

Statistical Analyses

Exploratory Factor Analysis (EFA). The first subset of the collected sample was used to identify the number of components underlying the personality items in our dataset, with a top-down approach as proposed by Goldberg (2006). This means that a series of EFAs was run within each item group allocated to a specific Big Five domain. Velicer's (1976) Minimum Average Partial (MAP) and Horn's (1965) Parallel Analysis (PA) methods were applied in order to guide the subsequent factor analysis. EFAs were calculated via Mplus (Muthen et al., 2012) using geomin rotation and Maximum Likelihood (ML) estimation. Decisions to retain facets were partly based on model fit information (CFI, RMSEA, SRMR) and partly on the interpretability of the facet solution. Additionally, alternative facet models inspired from other personality measures were considered and compared to the facet structure found. In case of omission of relevant content captured in other models, new items were added a-posteriori.

Reliability. Cronbach's α and McDonald's ω were estimated for each facet score to provide evidence for the test scores' internal consistency. For the domains, only McDonald's ω was estimated. The second subsample was used to compute these statistics.

Confirmatory Factor Analysis (CFA). To verify the structure outlined by EFAs, one CFA per facet was fitted using the second subsample. We restricted the number of possible indicators to a maximum of five per facet in order to obtain facets as balanced as possible (Ziegler, 2014). This selection was done based on item content and pattern of the factor loading matrix. CFAs were fitted using WLSMV (Weighted Least Squares adjusted for Means and Variances) for ordered indicators due to floor and ceiling effects on some item's response distribution. Model fit was determined based on the usual

goodness-of-fit indicators: the Cumulative Fit Index (CFI), for which a score > 0.95 indicates adequate fit; the Root Mean Square of Approximation (RMSEA), for which a value < 0.06 indicates approximate fit; and the Standardized Root Mean Residual (SRMR), for which a value < 0.05 indicates adequate fit.

Exploratory Structural Equation Modelling (ESEM). In a third step with the second subsample, the higher order structure of the facets was tested with ESEM (Asparouhov et al., 2009) using facet scores as indicators of the five domains. ESEM was the preferred procedure as it allows to relax the too strict independent clusters model in which CFA is usually performed (Marsh et al., 2010), allowing cross-loadings that would be otherwise constrained to zero, thereby accommodating personality data more realistically. As a control mechanism for content-validity, we eliminated any facet with non-significant loadings from its intended domain. The ESEM model was fitted using geomin oblique rotation and ML estimation.

Nomological network. In order to examine preliminary evidence of construct validity of our proposed facet model, a nomological network linking our constructs with external outcomes was tested. This network was constructed by examining associations with a set of linear models and zero-order correlations. Pearson correlations were calculated for each outcome with both facets and domains' scores. One linear model per domain and per criteria was fitted, using all facets included in the domains as predictors, but excluding the domain sum-scores. Standardized coefficients for each predictor (β) were reported, as well as the R^2 of the overall model -to represent associations at the domain level.

To guide the interpretation of the nomological network results, a set of hypotheses derived from research summarized in the introduction were investigated:

- H1. SWL will be predicted by facets of emotional stability mimicking NEO-PI-R depression, and facets of extraversion covering positive emotions, with a big to moderate effect size, in line with Schimmack et al. (2004). Emotional stability and extraversion will be most important domains in the personality-SWL association.
- H2. Conscientiousness will be associated with academic achievement with a small to moderate effect size. Openness will entail facets with positive effects and facets with negative effects on GPA scores.
- H3. Conscientiousness will yield the strongest associations with absenteeism at the domain level, and facets tapping volitional components such as goal orientation or wish to work will stand out. Some specific facets of openness and of extraversion will also be significantly associated with absenteeism. Overall, the facet level will provide a clearer picture to predict academic absenteeism from personality than the domain level.

References

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