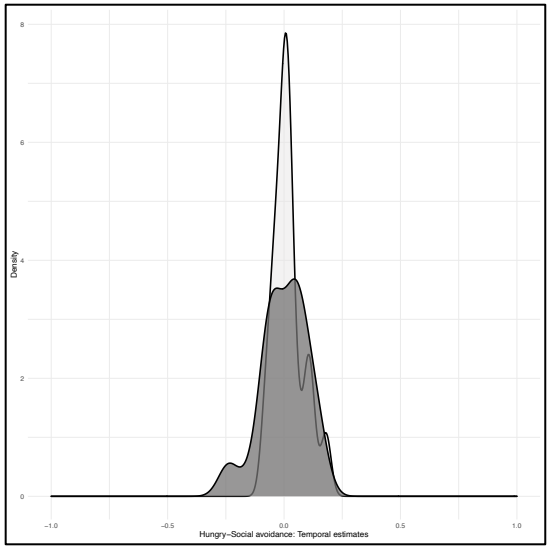
Accomplished - Focused



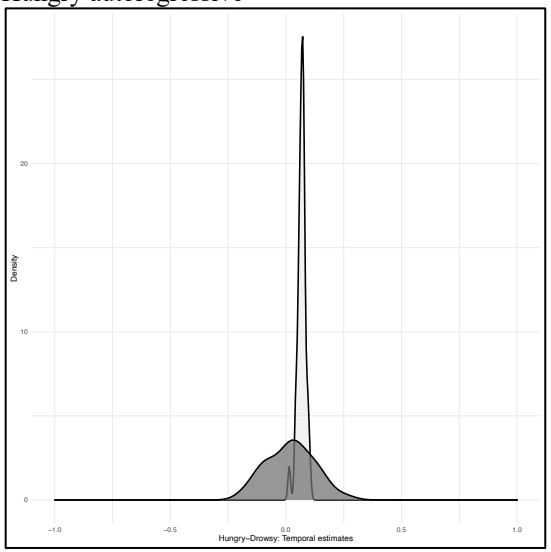
Hungry autoregressive



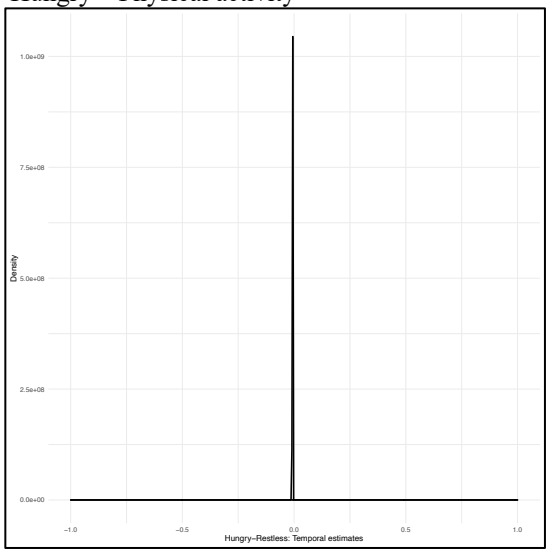
Hungry – Physical activity



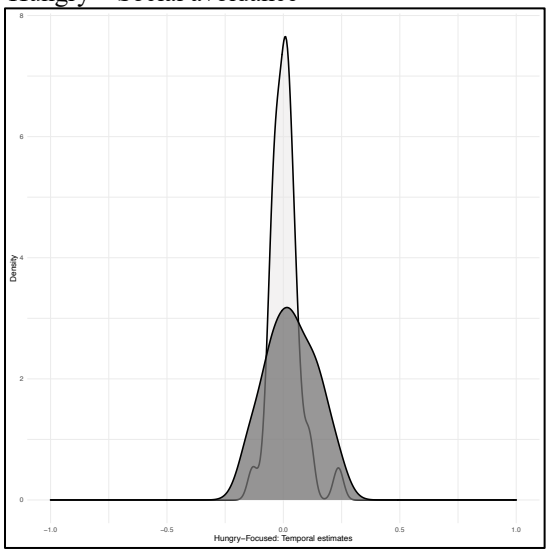
Hungry – Social avoidance



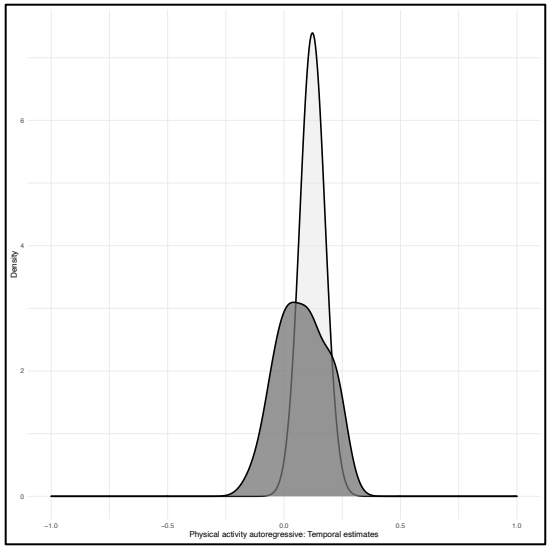
Hungry – Drowsy



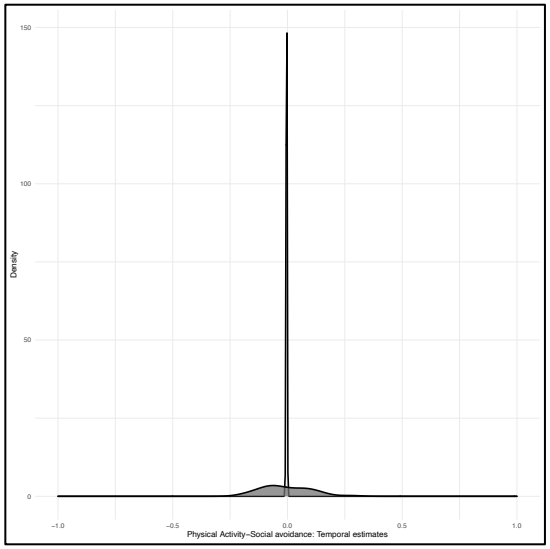
Hungry – Restless



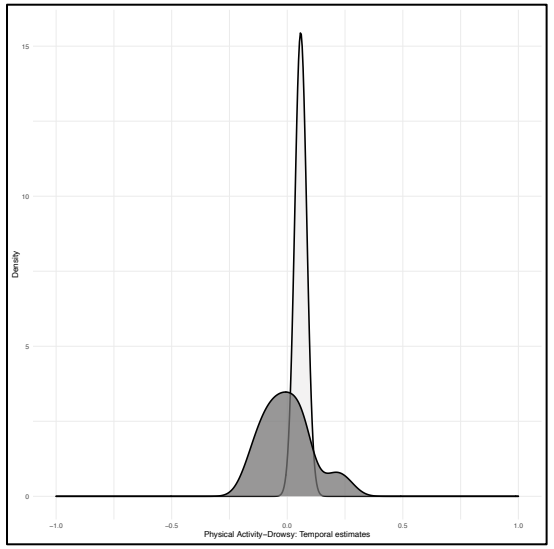
Hungry – Focused



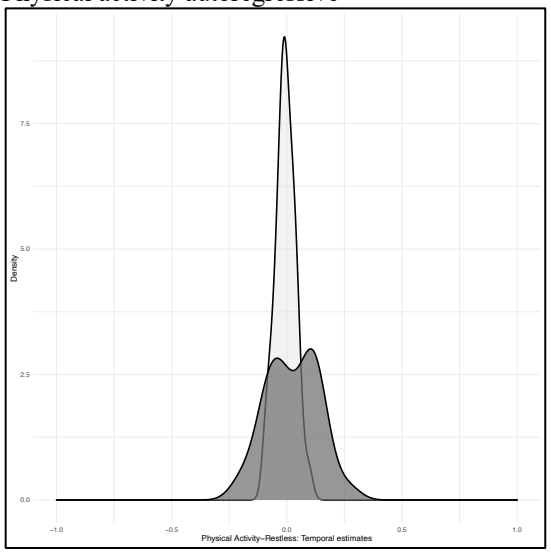
Physical activity autoregressive



