The Factor Structure of Big Five Personality Trait Measures at the Between- and Within-
Person Levels

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Author Note

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This paper makes use of data of the LISS (Longitudinal Internet studies for the Social Sciences) panel administered by CentERdata (Tilburg University, The Netherlands). This paper also uses unit record data from the Household, Income and Labour Dynamics in Australia Survey (HILDA) conducted by the Australian Government Department of Social Services (DSS). The findings and views reported in this paper, however, are those of the

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Abstract

The Big Five personality factors were discovered through exploratory factor analysis (EFA) of cross-sectional data. The cross-sectional factor structure is a weighted blend of the factor structure at the between-person level (i.e., the level of time-invariant interpersonal personality differences) and the factor structure at the within-person level (i.e., the level of intrapersonal personality fluctuations and changes). Thus, the Big Five might not represent the underlying factors at either of the two levels. To probe this issue, I fit multilevel confirmatory factor analysis (CFA) and EFA models to longitudinal data from a Dutch and an Australian panel study ($N = 15,085$ and $22,582$, respectively). In both data sets, the canonical Big Five factor structure emerged at the between-person but not at the within-person level. At the within-person level, a two-factor structure appeared to be most suitable. The first of the two factors reflected positivity bias. The second factor reflected neuroticism or negativity bias. This suggests that the used Big Five measures assessed changes in positive and negative attitudes towards the self rather than changes in the personality aspects that the Big Five items intended to assess. Thus, more research on how to measure and analyze changes in personality traits is needed.

Keywords: five factor model, personality development, personality change, personality structure, multilevel modeling

The Factor Structure of Big Five Personality Trait Measures at the Between- and Within-Person Levels

The Big Five personality factors were proposed in order to explain the relatively stable individual differences in people's cognition, emotion, and behavior. The five factors originated from the exploratory factor analysis (EFA) of cross-sectional associations among personality items (e.g., Goldberg, 1990; Norman, 1963; Tupes & Christal, 1961/1992). Yet, like any cross-sectional data analysis, cross-sectional EFA is unable to partition the observed personality data into (a) time-invariant between-person variation (i.e., average or typical response behavior across all measurement occasions) that might be due to an enduring signal from DNA variation and (b) within-person variation over time (i.e., temporal deviations from the typical response behavior, that is, fluctuations and changes in response behavior) that might be due to environmental influences such as a traumatic event (e.g., Borsboom et al., 2003; Cattell, 1955; Hamaker et al., 2017; Molenaar, 2004; Roberts, 2018).

The two levels are *not* analyzed separately in cross-sectional EFA. Thus, factor structures found in cross-sectional EFA are a weighted blend of between- and within-person factor structures (e.g., Hamaker et al., 2017). That is, responses to a personality trait questionnaire at a single measurement occasion and thus its cross-sectional factor structure are not only impacted by time-invariant between-person differences in personality but also by temporary within-person changes and fluctuations in personality. Because past empirical research has almost exclusively investigated the factor structure of Big Five trait measures with cross-sectional EFA, it is unclear whether the Big Five factor structure found in past research holds at the between-person level, at the within-person level, at both levels, or at neither level. For example, longitudinal data analysis of the Social Provision Scale suggested that the between-person variance of the scale is characterized by one common factor, whereas the within-person variance of the scale is characterized by two common factors (Hamaker et al., 2017). Similarly, the factor structures of the Big Five scales found at the between-and

within-person levels might differ from each other and from the Big Five factor structure found in past cross-sectional data analysis. These possibilities are examined in the current study.

Between- and within-person levels are increasingly distinguished by personality researchers in longitudinal data analysis of personality trait measures. Trait measures are measures that refer to long time frames such as “in general” as opposed to short time frames such as in the “last two hours” or “today”. However, the partitioning of the variance of trait measures into between- and within-person variance usually only occurs in the structural part of the analysis rather than in both the structural and measurement parts of the analysis. That is, longitudinal personality researchers typically apply structural equation models that have two major parts, the measurement model and the structural model. The measurement model specifies the relationships between latent variables and observed variables that are assumed to be indicators of the latent variables. The structural model specifies relationships among the latent variables and observed variables that are not indicators of any latent variables (e.g., Ho et al., 2012). The between- and within-person levels are usually, if at all, distinguished in the structural model but not in the measurement model. For example, personality researchers have distinguished the between- and within-person levels when investigating how personality traits are related to subjective well-being but not when specifying a measurement model for personality or subjective well-being scales (e.g., Fetvadjiev & He, 2019; Hill et al., 2012).

The underlying, untested assumption is that the between- and within-person factor structures are configurally and metrically invariant and do not need to be disaggregated in the measurement part of the analysis (e.g., Hamaker et al., 2007; Hamaker et al., 2017).

Configural invariance implies the same number of factors at both levels and that each item loads on the same factor at both levels. Metric (weak) factorial invariance additionally implies that the strengths of the unstandardized factor loadings are equivalent across both levels.

Figure 1 provides four examples of configural and metric factorial invariance, or lack thereof, across between- and within-person levels (Figure 1 and Figure S1). In the example displayed

in Panel A of Figure 1, the time-invariant random intercepts of Items 1 to 3 load on the between-person factor b_1 and the time-specific deviations from these random intercepts load on the within-person factor w_1 . The time-invariant random intercepts of Items 4 to 6 load on the between-person factor b_2 and the time-specific deviations from these random intercepts load on a within-person factor w_2 . That is, all six items show configural invariance across the two levels. Furthermore, as indicated by the identical parameter labels in Panel A, the strengths of the unstandardized factor loadings are identical at the between- and within-person levels. That is, all six items show also metric invariance. This invariance suggests that b_1 and w_1 represent the same construct. The variable b_1 would refer to enduring individual differences in the construct and the variable w_1 would refer to fluctuations or changes in the same construct. When configural and metric factorial invariance hold like it is the case in Panel A, the factor solution obtained via a cross-sectional factor analysis adequately represents both the between-person factor structure and the within-person factor structure because the two are identical (for details, see Hamaker et al., 2017). In this case, it would not be necessary to disaggregate the between- and within-person levels in the measurement part of the analysis.

