**Supplementary Material (S1)**

***Statistical Analysis Section (S1)***

*Standard and penalized binary logistic regression (LR)*. Standard LR and LASSO analyses were conducted using the *glmnet* package (Friedman, Hastie & Tibshirani, 2010). All predictors were entered into the model simultaneously as main effects (no interactions). Standard LR imposes no penalisation on regression coefficients. Penalised logistic regression was estimated using the least absolute shrinkage and selection operator (LASSO) (Tibshirani, 1996). The LASSO employs the L1 penalty (constraint based on the sum of the absolute value of regression coefficients) which shrinks the coefficients of unimportant predictors towards 0. Automatic feature selection occurs whereby selected predictors have coefficients greater than 0. The strength of LASSO penalty was selected using 5-fold cross-validation.

Predictive performance of both standard and LASSO regression was determined based on 100 iterations of training-testing data splits. For the LASSO, 10 iterations of 5-fold cross-validation were implemented to select penalty strength in the training data. Identified predictors of both standard and LASSO logistic regression were identified using the full sample (no training-testing split) as suggested (Ahn et al., 2016).

*Prediction rule ensemble*. PREs (Fokkema & Strobl, 2020) take as inputs a set of possible predictor variables, which are evaluated for their capacity to distinguish categories of a binary outcome (ED vs Non-ED, and AN vs BN in this study). Each predictor can be entered into the model as an individual predictor (i.e., a main effect) or in combination with one or more additional predictors (i.e., an interaction effect). Unlike main effects and interaction terms in conventinal LRs, PREs use an automated search function (a recursive partitioning approach) that tries to find a cutting point on independent variables that maximally separates the categories of the binary outcome. This process continues until a stop rule criterion is met (e.g., limit to the number of predictors to include in the final model, or absence of additional predictors that could significantly improve group membership prediction). As an ensemble approach, PREs repeat this process of generating a predictor set (500 times, by default) and provide a statistical average across these iterations that is more accurate than relying on a single model/set of results. The output of this ensemble is a set of prediction rules, in the form of IF…THEN statements, with coefficients expressed in log odds to indicate likelihood of belonging to the target outcome group (e.g., an individual with BMI > 30 and family history of an ED has log odds of .50 for having an ED).

In the present study, the *pre*-package in R (Fokkema & Strobl, 2020) was used for PREs on the current dataset. Default settings in *pre* tend to err on the side of avoiding model overfitting, and were thus retained in the present study. Supplementary analyses show that adjustments to these defaults only marginally improve model accuracy, justifying retention of these default settings. In the Results section, we report decision rules deriving from our PREs, coefficients to indicate the relative importance of each of these decision rules, and feature importance statistics to further clarify the key predictor variables that enabled differentiation of the categories of our outcome variables.

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