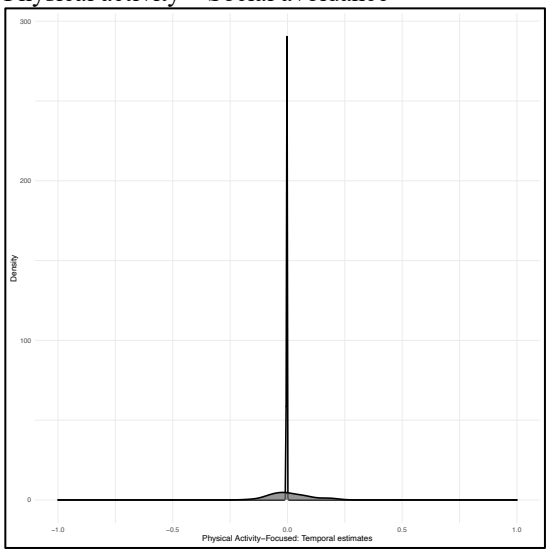
Physical activity – Social avoidance



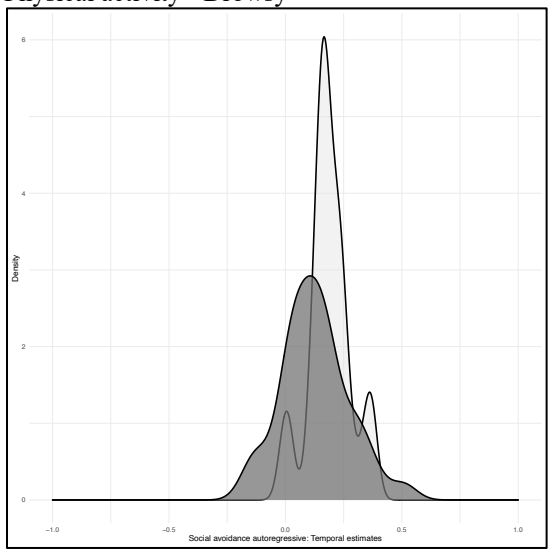
Physical activity - Drowsy



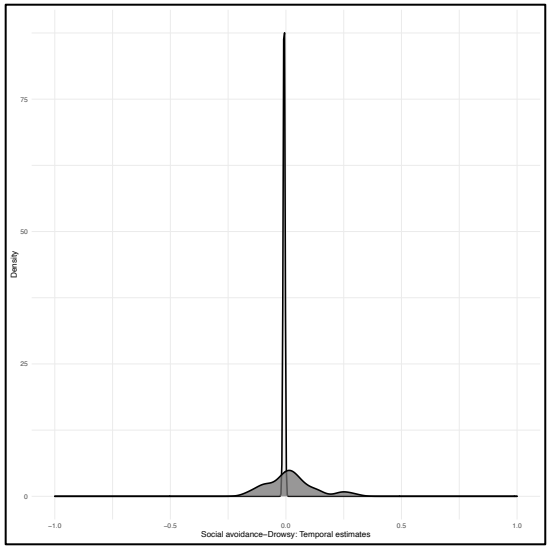
Phsical activity – Restless



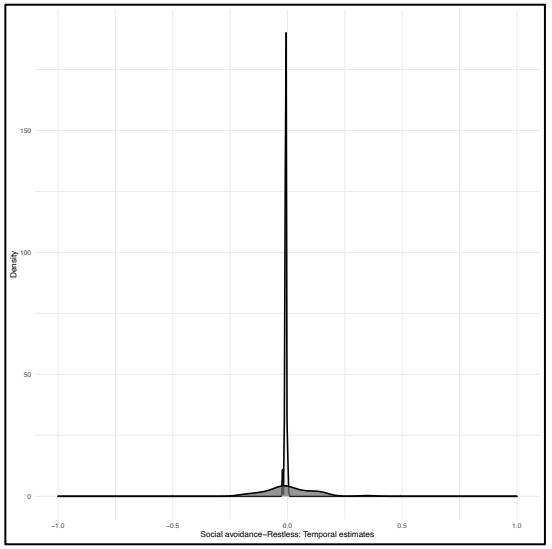
Physical activity – Focused



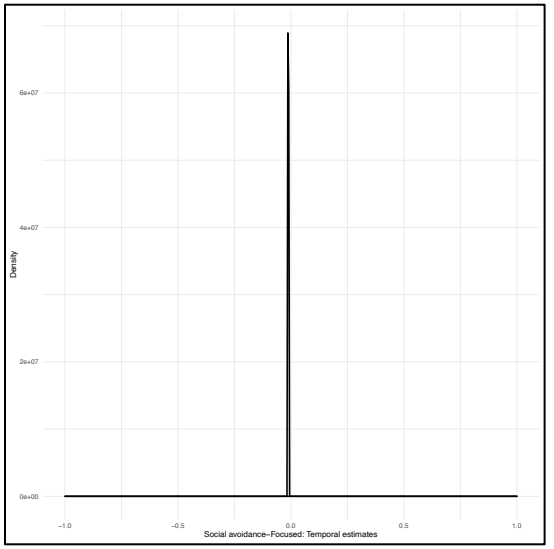
Social avoidance autoregressive



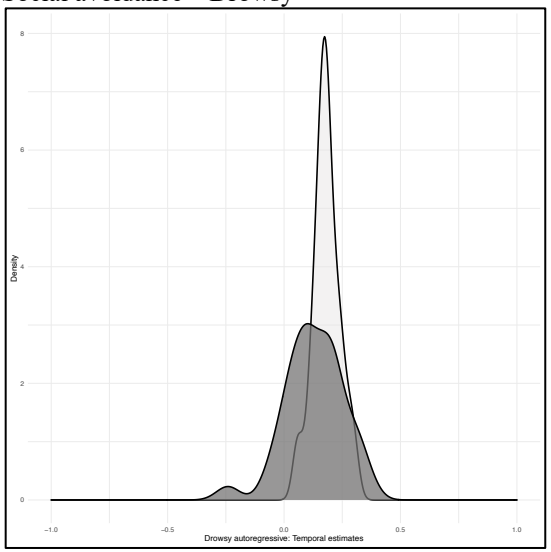
Social avoidance – Drowsy



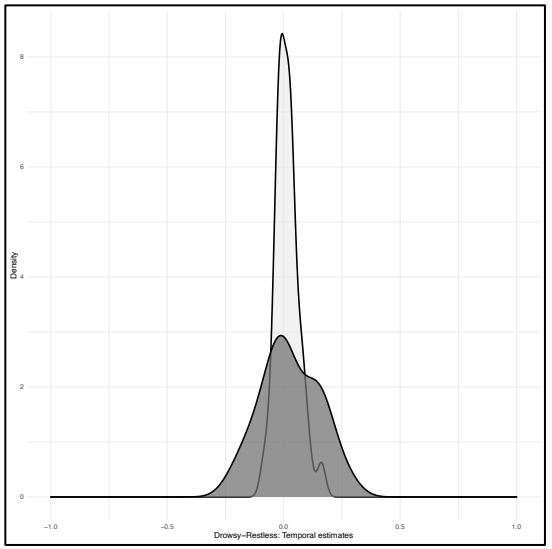
Social avoidance – Restless



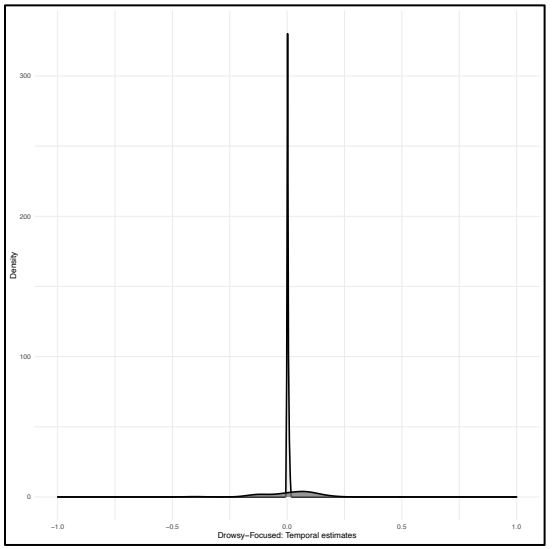