The assumption of configural and metric invariance (Panel A) may be violated in several ways. First, in the violation displayed in Panel B of Figure 1, the same items load on b_1 and w_1 and the same items load on b_2 and w_2 (i.e., the items show configural invariance). Yet, the strengths of the unstandardized loadings are not identical across between- and within-person levels (i.e., there is a lack of metric invariance). For example, the random intercept of Item 1 may have an unstandardized loading of .50 on b_1 but the deviations from Item 1's random intercept may have an unstandardized loading of .30 on w_1 while Item 2 may have an unstandardized loading of .20 on b_1 but the deviations from Item 2's random intercept may have an unstandardized loading of .50 on w_1 . This lack of metric measurement invariance would indicate that b_1 on the one hand and w_1 on the other hand do not represent the same

construct. Second, in the violation displayed in Panel C of Figure 1, the items that load on b_1 at the between-person level are not the same items that load on w_1 at the within-person level. That is, there is a lack of configural invariance. For example, the random intercepts of Items 1, 2, and 3 load on b_1 but deviations from the random intercepts of Items 1, 2, and 4 load on w_1 . This lack of configural factorial invariance would also indicate that b_1 and w_1 do not represent the same construct. Third, in the violation displayed in Panel D of Figure 1, even the number of common factors varied across the two levels. The six items measure two common factors (b_1 and b_2) at the between-person level but only one common factor (w_1) at the within-person level. Again, this pattern suggests that b_1 and w_1 do not represent the same construct.

Figure 1

Multilevel Factor Models Illustrating (a) Configural and Metric Invariance Across Between- and Within-Person Levels, (b) Configural but not Metric Invariance, and (c and d) Absence of Configural and Metric Invariance

Note. b_1 and b_2 are common factors at the between-person level and w_1 and w_2 are common factors at the within-person level. r_1 to r_6 are the random intercepts for the six items. Unique between-person factors and unique within-person factors (including measurement error) are represented by arrows that point to the random intercepts and observed item scores, respectively. This illustration was inspired by figures in Muthén (2020) and the supplement of Hamaker et al. (2017). Longitudinal factor models illustrating the degrees of invariance can be found in Figure S1. $\lambda_{\#}$ = parameter label for unstandardized factor loading (identical labels indicate that the loadings are of equal strength); y_i = observed score on item i .

If any of these three violations are present (i.e., if there is a lack of metric and/or configural invariance across the two levels), the between-person and within-person factor structures differ from each other and would probably both differ from the cross-sectional factor structure as well. If these violations are present in data from Big Five trait measures, researchers studying time-invariant interpersonal personality differences or intrapersonal changes and fluctuations in personality may find it useful to assess and investigate the

personality dimensions that actually characterize the covariance of personality items at the between- or within-person level rather than the Big Five.

Let us imagine, for example, that the Big Five cannot be found at the between-person level, that only four factors can be identified at the between-person level. The implication would be that these four between-person factors are dimensions of personality differences that are time-invariant (at least over the course of the study). Completely time-invariant differences were called the “fixed system” of personality in the revised sociogenomic model by Roberts (2018). He referred to the stable portion of personality that is assumed to be primarily caused by an enduring signal from DNA variation that continues throughout one’s life.¹ Accordingly, if there were only four, rather than five, dimensions of time-invariant personality differences, then it would be reasonable for genetically informed studies to investigate the four dimensions rather than the Big Five as, theoretically, genes should be more strongly associated with the four between-person factors than with the five factors found in cross-sectional data. For example, genome-wide association studies (GWAS; e.g., Lo et al., 2017) could investigate how single nucleotide polymorphisms are associated with the four between-person dimensions rather than with the Big Five.

On the other hand, if it were to become clear that there are only three (not five) factors at the within-person level, say agency, communion, and morality, personality researchers could investigate how agency, communion, and morality develop and fluctuate over time rather than how the Big Five develop and fluctuate over time. In this case, it might *not* be meaningful to state that the Big Five traits conscientiousness, emotional stability, and agreeableness increase with age (i.e., maturity principle; e.g., Caspi et al., 2005; Brandes et al., 2021). Instead, theories on personality change might want to describe and explain how

¹ Please note that some research suggests that, although the stability of genetic influences is high throughout the life course, it is higher in adults than in youths (e.g., as a result of gene activation and deactivation related to puberty; Briley & Tucker-Drob, 2014). According to this research, genetic stability reaches unity at age 30 and remains nearly perfectly stably after 30.

and why agency, communion, and morality change with age. Furthermore, intensive longitudinal studies might want to focus on momentary fluctuations in agency, communion, and morality rather than the momentary fluctuations in the Big Five. Finally, personality interventions would probably be more effective if they targetted the three within-person factors (i.e., the dimensions in which individuals tend to differ from themselves over time) rather than between-person factors (i.e., dimensions of time-invariant personality differences) or the factors found in cross-sectional studies (i.e., weighted blend of between- and within-person factor structures; see also Hamaker et al., 2017). Taken together, the assumption that the Big Five factor structure holds across between- and within-person levels is fundamental to many research endeavors in personality psychology and a violation of this assumption has far-reaching consequences. Thus, an examination of this assumption seems to be warranted.

Some studies have already investigated the factor structure of the Big Five measures across between- and within-person levels. These studies used intensive longitudinal designs incorporating state measures (e.g., Borkenau & Ostendorf; 1998; Hamaker et al., 2005; Molenaar, 2004). The factorial invariance across between- and within-person levels cannot only be investigated with intensive longitudinal data and state measures but also with panel data and trait measures because trait measures assess not only time-invariant between-person differences but also fluctuations and changes in personality. Panel data and trait measures might be better equipped than intensive longitudinal data using state measures for discerning personality differences that are completely time-invariant from personality differences that are invariant only for a couple of weeks or months because panel data run for several years while intensive longitudinal studies tend to run only for a couple of weeks. Thus, the current study analyzed two panel data sets with multilevel confirmatory factor analysis (CFA) and EFA models (Asparouhov & Muthén, 2007; Hamaker et al., 2017) to investigate the factor structure of Big Five personality trait measures at the between- and within-person levels.

Previous research using state measures has typically focused on individual differences in the within-person factor structure and ideographic modeling techniques such as p-technique factor analysis (e.g., Beck & Jackson; 2020; Borkenau & Ostendorf, 1998; Cattell, 1955). The multilevel CFA and EFA models that I used did not investigate individual differences in the within-person factor structure but fixed the within-person covariances and the within-person factor structure across individuals. If there are no individual differences in the within-person structure, then the fixed within-person factor structure reflects the within-person factor structure of all panelists. If the within-person factor structure differs from individual to individual, then the fixed within-person factor structure is similar to the average of all within-person factor structures (Hamaker et al., 2017). The fixed within-person factor structure might not be very informative if there are individual differences because the number of factors, the meaning of the factors, and the causes, explanations, and underlying processes of the factors might vary from individual to individual. Thus, if there are individual differences, they should be investigated (e.g., Lee & Little, 2012). The current study was not able to investigate individual differences in the within-person factor structure because doing so would require data with a large two-digit number of measurement occasions (e.g., Lane et al., 2019). Instead, the current study nomothetically investigated the factor structure of Big Five personality trait measures at the between- and within-person levels.

