Supporting MPlus Code to Publication on Phenotypic Subtyping in Depression

The current repository will contain example input files for each of the analyses run as part of a paper called Identifying depression subtypes and investigating their consistency and transitions in a 1-year cohort analysis. These files are best used in conjunction with the paper.

Title: Identifying depression subtypes and investigating their consistency and transitions in a 1-year cohort analysis

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Abstract:

Major depressive disorder (MDD) is defined by an array of symptoms that make it challenging to understand the condition at a population level. Subtyping offers a way to unpick this phenotypic diversity for improved disorder characterisation. We aimed to identify depression subtypes longitudinally using the Inventory of Depressive Symptomatology: Self-Report (IDS-SR).

A secondary analysis of a two-year cohort study, collecting data every three months from patients with a history of recurrent MDD in the United Kingdom, the Netherlands, and Spain (N=619). We used latent class and latent transition analysis to identify subtypes at baseline, determined their consistency at 6- and 12-month follow-ups, and examined transitions over time.

We identified a 4-class solution: (1) severe with appetite decrease, (2) severe with appetite increase, (3) moderate severity and (4) low severity. These same classes were identified at 6- and 12-month follow-ups, and participants tended to remain in the same class over time. We found no statistically significant differences between the two severe subtypes regarding baseline clinical and sociodemographic characteristics.

The directionality of findings linking medication use and class membership should be interpreted cautiously as medication adherence was assessed using self-report and participants may have been exposed to polypharmacy.

Our findings emphasize severity differences over symptom types, suggesting that current subtyping methods provide insights akin to existing severity measures. When examining transitions, participants were most likely to remain in their respective classes over 1-year, indicating chronicity rather than oscillations in depression severity. Future work recommendations are made.

Base_LCA: Mplus input code to estimate the latent class analysis model

LCA_partial_dependence: Mplus input code to estimate the latent class analysis model with partial dependence

One-step_LTA_measurement_invariant: Mplus input code to estimate the latent transition analysis model with measurement invariance

One-step_LTA_measurement_variant: Mplus input code to estimate the latent transition analysis model without measurement invariance across time-points

Three-step LTA - Step1: Joint LCA model: Mplus input code for the three-step latent transition analysis procedure. Step 1: Running joint LCA model with measurement invariance (i.e., LTA without autoregressive pathways).

Three-step LTA - Step2.1: Running latent class analysis for time 1 (baseline): Next, we run LCAs at each timepoint, here you see the code for baseline analysis. The aim is to save the participant's most probable latent class at each timepoint, while also recording the measurement errors for each latent class variable as recorded in the output section called "Logits for the Classification Probabilities for the Most likely latent class membership". To do this the measurement models for each of the latent classes are fixed using the starting values from step 1.

Three-step LTA - Step2.2: Running latent class analysis for time 2: The c1.dat file includes all the variables from our data.txt file (that we marked as auxiliary) but now also includes the most likely latent class variable for each participant called N1. We now use that data file to obtain a variable for the most likely class for each participant at 6 months

Three-step LTA - Step2.3: Running latent class analysis for time 3: You do the exact same thing as in the previous steps: 2.1 and 2.2

Three-step LTA - Step3: Estimating the final auxiliary model: We use the most likely latent class variables at each of the timepoints (N1, N2, N3) and the pre-fixed error rates obtained from the "Logits for the Classification Probabilities for the Most likely latent class membership" section of each of the outputs in step 2, to run a final LTA model.

Three-step LTA with added covariates: To include covariates in the model, the three-step LTA code detailed in "Three-step LTA - Step 3" was amended by adding the below to the model. All covariates were entered separately into the models as predictors of baseline class status adjusting for age and gender. Models including only age and gender were estimated independently without any confounders.