Social avoidance – Focused



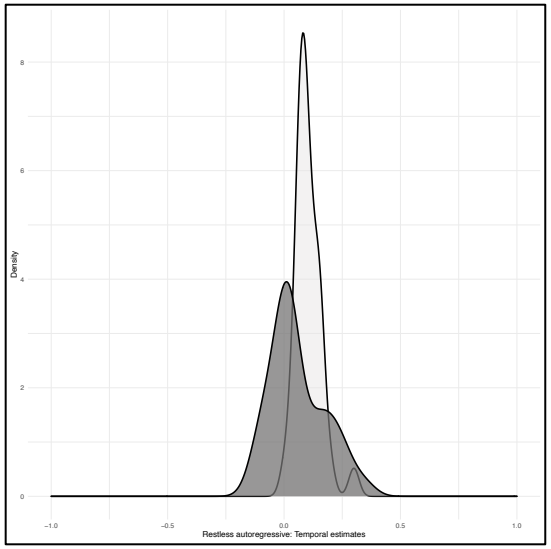
Drowsy autoregressive



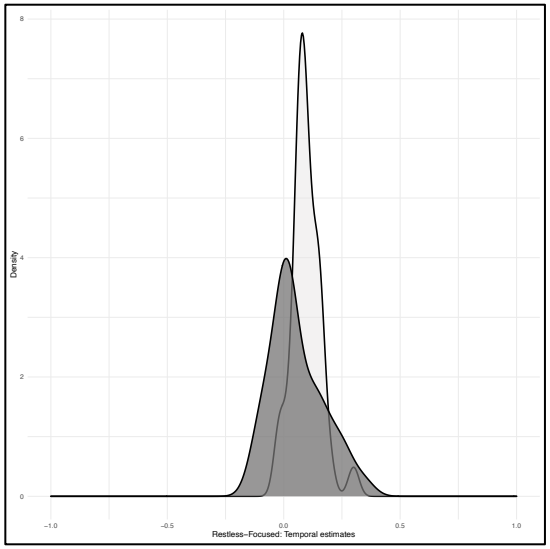
Drowsy – Restless



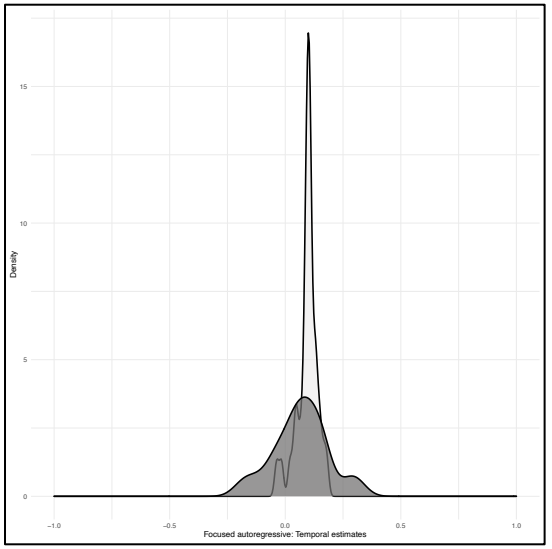
Drowsy – Focused



Restless autoregressive



Restless – Focused

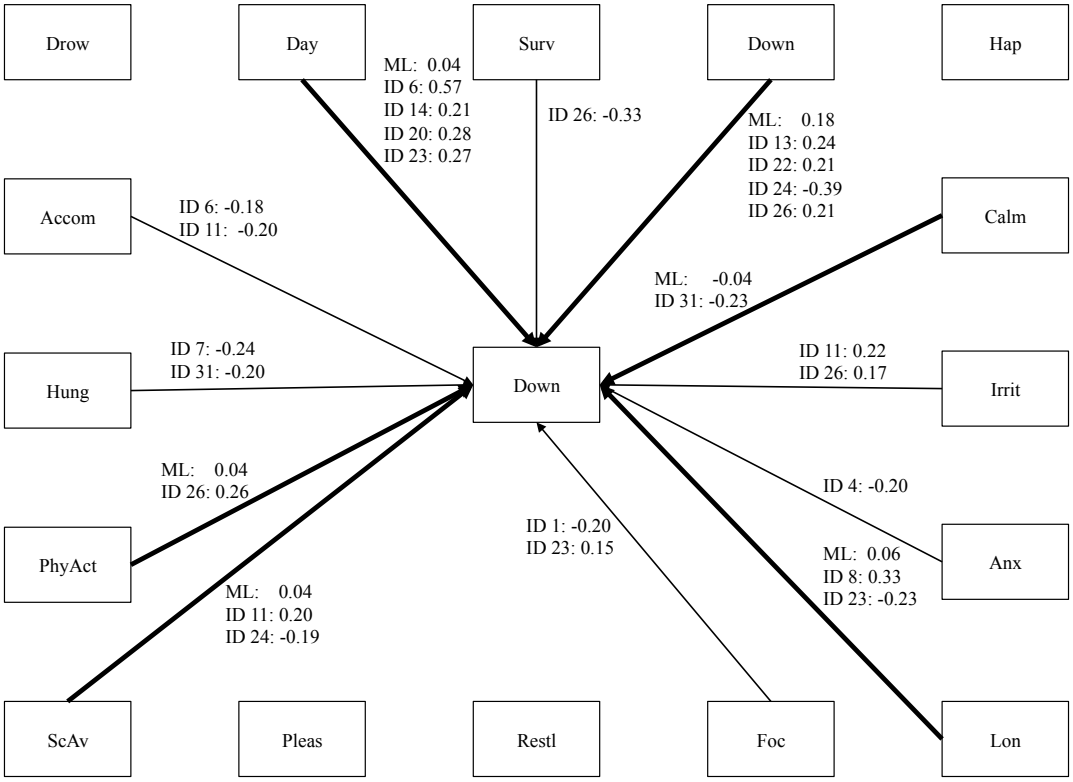


Focused autoregressive

Note. Density curves shaded in lighter grey represent the individual-level estimates from the ML-VAR model. Density curves shaded in darker grey represent the individual-level estimates from the person-specific VAR models.