Method

The R code, Mplus output files, and supplemental tables and figures for the current study are available on the OSF project page at https://osf.io/e9mkx/?view_only=699861f6ea264290ae4dbce57f9a53e1. The current study was exploratory. I did not preregister the study.

Participants and Procedure

LISS

The first data set was extracted from the ongoing Longitudinal Internet Studies for the Social sciences (LISS) panel administered by CentERdata (Tilburg University, The Netherlands; e.g., Scherpenzeel, 2011). Initial recruitment for the LISS panel was based on a probability sample of households drawn from the population register by Statistics Netherlands. I used data from 13 measurement occasions, spread across a period of 13 years: 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2017, 2018, 2019, 2020, and 2021. I did not use data from 2016 because the Big Five items were not administered in that year. I included all participants who had responded to at least some of the personality items on any of the 13 measurement occasions. The sample sizes for the 13 measurement occasions ranged from 508 to 6,791 (for details, see Table S1). The total sample size was 15,085. The mean age at Time 1 (in 2008) was 40.40 and 54% of respondents were women. For the question about the highest level of education completed, 6% indicated primary school, 21% indicated intermediate secondary education (junior high school), 11% indicated higher secondary education (senior high school), 23% indicated intermediate vocational education (junior college), 22% indicated higher vocational education (college), 11% indicated university, and the remaining 6% answered other or not yet completed/started. Researchers can apply for access to the data and attain further information about sampling, recruitment, response rates, and all core and background variables at <https://www.lissdata.nl/>. A list of publications that have utilized Big Five data from the LISS panel can be found at https://www.dataarchive.lissdata.nl/study_units/view/14.

HILDA

The second data set was extracted from the ongoing Household, Income and Labour Dynamics in Australia Survey (HILDA) conducted by the Australian Government Department of Social Services (DSS; e.g., Summerfield et al., 2020; Wilkins et al., 2020). Initial recruitment was based on a large national probability sample of Australian households occupying private dwellings. I used data from four measurement occasions spread across a

12-year period: 2005, 2009, 2013, and 2017. I choose these four measurement occasions because the Big Five items were only administered in these four years. In the current analysis, I included all participants who had responded to at least some of the personality items on any of the four measurement occasions. The sample sizes for the four measurement occasions ranged from 11,371 to 16,000 (for details, see Table S2). The total sample size was 22,582. The mean age at Time 1 (in 2005) was 35.98 and 53% of respondents were women. For the question about the highest level of education completed, 34% indicated less than high school completion (i.e., year 11 or below), 44% indicated that they completed high school (i.e., year 12) or other post-school qualification, and 22% indicated a Bachelor degree or higher degree (i.e., grad diploma, grad certificate, masters, or doctorate). Further information about the HILDA survey, including a list of publications that have used the data, can be found at <https://melbourneinstitute.unimelb.edu.au/hilda>. Researchers can apply for access to the data at <https://dataverse.ada.edu.au/dataverse.xhtml?alias=hilda>.

Measures

In the LISS panel, the Big Five personality traits were assessed with the 50-item International Personality Item Pool—Five-Factor Model measure (Goldberg, 1992; Goldberg et al., 2006). The items were administered with a 5-point rating scale ranging from 1 (*very inaccurate*) to 5 (*very accurate*). In the HILDA panel, the Big Five personality traits were assessed using a 36-item inventory following the trait descriptive adjectives approach of Saucier (1994). The items were administered with a 7-point rating scale ranging from 1 (*Does not describe me at all*) to 7 (*Describes me very well*). Negatively worded Big Five items were reverse coded for the computations of the descriptive statistics for the Big Five scales (Tables S1 to S4) and the multilevel CFA. However, for the item statistics (Tables S5 and S6) and the multilevel EFA, I did not reverse code the negatively worded items because it was unclear what personality dimension each item measures at the between- and within-person levels.

Reliabilities for all scales were acceptable to high (for α s, ω s, means, and standard deviations, see Tables S1 and S2). The zero-order correlations among the unweighted item means of each of the Big Five scales across the measurement occasions can be found in Tables S3 and S4.

Statistical Analyses

I used structural equation modeling and maximum likelihood estimation with corrected standard errors and chi-square test statistics (MLR) in Mplus (Version 8; Muthén & Muthén, 2017). I used MLR rather than conventional maximum likelihood estimation because MLR is considered superior to when ordinal response variable data are employed in latent variable modeling (e.g., Bandalos, 2014; Li, 2016). I ran all analyses using the R package MplusAutomation (version 0.7-3; Hallquist & Wiley, 2018).

Main Analysis

In the main analysis, I investigated configural factorial invariance across between- and within-person levels by examining the factor structure at the two levels using multilevel CFA and EFA (Asparouhov & Muthén, 2007; Hamaker et al., 2017; Muthén, 2020).² In the multilevel CFA and EFA models, the Level 1 units, the measurement occasions, were nested within the Level 2 units, the individuals. Level 2, the between-person level, represented time-invariant differences in item responses (i.e., random intercepts). Each panelist's value on an item at the between-person level was similar to the response of the panelist to the item averaged across all measurement occasions. Level 1, the within-person level, represented fluctuations and changes in item responses (i.e., time-specific deviations from the random intercepts). The multilevel CFA and EFA distinguished between four sources of variance: (a)

² For all multilevel models, Mplus issued the warning that the personality items had no variation within numerous clusters (i.e., participants). An item has no variation within a cluster when a participant chooses the same response category to a personality item at each measurement occasion. What is not known is the extent to which the lack of variation in some clusters (participants) influences the quality of the estimation (for details, see the Mplus output files on the OSF project page and <https://www.statmodel.com/download/WARNING%20One%20or%20more%20individual-level%20variables%20have%20no%20within-cluster%20variance>).

time-invariant sources of variance that were measured by more than one item and were thus represented by the common factors at the between-person level, (b) time-invariant sources of variance that were measured by only one item and were thus represented by the residual variances at the between-person level (see also *personality nuances* or *method effects*; e.g., Möttus et al., 2017; Geiser & Lockhart, 2012), (c) time-varying sources of variance that were measured by more than one item and were thus represented by the common factors at the within-person level, and (d) time-varying sources of variance that were measured by only one item and were thus represented by the residual variances at the within-person level (Hamaker et al., 2017; Muthén, 2020; Figure 1). The residual variances at the within-person level contained random measurement error.

