**Supplement**

The present study used time homogeneous Latent Markov Modelling (LMM) to identify latent states and latent transition classes. LMM is preferable to non-latent-variable techniques because it reduces the impact of measurement error on parameter estimates and standard errors that originate from self-report of, for example, alcohol use, and thus on its impact on defining states and transitions between states over time [1]. Time-homogeneous LMM with increasing numbers of latent states and transition classes were estimated using the Markov module of the statistical programme Latent GOLD 5.1 [2].

First, latent states were identified. This was based on two dichotomous variables (high average alcohol consumption (HAAC) and alcohol use disorder (AUD)) while using data from all four waves. Based on previous research [3,4], we expected to find a 4-state model, but to be complete, we examined a broader range of 1-5 states. Second, we examined whether 3-year transitions between states could be classified in latent transition classes. By default, first unrestricted models were explored in which any type of transition class can be observed in the data. We also looked at a special type of transition model, namely the Mover-Stayer LMM which assumes the presence of two specific types of transition classes: ‘stayers’ who remain in their original state during all waves, and ‘movers’ with probabilities significantly larger than zero of a transition from one state to another between any of two consecutive waves. To avoid convergence to local maxima, the number of random start-sets and initial iterations per start-set were set at 160 and 2500, respectively. To determine the optimal number of latent states and classes, we used the Bayesian Information Criterion (BIC, smallest value preferred), the Akaike Information Criterion (AIC, smallest value preferred), and the corrected AIC with a penalty factor of 3 (AIC3, smallest value preferred), as well as the interpretability of the derived models (in keeping with [5]).

Lastly, respondents were assigned to the latent states at the four waves and to the transition classes with weights reflecting the certainty of their states and class membership. This was automatically achieved by storing the posterior classifications.

*Identifying latent states and classes*

First, time-homogeneous LMM with 1-5 latent states were examined (see ‘step a’ in Table S1). The BIC of the 3-state solution was lowest, but AIC and AIC3 were lower for the 4-state solution. The 5-state solution showed somewhat worse fit statistics than the 4-state model and resulted in some very small states without clear interpretability. Therefore, latent transition classes were only examined for the 3- and 4-state models.

The unrestricted models revealed transition patterns similar to the predefined patterns in the restricted mover-stayer models. As the restricted mover-stayer models were more parsimonious, easier to interpret and had slightly better fit statistics, the unrestricted models were rejected at this point (‘step b’ in Table S1).

Fit statistics of the 3- and 4-state mover-stayer models were somewhat comparable, but the profile plots revealed that the 4-state mover-stayer model identified a meaningful, but small state which was lumped together in the 3-state model. This state represented a problematic group with high proportions of both HAAC and AUD (see state 4 in Table 1). Thus, the 4-state mover-stayer model described our data best.

[Table S1]

**References**

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