Figure S6.

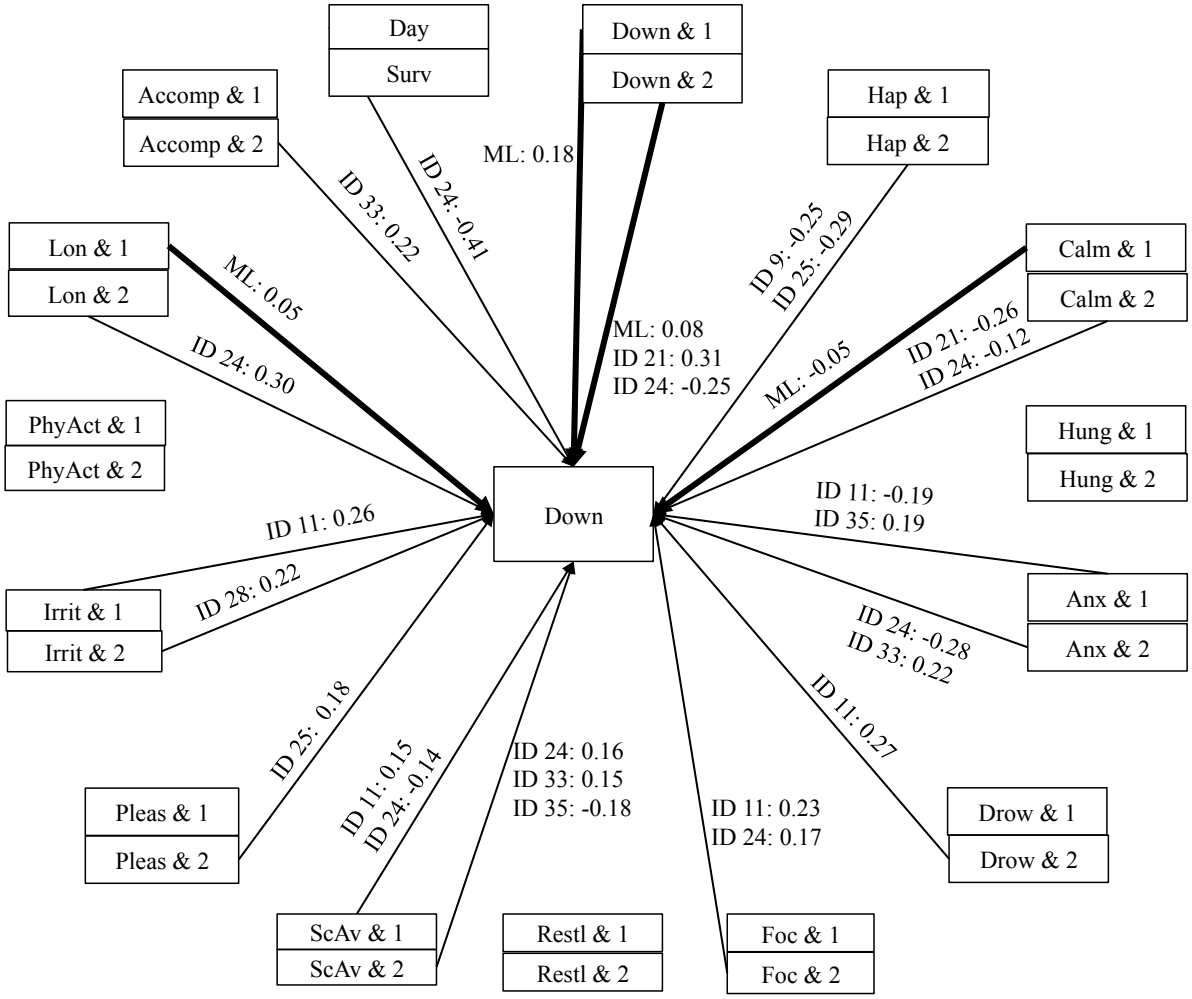
Statistically significant pathways from Lag 1 ML-DSEM and DSEM models



Note. Only standardized pathways with credible intervals that do not include 0 (analogous to statistical significance) are demonstrated here. ID = Participant ID number; ML = Multilevel; Hap = Happy; Irrit = Irritable; Anx = Anxious; Lon = Lonely; Foc = Focused; Restl = Restless; Pleas = Pleased; ScAv = Social avoidance; PhAct = Physical activity; Hung = Hungry; Accom = Accomplished; Drow = Drowsy; Surv = Survey.

Figure S7.