Confirmatory Factor Analysis Models. In the multilevel CFA model with metric invariance constraints, the items loaded on the same factors at both levels (i.e., each item loading on its designated factor according to the canonical Big Five) and the unstandardized factor loadings were constrained to equality across the two levels (see Panel A in Figure 1). In the multilevel CFA model with configural invariance constraints, the items loaded again on the same factors at both levels (i.e., each item loading on its designated factor according to the canonical Big Five) but the unstandardized factor loadings were *not* constrained to equality across the two levels (see Panel B in Figure 1).

I judged the model fit of the CFA models on the basis of conventional guidelines as good (acceptable) if $CFI \geq .97$ ($\geq .95$), $RMSEA \leq .05$ ($\leq .08$), and $SRMR \leq .05$ ($\leq .10$; Schermelleh-Engel et al., 2003). The fit indices of the two CFA models would indicate metric noninvariance if $\Delta CFI \geq .01$ and $\Delta RMSEA \geq .015$ or $\Delta SRMR \geq .030$ (Chen, 2007).

Exploratory Factor Analysis Models. In the multilevel EFA analysis, I estimated nine EFA models with consecutively increasing number of factors (from 1 to 9) at the between-person level. In each of the nine models, an unrestricted (saturated) model was estimated at the within-person level. An unrestricted model is the H1 model which consists of

means, variances, and covariances but no factors. Vice versa, I estimated nine EFA models with consecutively increasing number of factors (from 1 to 9) at the within-person level while an unrestricted model was estimated at the between-person level in each of the nine models. For comparison, I also fit cross-sectional single-level EFA models to the LISS and HILDA data, respectively. In each of the 17 cross-sectional single-level EFA, I used data from only one of the measurement occasions of the LISS and HILDA panel, respectively.

To determine the optimal number of common factors for each of the EFA models, I inspected scree plots of eigenvalues, the RMSEA, and the differences in RMSEAs between a given model and the model with one additional factor, and I applied the Hull method (e.g., Lorenzo-Seva et al., 2011). Guidelines for EFA propose that all factor solutions with $RMSEAs < .050$ are good, differences in $RMSEAs \geq .020$ between a given model and the model with one additional factor are substantial, and differences in $RMSEAs \geq .010$ are marginally meaningful (e.g., Fabrigar & Wegener, 2012). For comparison, I also reported SRMRs but these fit indices played no role in the selection of the number of factors. I did not run a parallel analysis because parallel analysis for multilevel EFA was not accessible in Mplus.

In the first step of the Hull method, the range of factors to be considered is determined. I used a range from zero to nine factors. In the second step, the goodness-of-fit of a series of factor solutions is assessed. I used the CFI as a goodness-of-fit indicator (Lorenzo-Seva et al., 2011). To attain a CFI for zero factors, I fitted a multilevel CFA model with no factors at the level of interest and unrestricted covariances at the other level. In the third step, scree test values for all solutions placed on the convex hull of a hull plot are computed. The solution with the highest scree test value is considered to be the optimal number of factors.

After determining the optimal number of common factors, I used four different rotation criteria to obtain factor pattern matrices: geomin, oblimin, CF-varimax, and CF-equamax (e.g., Schmitt & Sass, 2011). I focused exclusively on the pattern matrices of

oblique rotations (as opposed to orthogonal rotations) because oblique rotations are the recommended standard, especially when some factors are correlated (e.g., Fabrigar & Wegener, 2012).

Robustness Checks

Chain-P Technique Factor Analysis. As a robustness check, I investigated the within-person factor structure with a chain-P technique factor analysis (e.g., Cattell & Scheier, 1961; Lee & Little, 2012). To do so, each individual's scores were standardized to her/his own item specific mean and standard deviation. Afterwards, the data from all individuals were chained (i.e., stacked) to create one large data set and these data were then analyzed with a single-level EFA. Because the mean and standard deviation for the standardization cannot be properly attained for panelists that responded to only a few measurement occasions, I only included panelists that answered the Big Five items on at least four measurement occasions (remaining $N = 6,345$ and $5,747$ in the LISS and HILDA panel, respectively).

In the chain-P technique factor analysis, I used not only the geomin rotation but also a target rotation (e.g., Browne, 2001). I used the target rotation for a solution with five factors and I specified zero as the target value for four of the five loadings of each item. The one loading with no target value was the loading on the factor that the item was supposed to load according to the canonical Big Five. The target rotation makes the corresponding loadings of the rotated factor pattern matrix as close to the specified zeros as possible. Thus, this is a conservative test of whether the Big Five structure can be found at the within-person level or not.

Excluding Adjacent Measurement Occasions. As another robustness check, I reran the multilevel EFA models for the LISS data containing only three nonadjacent measurement occasions: 2008, 2014, and 2020. I removed all other measurement occasions from the data for this robustness check because past research has shown that adjacent measurement

occasions tend to be more strongly correlated with each other than distant measurement occasions (e.g., Anusic & Schimmack, 2016; Fraley & Roberts, 2005) and the multilevel EFA models of the main analysis cannot reflect these autocorrelations because their within-person factors cannot be correlated across measurement occasions. The absence of autocorrelations among adjacent measurement occasions at the within-person level may have impaired the estimation of the main analysis, especially in the LISS panel in which some measurement occasions were only one year apart from each other. To investigate whether unmodeled autocorrelations impacted the results, I reran the multilevel EFA models with the LISS data containing only distant measurement occasions that should not autocorrelate with each other.

Including Only Panelists who Had Completed High School. As an additional robustness check, I reran the the multilevel CFA and EFA with geomin rotation using only the data from panelists who indicated an education level of at least higher secondary education (senior high school) in the LISS panel (remaining $N = 10,189$) and high school (i.e., year 12) in the HILDA panel (remaining $N = 14,832$). I did so because previous studies have suggested that the Big Five factor structure emerges less clearly at lower education levels than at higher education levels due to acquiescence response tendencies ('yea-saying'; e.g., Rammstedt et al., 2010; Rammstedt et al., 2013).

Results

Main Analysis

Confirmatory Factor Analysis

It was possible to fit the CFA model with metric invariance constraints to both the LISS and HILDA panel data and the model with configural invariance constraints to the LISS panel data. However, at the between-person level of the CFA model with configural invariance constraints fitted to the HILDA data, one openness item ("complex") had a standardized factor loading slightly higher than 1 (1.01) and a negative residual variance. I was not able to rectify this issue by using starting values. Excluding the "complex" item from

the analysis had the consequence that another item had a negative residual variance. Thus, I did not exclude the “complex” item. Instead, I fixed its residual variance to 0 so that its standardized loading was 1. The factor loadings and the interfactor correlations for all four CFA models can be found in Tables S7 to S10.