Statistically significant pathways from Lag 2 ML-DSEM and DSEM models



Note. Estimates from the multilevel model and person-specific models are listed by ID. Only standardized pathways with credible intervals that do not include 0 (analogous to statistical significance) are shown here. Thicker lines indicate that the pathway was significant in the multilevel model. &1 refers to Lag 1; &2 refers to Lag 2; ID = Participant ID number; ML = Multilevel; Surv = Survey; Hap = Happy; Hung = Hungry; Anx = Anxious; Drow = Drowsy; Foc = Focused; Restl = Restless; ScAv = Social avoidance; Pleas = Pleased; Irrit = Irritable; PhAct = Physical Activity; Lon = Lonely; Accom = Accomplished

Data anlaytic code

Examining time trends: Example code

```
ggplot(MyMood036, aes(Time, Focused)) + geom_path(mapping = aes(Time, Focused), color =
"black", na.rm = TRUE) + theme_minimal() + geom_smooth()

ggplot(MyMood036, aes(Survey, Focused)) + geom_point(mapping = aes(Survey, Focused),
color = "black", na.rm = TRUE) + theme_minimal() + geom_smooth()
```

Preparing data: removing linear trends

```
residualize_df_MyMood <- function(df) {
  for (col in colnames(df)){
    if (col == "ID" |col == "Day" ||col =="Survey") {
      next;
    }
    formula = paste(col, "Day + Survey", sep="~")
    model = lm(formula, df)
    df[[col]][!is.na(df[[col]])] <- residuals(model)
  }
  return(df)
}
```

Preparing data: removing nonlinear trends

```
LOSresidualize_df_MyMood <- function(df) {
  for (col in colnames(df)){
    if (col == "ID" | col == "Day" | col =="Survey") {
      next;
    }
    formula = paste(col, "Day + Survey", sep="~")
    model = loess(formula, df)
    df[[col]][!is.na(df[[col]])] <- residuals(model)
  }
  return(df)
}
```

Calculating intraindividaul means, standard deviations: Example code

```
mean_Down <- c()
sd_Down <- c()
  for(i in unique(MyMoodCombined_nonresid$ID))
  {
    mean_Down <- c(mean_Down,
mean(as.numeric(MyMoodCombined_nonresid$Down[MyMoodCombined_nonresid$ID == i]),
na.rm =T))
    sd_Down <- c(sd_Down,
sd(as.numeric(MyMoodCombined_nonresid$Down[MyMoodCombined_nonresid$ID == i]),
na.rm =T))
```

```
  }

#Intraindividual means for Down-Mean
mean(mean_Down)
sd(mean_Down)

#Intraindividual means for Down-Var
mean(sd_Down)
sd(sd_Down)
```

Aim 1: Calculating multilevel network

```
MyMoodMLVAR_wcomp <- mlVAR(MyMoodCombinedShort, vars = c("DwnHapPls", "Calm", "Irritated", "Anxious", "Lonely", "Accomplish", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restless", "Focused"), idvar = c("ID"), dayvar = c("Day"), beepvar = c("Survey"), estimator = c("lmer"), contemporaneous = c("orthogonal"), temporal = c("orthogonal"))
```

Plotting contemporaneous multilevel network

```
ContempQgraph <- plot(MyMoodMLVAR_wcomp, "contemporaneous")
ContempCent <- centrality(ContempQgraph)
ContempOutExp <- round(ContempCent$OutExpectedInfluence, 3)
Contemp_wm <- getWmat(ContempQgraph)

mlVARNet_ <- qgraph(Contemp_wm, pie = abs(ContempOutExp), mar = c(7, 7, 7, 7), pieColor = list(c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white")), layout="circular", labels = colnames(Contemp_wm), label.prop = .6, posCol = "black", negCol = "black", negDashed = TRUE, edge.labels = TRUE, vsize=8, esize=8, rescale = TRUE, repulsion = .9, title = paste0("ML-VAR contemporaneous network with expected influence"))
```

Plotting temporal multilevel network

```
TempQgraph <- plot(MyMoodMLVAR_wcomp, "temporal")
TempQgraph2 <- plot(MyMoodMLVAR_wcomp, "temporal")
TempCent <- centrality(TempQgraph)

TempOutExp <- round(TempCent$OutExpectedInfluence, 3) #light grey
TempInExp <- round(TempCent$InExpectedInfluence, 3) #black
Temp_wm <- getWmat(TempQgraph)

mlVARNet_ <- qgraph(Temp_wm, pie = c(.186, .115, .05, .072, .081, 0.0, .068, .058, .051, .038, .047, .098), mar = c(7, 7, 7, 7), pieColor = list(c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white"), c("light grey", "white")), layout="circular", labels = colnames(Temp_wm), label.prop = .6, posCol = "black", negCol = "black", negDashed = TRUE,
```

```
edge.labels = FALSE, vsize=8, esize=8, rescale = TRUE, repulsion = .9, title = paste0("ML-VAR temporal network with expected influence"))
```

Aim 2: Calculating person-specific networks

```
MyMoodMLgraphicalVAR_wcomp <- mlGraphicalVAR(MyMoodCombinedShort, vars = c("DwnHapPls", "Calm", "Irritated", "Anxious", "Lonely", "Accomplish", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restless", "Focused"), idvar = c("ID"), dayvar = c("Day"), beepvar = c("Survey"))
```

Plotting contemporaneous person-specific networks: Example code

```
PCCQgraph_026 <- qgraph(MyMoodMLgraphicalVAR_wcomp$subjectPCC[[26]])
PCCCent_026 <- centrality(PCCQgraph_026)
P026_ContempOutExp <- round(PCCCent_026$OutExpectedInfluence, 3)

P026_ContNet <- qgraph(PCCQgraph_026, pie = abs(P026_ContempOutExp), mar = c(7, 7, 7, 7), pieColor = list(c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white")), layout="circular", labels = colnames(Contemp_wm), label.prop = .6, posCol = "dark blue", negCol = "#FA7534", edge.labels = FALSE, vsize=8, esize=8, rescale = TRUE, repulsion = .9, title = paste0("P026_graphicalVAR contemporaneous network with expected influence"), filetype = "pdf", filename = "Color_P026_graphicalVAR Contemporaneous Net with Expected Influence")
```

Plotting temporal person-specific networks: Example code

```
PDCQgraph_026 <- qgraph(MyMoodMLgraphicalVAR_wcomp$subjectPDC[[25]])
PDCCent_026 <- centrality(PDCQgraph_026)
P026_TempOutExp <- round(PDCCent_026$OutExpectedInfluence, 3)
P026_TempInExp <- round(PDCCent_026$InExpectedInfluence, 3)

P026_mlgraphicalVAR_Temp <- qgraph(PDCQgraph_026, pie = list(c(.19, .10), c(.12, .08), c(.05, .06), c(.07, .02), c(.08, .04), c(0.00, .01), c(.07, 0.0), c(.06, .004), c(.05, .13), c(.04, .13), c(.04, .10), c(.1, .09)), mar = c(7, 7, 7, 7), pieColor = list(c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black", "white"), c("light grey", "black",  "white"), c("light grey", "black", "white"), c("light grey", "black", "white")), layout="circular", labels = c("DwnHapPls", "Calm", "Irritated", "Anxious", "Lonely", "Accomplish", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restless", "Focused"), label.prop = .6, posCol = "black", negCol = "black", negDashed = TRUE, edge.labels = TRUE, vsize=8, esize=8, rescale = TRUE, repulsion = .9, layout="circular", title = paste0("mlgraphicalVAR temporal network with expected influence"), filetype = "pdf", filename = "
Color_P026_graphicalVAR: Temporal Net with Expected Influence ")
```

Calculating node-level predictability: Example code

```
#Impute missing data to facilitate model estimation using mgm
```

```
Library(missForest)
MyMood036rf <- missForest(MyMood036)
MyMood036rf <- MyMood036rf$ximp

#Remove linear time trend
MyMood036Rrf <- residualize_df_MyMood(MyMood036rf)

#Compute average composite node for depressed mood to reduce multicollinearity
MyMood036RCrf <- MyMood036Rrf %>% transmute(ID, Day, Survey, DwnHapPls = (Down - Happy - Pleased)/3, Calm, Irritated, Anxious, Lonely, Accomplish, Hungry, PhysAct, Avoid, Drowsy, Restless, Focused)

#Construct mgm model and calculate node-level predictability
Library(mgm)
MyMood036mgm <- mgm(data = MyMood036RCrf[4:15], type = rep("g", 12), level = rep(1, 12), lambdaSel = "EBIC", lamdaGam = .5, alphaSel = "EBIC", alphaGam = .5)
PCCPred_036<- predict(MyMood036mgm, MyMood036Crf[4:15])

#Plot mgm model
MyMood036mgm$pairwise$edgecolor <- matrix(recode(MyMood036mgm$pairwise$edgecolor, red = "#FA7534", darkgreen = "darkblue"), nrow = 12, ncol = 12)

namesmgm <- c("DHP", "Calm", "Irritated", "Anxious", "Lonely", "Accomplish", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restless", "Focused")
P036_ContNetMGM <- qgraph(MyMood036mgm$pairwise$wadj, edge.color =

MyMood036mgm$pairwise$edgecolor, pie = abs(PCCPred_036$errors$R2), mar = c(7, 7, 7, 7), pieColor = list(c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white"), c("black", "white")), layout="circular", labels = namesmgm, label.prop = .6, negDashed = FALSE, edge.labels = FALSE, vsize=8, esize=8, rescale = TRUE, repulsion = .9, title = paste0("P036_MGM network with R2"), filetype = "pdf", filename = "Color_P036_MGM Net with R2")
```

Aim 3: Sample code for plotting distributions of individaul-level estimates from ML-VAR and person-specific VAR models

```
#Creating correlation matrix (Table 2)
corr_matrix = matrix(,nrow=length(item_measures),ncol=length(item_measures))
for (measure_idx in 1:length(item_measures)){
  for(next_measure_idx in 1:measure_idx){
    person_data_mlvar = c()
    person_data_gvar = c()
    for (i in 0:34){
      column_suffix = if(i==0) '' else paste('.',i,sep='')
      column_name = paste(item_measures[next_measure_idx], column_suffix,sep='')
```

```
     person_data_mlvar = c(person_data_mlvar,
mlvar_ind_cont[[column_name]][[measure_idx]])
     person_data_gvar = c(person_data_gvar, gvar_ind_cont[[column_name]][[measure_idx]])
   }
   corr_matrix[measure_idx, next_measure_idx] = cor(person_data_mlvar,
person_data_gvar,method='spearman')
  }
}
```

#Calculating correlations between indiviudal-level ML-VAR adjacency matrices and person-specific VAR adjacency matrices

#Plotting density curves of indiivdual-level estimates from ML-VAR and person-specific VAR models: Example code

```
ggplot(data = P0_Contempgraphs_ml, aes(x=DHPCm)) + geom_density(color = "black", fill =
"#e8e6e6", alpha = .5, size = 1) + geom_density(data = P0_Contempgraphs_gv, color = "black",
fill = "#757474", alpha = .75, size = 1) + theme_minimal() + labs(x = "Depressed mood-Calm:
Contemporaneous estimates", y = "Density")
```

Calcualting ML-VAR model stability

```
MyMoodMLVAR_wcomp_RS_c_expinf <- matrix(ncol=12)
MyMoodMLVAR_wcomp_RS_t_in_expinf <- matrix(ncol=12)
MyMoodMLVAR_wcomp_RS_t_out_expinf <- matrix(ncol=12)

counter <- 0
while(counter < 100)
{
  MyMoodMLVAR_wcomp_RS <-
mlVAR(MyMoodCombinedShort[MyMoodCombinedShort$ID %in%
sample(unique(MyMoodCombinedShort$ID),28),],
            vars = colnames(MyMoodCombinedShort)[4:15],
            idvar = "ID",
            dayvar = "Day",
            beepvar = "Survey",
            contemporaneous = "correlated",
            temporal = "correlated")
  counter <- counter + 1
}
```

#Saving centrality estimates from resampled network

```
MyMoodMLVAR_wcomp_RS_c_expinf <-
rbind(MyMoodMLVAR_wcomp_RS_c_expinf,centrality(getWmat(plot(MyMoodMLVAR_wco
mp_RS, "contemporaneous", DoNotPlot = TRUE)))$InExpectedInfluence)
```

```
MyMoodMLVAR_wcomp_RS_t_in_expinf <-
rbind(MyMoodMLVAR_wcomp_RS_t_in_expinf,centrality(getWmat(plot(MyMoodMLVAR_w
comp_RS, "temporal", DoNotPlot = TRUE)))$InExpectedInfluence)

MyMoodMLVAR_wcomp_RS_t_out_expinf <-
rbind(MyMoodMLVAR_wcomp_RS_t_out_expinf,centrality(getWmat(plot(MyMoodMLVAR_
wcomp_RS, "temporal", DoNotPlot = TRUE)))$OutExpectedInfluence)

colnames(MyMoodMLVAR_wcomp_RS_c_expinf) <- c("DHP", "Calm", "Irritated", "Anxious",
"Lonely", "Accomp", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restl", "Focused")
MyMoodMLVAR_wcomp_RS_c_expinf <- MyMoodMLVAR_wcomp_RS_c_expinf[2, ]

colnames(MyMoodMLVAR_wcomp_RS_t_in_expinf) <- c("DHP", "Calm", "Irritated",
"Anxious", "Lonely", "Accomp", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restl", "Focused")
MyMoodMLVAR_wcomp_RS_t_in_expinf <- MyMoodMLVAR_wcomp_RS_t_in_expinf[2, ]

colnames(MyMoodMLVAR_wcomp_RS_t_out_expinf) <- c("DHP", "Calm", "Irritated",
"Anxious", "Lonely", "Accomp", "Hungry", "PhysAct", "Avoid", "Drowsy", "Restl", "Focused")
MyMoodMLVAR_wcomp_RS_t_out_expinf <- MyMoodMLVAR_wcomp_RS_t_out_expinf[2,
]

#Saving centrality estimates from original network
MyMoodMLVAR_wcomp_c_expinf <- centrality(getWmat(plot(MyMoodMLVAR_wcomp,
"contemporaneous", DoNotPlot = TRUE)))$InExpectedInfluence

MyMoodMLVAR_wcomp_t_in_expinf <- centrality(getWmat(plot(MyMoodMLVAR_wcomp,
"temporal", DoNotPlot = TRUE)))$InExpectedInfluence

MyMoodMLVAR_wcomp_t_out_expinf <-
centrality(getWmat(plot(MyMoodMLVAR_wcomp)))$OutExpectedInfluence

#Correlating centrality estimates from original and resampled networks
MLVARrsExpInfcor <- round(cor(MyMoodMLVAR_wcomp_RS_c_expinf,
MyMoodMLVAR_wcomp_c_expinf, method = 'spearman'),3)

MLVARrsInExpInfcor <- round(cor(MyMoodMLVAR_wcomp_RS_t_in_expinf,
MyMoodMLVAR_wcomp_t_in_expinf, method = 'spearman'),3)

MLVARrsOutExpInfcor <- round(cor(MyMoodMLVAR_wcomp_RS_t_out_expinf,
MyMoodMLVAR_wcomp_t_out_expinf, method = 'spearman'),3)

MLVARrsCor <- rbind(MLVARrsExpInfcor, MLVARrsInExpInfcor, MLVARrsOutExpInfcor)

sink("MLVARrsCor_9.27.21.txt")
MLVARrsCor
sink()
```