In the LISS panel, the model with metric invariance constraints fitted well according to the RMSEA (.032) and the SRMR at the within-person level (.040) but poorly according to the CFI (.707) or the SRMR at the between-person level (.120). The less restrictive model with configural invariance constraints fitted almost equally well/poorly (RMSEA = .032; SRMR at the within-person level = .041; CFI = .715; SRMR at the between-person level = .130). The relatively small difference in fit between the two models would suggest that metric factorial invariance held across the between- and within-person levels. However, both models fit poorly according to the CFI and between-person SRMR. Thus, configural invariance—which is a precondition for metric invariance—might not be tenable. That is, the reason for the poor CFI and between-person SRMR might be that configural measurement invariance was imposed in both CFA models (i.e., the items needed to load on the same factors across the two levels and the number of factors was constrained to be five at both levels). An alternative explanation might be that both CFA models restricted each item to load on only one factor. This might have reduced the fit because Big Five items are likely to have secondary loadings (e.g., Beauducel & Wittmann, 2005; Marsh et al., 2010).

In the HILDA panel, the fit of the model with metric invariance was acceptable according to the RMSEA (.055) and the SRMR at the within-person level (.097) but it was very poor according to the CFI (.542) and the SRMR at the between-person level (.164). The less restrictive model with configural invariance constraints fitted better according to the CFI (.641) and RMSEA (.049) but not according to the SRMRs at the between-person level (.183) and within-person level (.119). The large difference in CFI was not supplemented by a large enough positive difference in RMSEA or SRMR to indicate metric noninvariance according

to the guidelines by Chen (2007). However, both CFA models fit poorly according to the CFI and SRMRs. Thus, configural invariance—which is a precondition for metric invariance—does not seem to be tenable.

Exploratory Factor Analysis

Figure 2 displays scree plots containing the eigenvalues for the between- and within-person levels and the average eigenvalues across multiple cross-sectional EFAs, respectively.

Table 1 presents fit indices and scree test values of the hull method for the between- and within-person levels of the multilevel EFA models and average fit indices across the cross-sectional EFA models.

Figure 2

Scree Plots of Eigenvalues for the Between- and Within-Person Levels of the Multilevel Exploratory Factor Analyses and Average Eigenvalues Across Several Cross-Sectional Single-Level Exploratory Factor Analyses

Table 1*Fit and Scree Test Values st for Multilevel and Cross-sectional Exploratory Factor Analysis Models*

# factors	df	Between-person level				Within-person level				Cross-sectional (average)			
		RMSEA	SRMR	CFI	Hull <i>st</i>	RMSEA	SRMR	CFI	Hull <i>st</i>	RMSEA	SRMR	CFI	Hull <i>st</i>
LISS Panel													
0	1225	.051	.313	.618	– ^a	.045	.084	.711	– ^a	.110	.191	.000	– ^a
1	1175	.047	.223	.691	1.06	.034	.050	.844	1.89	.093	.119	.316	1.32
2	1126	.043	.172	.758	– ^b	.026	.033	.913	2.60	.077	.088	.551	1.44
3	1078	.037	.105	.825	1.41	.022	.025	.939	1.70	.063	.061	.712	1.94
4	1031	.033	.075	.871	1.02	.019	.021	.954	1.22	.054	.045	.792	1.07
5	985	.027	.043	.915	2.87	.017	.017	.966	1.47	.045	.031	.866	2.21
6	940	.025	.035	.930	1.22	.015	.015	.974	1.30	.040	.025	.899	1.77
7	896	.023	.032	.942	1.95	.014	.013	.980	1.95	.037	.022	.917	– ^b
8	853	.023	.027	.948	1.17	.013	.012	.983	1.47	.034	.020	.934	1.93
9	811	.022	.024	.953	– ^a	.013	.011	.985	– ^a	.032	.019	.943	– ^a
HILDA Panel													
0	630	.054	.340	.766	– ^a	.059	.129	.721	– ^a	.126	.206	.000	– ^a
1	594	.051	.250	.806	– ^b	.049	.090	.821	– ^b	.104	.131	.358	1.46
2	559	.046	.189	.854	1.22	.033	.041	.925	6.11	.085	.080	.597	1.91
3	525	.042	.150	.884	– ^b	.030	.034	.941	1.11	.073	.059	.719	1.30
4	492	.036	.113	.922	1.35	.027	.028	.955	1.36	.062	.043	.810	1.68
5	460	.031	.059	.946	1.11	.025	.024	.965	1.73	.055	.033	.862	1.42
6	429	.025	.051	.967	2.54	.024	.022	.970	– ^b	.051	.027	.888	– ^b
7	399	.022	.030	.975	1.27	.022	.019	.976	1.05	.042	.020	.932	2.34
8	370	.020	.025	.981	– ^b	.020	.017	.981	1.61	.038	.018	.945	– ^b
9	342	.017	.017	.987	– ^a	.020	.015	.984	– ^a	.034	.015	.960	– ^a

Note. The fit for the between-person level stems from the multilevel exploratory factor analysis models in which various numbers of factors were extracted at the between-person level while having an unrestricted covariance at the within-person level. Vice versa, the fit for the within-person level stems from the multilevel exploratory factor analysis models in which various numbers of factors were extracted at the within-person level while having an unrestricted covariance at the between-person level. The cross-sectional fit is the average fit across single-level exploratory factor analysis models, one model for each measurement occasion. Further details can be found in the Method section and in the R code and Mplus output files on the OSF project page: https://osf.io/e9mkx/?view_only=699861f6ea264290ae4dbce57f9a53e1. CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; st = Scree Test values that were computed on the basis of the CFI for the solutions placed on the convex hull of the hull plot.

^a The Scree Test value cannot be computed for the lowest and highest number of factors (e.g., Lorenzo-Seva et al., 2011).

^b The Scree Test value was not computed because this solution was not placed on the convex hull of the hull plot.

At the between-person level, the inflection point in the scree plot was at Factor 6 in both the LISS and the HILDA panel data (Figure 2). That is, the last major drop occurred between Factors 5 and 6. In other words, the eigenvalues for Factors 6, 7, 8, and 9 were small in comparison to the first five eigenvalues and thus seem to represent the effects of minor common factors (e.g., MacCallum & Tucker, 1991). Thus, the scree plots suggest that five factors should be extracted at the between-person level in both panel data sets. The RMSEA fit indices indicated that almost all models showed good fit (almost all RMSEAs < .050). None of the changes in the RMSEA values between a given model and the model with one additional factor were marginally meaningful (all Δ RMSEAs < .010; Table 1). Hence, the RMSEA fit indices were not very informative about how many factors to retain. According to the Hull method, the solution with five common factors had the highest scree test value in the LISS panel and the solution with six factors had the highest scree test value in the HILDA panel (Table 1). These values indicate that five factors should be retained in the LISS panel and six factors in the HILDA panel. I decided to extract five factors at the between-person level in both data sets because the scree plots suggested five factors and the personality questionnaires used in the LISS and HILDA were designed to measure five major personality dimensions on which people differ from one another according to the literature (e.g., Goldberg, 1990). For the HILDA panel, I additionally reported the between-person pattern matrix of a six-factor solution in the supplemental material given that the Hull method suggested six factors and some researchers have argued that the number of major personality dimensions ought to be six rather than five (e.g., Ashton & Lee, 2020).

At the within-person level, the inflection point in the scree plots for the LISS panel was not clear (Figure 2). It occurred at either Factor 2 or Factor 3, tentatively suggesting that one or two factors should be retained. The inflection for the HILDA panel was clearly at Factor 3 suggesting that two factors should be retained. According to the RMSEA values reported in Table 1, all factor solutions except for the zero factor solution in the HILDA panel

fit well (all RMSEAs < .050). In both panels, the difference in RMSEAs between the model with zero factors and the model with one factor were marginally meaningful (Δ RMSEAs = .011 and .010, respectively). In the HILDA panel, the difference in RMSEA between the model with one factor and the model with two factors was also marginally meaningful (Δ RMSEAs = .016). None of the other differences in RMSEAs between a given model and the model with one additional factor were substantial or marginally meaningful in the LISS or HILDA panel (all Δ RMSEAs < .010). The RMSEAs thus suggested that one and two factors, respectively, should be extracted. According to the Hull method, the solutions with two common factors had clearly the highest scree test values in both panels (Table 1). This indicates that two factors should be retained in both panels. I decided to extract two factors from both data sets because the scree plot and the Hull method suggested two factors for both panels. For the LISS panel, I additionally reported the within-person pattern matrix of a one-factor solution because the scree plot and RMSEAs suggested that one factor should be retained. Moreover, I reported the within-person pattern matrices of a five-factor solution in both panels because the personality questionnaires used in both panels were designed to measure five factors.

Tables S11 to S14 display the pattern matrices for the four rotation criteria for the between- and within-person levels of the two panel data sets. The four different rotation criteria produced very similar pattern matrices. Hence, here in the Results section, I focus exclusively on the Geomin rotation displayed in Tables 2 and 3.

The factor loadings of the pattern matrices are similar to standardized partial regression coefficients (e.g., Fabrigar & Wegener, 2012). They reflect the standardized units of increase in the measured variable given one standard unit of increase in the common factor while adjusting for all other common factors in the EFA at the respective level of analysis. In both panel data sets, the factor loadings tended to be smaller at the within-person level than at the between-person level. Arguably, the reason for the smaller factor loadings at the within-

person level is that random measurement error contributes to variation at the within-person but not at the between-person level.

In the five-factor solutions at the between-person level of the LISS panel (Table 2) and HILDA panel (Table 3), almost all items showed the strongest loading on the Big Five factor that they were supposed to measure. There were a few items that loaded slightly stronger on another Big Five factor and there were also several substantial secondary loadings. Yet, the canonical Big Five by and large emerged at the between-person level in both panel data sets. All of the Big Five except for openness also clearly emerged when 6 factors were retained in the HILDA panel (Table S13). The openness items loaded on two separate factors, a factor that appeared to measure intellectuality (e.g., “complex” and “philosophical”) and a factor that appeared to measure creativity (“imaginative” and “creative”). However, only two items showed substantial loadings on the creativity factor. All in all, the Big Five largely emerged at the between-person level in both panel data.

In the two-factor solution at the within-person level of the LISS panel (Table 2), the items with loadings equal to or larger than $|\lambda|.30$ on Factor 1 were six agreeableness items (e.g., “Sympathize with others’ feelings” and “take time out for others”), three extraversion items (e.g., “Feel comfortable around people”), three openness items (e.g., “Am full of ideas”), and one conscientiousness item (“Pay attention to details”). This factor seems to reflect positivity bias (also called evaluative bias, halo, or attitude toward the target; e.g., Anusic et al., 2009; Wessels et al., 2020; Rau et al., 2021) because items with positive loadings were positively worded and had socially desirable item content and items without positive loadings had neutral or socially undesirable item content. That said, the neuroticism (and conscientiousness) items loaded less strongly (negatively) on the factor than would be expected on the basis of previously found relationships between neuroticism, conscientiousness and positivity bias (e.g., Anusic et al., 2009; Rau et al., 2020). The other within-person factor of the LISS panel reflected neuroticism because eight of the nine items

with loadings above .30 were neuroticism items. In the one-factor solution at the within-person level of the LISS panel, the one factor reflected both positivity and negativity bias because items with positive loadings were negatively worded and had socially undesirable and neurotic item content and items with negative loadings were positively worded and had socially desirable item content. In the five-factor solution at the within-person level of the LISS panel, the canonical Big Five and in particular conscientiousness and openness emerged only partially.

In the two-factor solution at the within-person level of the HILDA panel (Table 3), the items with the highest loadings on Factor 1 were again extraversion, agreeableness, conscientiousness, and openness items with positive wording and socially desirable item content (e.g., “enthusiastic,” “warm,” “efficient,” “kind,” and “imaginative”) while neutral or socially undesirable items with negative wording barely loaded on this factor. Thus, this factor also reflected positivity bias. The second within-person factor of the HILDA panel reflected neuroticism or negativity bias because the items with positive loadings were neuroticism items (e.g., “temperamental” and “moody”) and items from other domains with negative wording and neurotic or socially undesirable item content (e.g., “withdrawn” and “harsh”). In the five-factor solution at the within-person level of the HILDA panel, the canonical Big Five did hardly emerge. Taken together, the EFAs at the within-person level tentatively suggested two factors in both the LISS and HILDA panel data and the meanings of these two factors were similar across the two data sets. The first within-person factor reflected positivity bias and the second factor reflected neuroticism or negativity bias.