Code from previous data analytic approach using dynamic structural equation modeling

Aim 1: Mplus Code for Lag 1 Multilevel Models

```
INPUT INSTRUCTIONS
TITLE: MyMood Multilevel Model - Down variable only
DATA: file is MyMood_datafull_DSEM.csv;
VARIABLE:
NAMES      = ID Day Surv No Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct SocAv
Drow Pleas Restl Foc;
CLUSTER    = ID;
USEVAR     = Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct SocAv Drow Pleas Restl
Foc Day Surv;
LAGGED     = Down(1) Hap(1) Calm(1) Irrit(1) Anx(1) Lon(1) Accomp(1) Hung(1) PhyAct(1)
SocAv(1) Drow(1) Pleas(1) Restl(1) Foc(1);
TINTERVAL  = No(1);
MISSING    = all(-99);
ANALYSIS:  TYPE IS TWOLEVEL RANDOM;
ESTIMATOR = BAYES;
PROC = 2;

MODEL:
 %WITHIN%
!Random slope for Down_t regressed on Down_t-1 (autoregression), etc.
p_Dwn | Down ON Down&1;

!Random slope for Hap_t-1, etc. predicting Down_t (cross-lagged)
p_HapD | Down ON Hap&1;
p_ClmD | Down ON Calm&1;
p_IrrD | Down ON Irrit&1;
p_AnxD | Down ON Anx&1;
p_LonD | Down ON Lon&1;
p_AccD | Down ON Accomp&1;
p_HngD | Down ON Hung&1;
p_PhAD | Down ON PhyAct&1;
p_SAvD | Down ON SocAv&1;
p_DrwD | Down ON Drow&1;
p_PlsD | Down ON Pleas&1;
p_RstD | Down ON Restl&1;
p_FocD | Down ON Foc&1;

!Random slope for Down_t regressed on Day, etc.
Day_Dwn | Down ON Day;
Day_Hap | Hap ON Day;
Day_Clm | Calm ON Day;
Day_Irr | Irrit ON Day;
Day_Anx | Anx ON Day;
```

```
Day_Lon | Lon ON Day;
Day_Acc | Accomp ON Day;
Day_Hng | Hung ON Day;
Day_PhA | PhyAct ON Day;
Day_SAv | SocAv ON Day;
Day_Drw | Drow ON Day;
Day_Pls | Pleas ON Day;
Day_Rst | Restl ON Day;
Day_Foc | Foc ON Day;

!Random slope for Down_t regressed on Surv, etc.
Surv_Dwn | Down ON Surv;
Surv_Hap | Hap ON Surv;
Surv_Clm | Calm ON Surv;
Surv_Irr | Irrit ON Surv;
Surv_Anx | Anx ON Surv;
Surv_Lon | Lon ON Surv;
Surv_Acc | Accomp ON Surv;
Surv_Hng | Hung ON Surv;
Surv_PhA | PhyAct ON Surv;
Surv_SAv | SocAv ON Surv;
Surv_Drw | Drow ON Surv;
Surv_Pls | Pleas ON Surv;
Surv_Rst | Restl ON Surv;
Surv_Foc | Foc ON Surv;

!Random unique innovation variance (error)
errD | Down;
errH | Hap;
errC | Calm;
errI | Irrit;
errA | Anx;
errL | Lon;
errAc | Accomp;
errHn | Hung;
errPA | PhyAct;
errSA | SocAv;
errDr | Drow;
errP | Pleas;
errR | Restl;
errF | Foc;

%BETWEEN%
p_Dwn;
p_HapD;
p_ClmD;
```

```
p_IrrD;
p_AnxD;
p_LonD;
p_AccD;
p_HngD;
p_PhAD;
p_SAvD;
p_DrwD;
p_PlsD;
p_RstD;
p_FocD;

OUTPUT: TECH1 TECH8 STDYX STAND(CLUSTER) FSCOMPARISON;
PLOT: TYPE = PLOT3; FACTOR =ALL;
savedata: file is ests2-21-19.dat;
save = fscores (1000);
missflag=-99;
```