For the cross-sectional EFA that I conducted for comparison, I averaged the fit indices across measurement occasion separately for each of the two panels. For the LISS panel, five factors should be extracted according to the scree plots, absolute RMSEAs and the Hull method but not according to the differences in RMSEAs (Figure 2 and Table 1). For the HILDA panel, the scree plot suggested two factors, the absolute RMSEAs and the Hull

method suggested seven factors, and the differences in RMSEAs suggested one or four factors. I extracted five factors in all cross-sectional EFA models because the scree plots, RMSEAs and the Hull method suggested five factors in the LISS panel and were inconclusive in the HILDA panel. The canonical Big Five structure emerged roughly in the pattern matrices of all 17 EFA models (for pattern matrices of the Geomin rotation of the 17 cross-sectional EFAs, see Tables S15 and S16).

Robustness Checks

The results of the chain-P technique factor analysis can be found in Figure S2 and Tables S17 to S21. The results were similar to the results of the multilevel EFA at the within-person level (Figure 2 and Tables 2 and 3). One difference was that the Hull method slightly supported a one-factor solution over a two-factor solution in the chain-P technique factor analysis of the LISS data. In the HILDA panel, one difference was that the Big Five structure emerged more clearly when the target rotation was used in the chain-P technique factor analysis than at the within-person level of the multilevel EFA.

The results of the robustness check without adjacent measurement occasions which was only performed for the LISS panel (Figure S3 and Tables S22 and S24) were largely similar to the main results for the LISS panel (Figure 2 and Table 2). The most important difference was that the Hull method suggested to extract six rather than five factors at the between-person level.³ Thus, I extracted not only five but also six factors at the between-person level (Table S24). All of the Big Five emerged in the pattern matrix of the five factor solution, and all of the Big Five except for openness emerged in the pattern matrix of the six factor solution. In the six factor solution, the openness items loaded on two separate factors, a factor that appeared to measure intellect (e.g., “Have a rich vocabulary” and “Have difficulty

³ In the robustness check without adjacent measurement occasions, the Hull method also suggested to extract seven or eight rather than two factors at the within-person level. I did not extract seven or eight factors at the within-person level because the scree plot did not suggest seven or eight factors and the seven and eight factor solutions fitted barely better than the solutions with fewer factors.

understanding abstract ideas”) and a factor that appeared to measure creativity (e.g., “Have a vivid imagination” and “Am full of ideas”). A similar split in openness was found in the six factor solution at the between-person level in the HILDA panel (Table S13). This split is somewhat in line with research distinguishing intellect and openness (e.g., DeYoung et al., 2014). Apart from the better fit of the six factor solution at the between-person level, the results of the robustness check without adjacent measurement occasions were similar to the main results. Hence, it is probable that the absence of autocorrelations at the within-person level of the multilevel EFA barely impaired the results of the main analysis.

Finally, the results of the robustness check based on the data that only included those panelists who had, at a minimum, completed high school (Figure S4 and Tables S25 to S28) were also similar to the main results (Figure 2 and Tables 1 to 3).

Table 2*Factor Loadings of the Pattern Matrices at the Between- and Within-Person Levels in the LISS Panel*

		Between-Person Level					Within-Person Level							
		Five-factor solution					Two-factor solution		One-factor solution	Five-factor solution				
	Item content	f1	f2	f3	f4	f5	f1	f2	f1	f1	f2	f3	f4	f5
ex01	Am the life of the party.	.71	.04	.00	-.03	.03	.28	-.04	-.26	-.30	.06	-.02	.08	.16
ex02	Don't talk a lot.	-.82	-.14	-.14	-.03	.02	-.17	.12	.23	.38	-.03	-.02	.07	.04
ex03	Feel comfortable around people.	.64	.30	-.19	.00	-.09	.36	-.10	-.36	-.27	.18	-.08	.05	.14
ex04	Keep in the background.	-.93	.11	-.02	.02	-.02	-.12	.14	.22	.45	.05	.00	.05	.05
ex05	Start conversations.	.80	.20	.04	.06	.02	.35	-.05	-.31	-.37	.10	.01	.03	.15
ex06	Have little to say.	-.64	-.22	.09	-.11	-.22	-.22	.20	.34	.33	-.06	.07	.13	-.01
ex07	Talk to a lot of different people at parties.	.82	.16	-.04	.00	-.13	.33	-.06	-.31	-.37	.10	-.01	.06	.14
ex08	Don't like to draw attention to myself.	-.79	.30	-.06	.11	-.08	.02	.07	.04	.31	.10	-.02	-.03	.09
ex09	Don't mind being the center of attention.	.75	-.22	-.03	-.06	.13	.17	.00	-.14	-.28	-.03	.03	.08	.12
ex10	Am quiet around strangers.	-.89	.00	.09	-.05	.07	-.15	.18	.26	.40	.01	.04	.06	.04
ag01	Feel little concern for others.	-.10	-.82	.04	.01	-.04	-.17	.10	.22	.08	-.25	.02	.09	.10
ag02	Am interested in people.	.17	.85	.00	-.07	.06	.39	.00	-.31	-.09	.37	-.01	.04	.09
ag03	Insult people.	.20	-.51	.25	-.23	.10	-.12	.18	.23	-.04	-.20	.10	.20	.07
ag04	Sympathize with others' feelings.	-.04	.94	.16	-.02	.01	.42	.05	-.28	.03	.50	.03	.03	.07
ag05	Am not interested in other people's problems.	-.05	-.87	.00	.06	-.06	-.23	.09	.26	.10	-.36	-.01	.10	.14
ag06	Have a soft heart.	.04	.35	.50	-.03	-.02	.17	.27	.07	.04	.17	.22	.06	.08
ag07	Am not really interested in others.	-.19	-.86	.06	.04	-.02	-.30	.13	.34	.14	-.42	.02	.09	.13
ag08	Take time out for others.	.02	.85	-.01	.02	.01	.41	.00	-.31	.02	.39	-.02	-.01	.14
ag09	Feel others' emotions.	.04	.76	.23	.00	.17	.40	.07	-.25	-.01	.36	.05	.01	.15
ag10	Make people feel at ease.	.34	.59	.02	.09	.02	.40	-.01	-.32	-.07	.25	-.03	.00	.21