Mplus Code for Lag 2 Multilevel Models

```
INPUT INSTRUCTIONS
TITLE: MyMood Multilevel Model - Down variable only, lag 2
DATA: file is MyMood_datafull_DSEM.csv;
VARIABLE:
NAMES      = ID Day Surv No Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct SocAv
Drow Pleas Restl Foc;
CLUSTER    = ID;
USEVAR     = Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct SocAv Drow Pleas Restl
Foc Day Surv;
LAGGED     = Down(2) Hap(2) Calm(2) Irrit(2) Anx(2) Lon(2) Accomp(2) Hung(2) PhyAct(2)
SocAv(2) Drow(2) Pleas(2) Restl(2) Foc(2);
TINTERVAL  = No(2);
MISSING    = all(-99);
ANALYSIS:  TYPE IS TWOLEVEL RANDOM;
ESTIMATOR = BAYES;
PROC = 2;

MODEL:
 %WITHIN%
!Random slope for Down_t regressed on Down_t-1 (autoregression), etc.
p_Dwn | Down ON Down&1;
p_Dwn2 | Down ON Down&2;

!Random slope for Hap_t-1, etc. predicting Down_t (cross-lagged)
p_HapD | Down ON Hap&1;
p_ClmD | Down ON Calm&1;
p_IrrD | Down ON Irrit&1;
```

```
p_AnxD | Down ON Anx&1;
p_LonD | Down ON Lon&1;
p_AccD | Down ON Accomp&1;
p_HngD | Down ON Hung&1;
p_PhAD | Down ON PhyAct&1;
p_SAvD | Down ON SocAv&1;
p_DrwD | Down ON Drow&1;
p_PlsD | Down ON Pleas&1;
p_RstD | Down ON Restl&1;
p_FocD | Down ON Foc&1;

p_HapD2 | Down ON Hap&2;
p_ClmD2 | Down ON Calm&2;
p_IrrD2 | Down ON Irrit&2;
p_AnxD2 | Down ON Anx&2;
p_LonD2 | Down ON Lon&2;
p_AccD2 | Down ON Accomp&2;
p_HngD2 | Down ON Hung&2;
p_PhAD2 | Down ON PhyAct&2;
p_SAvD2 | Down ON SocAv&2;
p_DrwD2 | Down ON Drow&2;
p_PlsD2 | Down ON Pleas&2;
p_RstD2 | Down ON Restl&2;
p_FocD2 | Down ON Foc&2;

!Random slope for Down_t regressed on Day, etc.
Day_Dwn | Down ON Day;
Day_Hap | Hap ON Day;
Day_Clm | Calm ON Day;
Day_Irr | Irrit ON Day;
Day_Anx | Anx ON Day;
Day_Lon | Lon ON Day;
Day_Acc | Accomp ON Day;
Day_Hng | Hung ON Day;
Day_PhA | PhyAct ON Day;
Day_SAv | SocAv ON Day;
Day_Drw | Drow ON Day;
Day_Pls | Pleas ON Day;
Day_Rst | Restl ON Day;
Day_Foc | Foc ON Day;

!Random slope for Down_t regressed on Surv, etc.
Surv_Dwn | Down ON Surv;
Surv_Hap | Hap ON Surv;
Surv_Clm | Calm ON Surv;
Surv_Irr | Irrit ON Surv;
```

```
Surv_Anx | Anx ON Surv;
Surv_Lon | Lon ON Surv;
Surv_Acc | Accomp ON Surv;
Surv_Hng | Hung ON Surv;
Surv_PhA | PhyAct ON Surv;
Surv_SAv | SocAv ON Surv;
Surv_Drw | Drow ON Surv;
Surv_Pls | Pleas ON Surv;
Surv_Rst | Restl ON Surv;
Surv_Foc | Foc ON Surv;

!Random unique innovation variance (error)
errD | Down;
errH | Hap;
errC | Calm;
errI | Irrit;
errA | Anx;
errL | Lon;
errAc | Accomp;
errHn | Hung;
errPA | PhyAct;
errSA | SocAv;
errDr | Drow;
errP | Pleas;
errR | Restl;
errF | Foc;

%BETWEEN%
p_Dwn;
p_HapD;
p_ClmD;
p_IrrD;
p_AnxD;
p_LonD;
p_AccD;
p_HngD;
p_PhAD;
p_SAvD;
p_DrwD;
p_PlsD;
p_RstD;
p_FocD;

p_Dwn2;
p_HapD2;
p_ClmD2;
```

```
p_IrrD2;
p_AnxD2;
p_LonD2;
p_AccD2;
p_HngD2;
p_PhAD2;
p_SAvD2;
p_DrwD2;
p_PlsD2;
p_RstD2;
p_FocD2;

OUTPUT: TECH1 TECH8 STDYX STAND(CLUSTER) FSCOMPARISON;
PLOT: TYPE = PLOT3; FACTOR =ALL;
savedata: file is estslagtwo2-25-19.dat;
save = fscores (1000);
missflag=-99;
```

Aim 2: Mplus Code for Lag 1 Person-specific Models

```
INPUT INSTRUCTIONS
TITLE:     DSEM for MyMood_001: Down only
DATA:      FILE IS MyMood_001mplusDSEM.csv;
VARIABLE:  NAMES ARE Day Surv Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct
SocAv Drow Pleas Restl Foc;
USEVARIABLES ARE Day Surv Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct SocAv
Drow Pleas Restl Foc;
lagged = Down(1) Hap(1) Calm(1) Irrit(1) Anx(1) Lon(1) Accomp(1) Hung(1) PhyAct(1)
SocAv(1) Drow(1) Pleas(1) Restl(1) Foc(1);
MISSING = ALL (-99);
ANALYSIS: ESTIMATOR = BAYES;
PROCESSORS = 2;
fbiter = (20800);
!thin = 100;

model:
Down on Surv;
Hap on Surv;
Calm on Surv;
Irrit on Surv;
Anx on Surv;
Lon on Surv;
Accomp on Surv;
Hung on Surv;
PhyAct on Surv;
SocAv on Surv;
Drow on Surv;
```

```
Pleas on Surv;
Restl on Surv;
Foc on Surv;

Down on Day;
Hap on Day;
Calm on Day;
Irrit on Day;
Anx on Day;
Lon on Day;
Accomp on Day;
Hung on Day;
PhyAct on Day;
SocAv on Day;
Drow on Day;
Pleas on Day;
Restl on Day;
Foc on Day;

Down on Down&1 Hap&1 Calm&1 Irrit&1 Anx&1 Lon&1 Accomp&1 Hung&1
PhyAct&1 SocAv&1 Drow&1 Pleas&1 Restl&1 Foc&1;

OUTPUT: TECH1 TECH8;
stand;
PLOT: TYPE = PLOT3;
```

Mplus Code for Lag 2 Person-specific Models

```
INPUT INSTRUCTIONS
TITLE:     DSEM for MyMood_003: Down only
DATA:      FILE IS MyMood_003mplusDSEM.csv;
VARIABLE:  NAMES ARE Day Surv Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct
SocAv Drow Pleas Restl Foc;
USEVARIABLES ARE Day Surv Down Hap Calm Irrit Anx Lon Accomp Hung PhyAct SocAv
Drow Pleas Restl Foc;
lagged = Down(2) Hap(2) Calm(2) Irrit(2) Anx(2) Lon(2) Accomp(2) Hung(2) PhyAct(2)
SocAv(2) Drow(2) Pleas(2) Restl(2) Foc(2);
MISSING = ALL (-99);
ANALYSIS: ESTIMATOR = BAYES;
PROCESSORS = 2;
fbiter = (10400);
!thin = 100;

model:
Down on Surv;
Hap on Surv;
Calm on Surv;
```

```
Irrit on Surv;
Anx on Surv;
Lon on Surv;
Accomp on Surv;
Hung on Surv;
PhyAct on Surv;
SocAv on Surv;
Drow on Surv;
Pleas on Surv;
Restl on Surv;
Foc on Surv;

Down on Day;
Hap on Day;
Calm on Day;
Irrit on Day;
Anx on Day;
Lon on Day;
Accomp on Day;
Hung on Day;
PhyAct on Day;
SocAv on Day;
Drow on Day;
Pleas on Day;
Restl on Day;
Foc on Day;

Down on Down&1 Hap&1 Calm&1 Irrit&1 Anx&1 Lon&1 Accomp&1 Hung&1
PhyAct&1 SocAv&1 Drow&1 Pleas&1 Restl&1 Foc&1;

Down on Down&2 Hap&2 Calm&2 Irrit&2 Anx&2 Lon&2 Accomp&2 Hung&2
PhyAct&2 SocAv&2 Drow&2 Pleas&2 Restl&2 Foc&2;

OUTPUT: TECH1 TECH8;
stand;
PLOT: TYPE = PLOT3;
```