co01	Am always prepared.	.00	-.07	.00	.58	.26	.20	-.01	-.16	.04	-.01	-.03	-.12	.25
co02	Leave my belongings around.	.03	.10	.09	-.85	.09	-.08	.15	.18	-.01	.02	.00	.42	-.02
co03	Pay attention to details.	-.07	.19	.13	.43	.45	.32	.05	-.21	.02	.09	.03	-.11	.29
co04	Make a mess of things.	-.01	-.10	.42	-.64	-.01	-.15	.31	.36	.01	-.04	.19	.35	-.04
co05	Get chores done right away.	.11	.04	-.04	.63	-.11	.22	-.02	-.19	.01	.00	-.01	-.17	.23
co06	Often forget to put things back in their proper place.	.01	.02	.15	-.80	-.02	-.10	.21	.25	.01	.02	.06	.41	-.03
co07	Like order.	.02	-.02	.16	.85	.01	.26	.03	-.18	.06	.04	.06	-.26	.26
co08	Shirk my duties.	-.02	-.34	.31	-.46	-.01	-.18	.24	.32	-.01	-.14	.16	.24	-.03
co09	Follow a schedule.	.05	-.04	.09	.65	.20	.26	.04	-.17	.04	.00	.03	-.16	.31
co10	Am exacting in my work.	.07	.01	.10	.33	.40	.26	.09	-.14	.00	.01	.06	-.08	.29
ne01	Get stressed out easily.	-.01	.10	.88	.05	-.03	.02	.44	.32	.04	.07	.43	.02	-.03
ne02	Am relaxed most of the time.	.05	.01	-.82	-.06	.05	.12	-.28	-.31	.00	.00	-.37	.12	.19
ne03	Worry about things.	-.09	.26	.76	.14	.03	.18	.36	.14	.06	.16	.34	-.03	.08
ne04	Seldom feel blue.	.06	.02	-.77	.01	-.01	.06	-.22	-.20	.04	-.01	-.32	.14	.14
ne05	Am easily disturbed.	-.04	.18	.85	.11	-.17	.07	.46	.29	.07	.09	.42	.03	.04
ne06	Get upset easily.	-.03	.14	.90	-.04	-.15	.01	.54	.39	.05	.07	.50	.09	-.02
ne07	Change my mood a lot.	.06	-.14	.85	-.11	.01	.00	.51	.38	-.04	-.05	.52	.03	.03
ne08	Have frequent mood swings.	.04	-.12	.87	-.12	.00	-.01	.58	.43	-.07	-.07	.60	.01	.02
ne09	Get irritated easily.	.06	-.26	.72	.02	.06	.00	.42	.32	.02	-.07	.39	.02	.07
ne10	Often feel blue.	-.10	-.09	.84	-.09	.02	-.07	.56	.47	.00	-.05	.59	-.02	-.06
op01	Have a rich vocabulary.	.09	.08	-.09	.01	.60	.27	.00	-.21	-.09	.00	-.02	-.04	.28
op02	Have difficulty understanding abstract ideas.	.06	.05	.27	.03	-.78	-.14	.15	.22	.14	.03	.04	.22	-.06
op03	Have a vivid imagination.	.11	.04	.16	-.16	.54	.26	.10	-.12	-.07	.06	.04	.08	.25
op04	Am not interested in abstract ideas.	.09	-.04	.17	.09	-.76	-.10	.09	.16	.12	-.01	-.02	.20	.00
op05	Have excellent ideas.	.15	-.08	-.05	.08	.72	.34	.00	-.26	-.08	-.02	-.04	-.03	.40
op06	Do not have a good imagination.	-.02	-.20	.14	-.03	-.54	-.10	.14	.19	.07	-.06	.08	.11	-.01
op07	Am quick to understand things.	.01	.06	-.22	.09	.66	.34	-.04	-.29	-.04	.05	-.06	-.09	.33
op08	Use difficult words.	.05	-.13	.11	-.13	.60	.12	.14	.01	-.09	-.11	.11	.04	.22
op09	Spend time reflecting on things.	-.25	.22	.03	.28	.49	.28	.05	-.18	.07	.09	.01	-.09	.28

op10	Am full of ideas.	.19	.00	.00	-.01	.70	.37	.00	-.28	-.12	.00	-.04	-.01	.40
Intercorrelations														
f2		.25					-.20			-.23				
f3		-.21	-.12							.27	-.16			
f4		-.04	.25	-.16						.04	-.21	.30		
f5		.30	.20	-.06	.04					-.12	.35	-.01	-.06	

Note. The table presents the pattern matrices at the between- and within-person levels from a multilevel exploratory factor analysis of 50 personality items administered at 13 measurement occasions of the LISS panel ($N = 15,085$). All loadings equal to or larger than $|.30|$ are in boldface.

Table 3*Factor Loadings of the Pattern Matrices at the Between- and Within-Person Levels in the HILDA Panel*

		Between-Person Level					Within-Person Level						
		Five-factor solution					Two-factor solution		Five-factor solution				
	Item content	f1	f2	f3	f4	f5	f1	f2	f1	f2	f3	f4	f5
ex01	Bashful	.52	.05	.40	-.03	.10	.12	.36	.34	.01	.20	.09	.01
ex02	Enthusiastic	-.45	.33	-.07	.15	.47	.56	-.02	-.01	.62	-.11	.00	.05
ex03	Extroverted	-.68	-.03	.11	-.06	.33	.24	.20	.23	.21	-.24	.03	-.01
ex04	Lively	-.62	.27	-.01	.06	.23	.45	-.05	-.03	.50	-.21	.03	-.03
ex05	Quiet	.94	.00	-.01	.06	.07	.09	.21	.17	.03	.47	.07	-.01
ex06	Shy	.81	.07	.28	-.03	.02	.07	.33	.29	.08	.43	-.01	-.07
ex07	Talkative	-.76	.26	.19	-.06	.04	.28	.03	.07	.10	-.41	.27	-.03
ex08	Withdrawn	.52	-.21	.49	-.04	.13	-.02	.45	.44	-.16	.24	.04	.06
ag01	Cold	.13	-.64	.40	.03	.00	-.08	.44	.44	.01	.06	-.21	.02
ag02	Cooperative	.09	.59	-.16	.17	.25	.48	-.05	-.06	.27	.12	.32	.04
ag03	Harsh	-.15	-.55	.52	.13	.07	-.01	.45	.48	-.07	-.03	-.12	.16
ag04	Kind	.02	.85	.06	.05	.17	.50	-.03	-.04	.19	.07	.48	-.02
ag05	Selfish	-.03	-.44	.50	-.09	.11	-.09	.44	.44	.02	-.04	-.20	-.05
ag06	Sympathetic	.00	.83	.11	.01	.19	.41	.00	.01	.00	-.09	.58	.00
ag07	Warm	-.09	.81	.00	-.01	.26	.54	.00	-.01	.40	.08	.26	-.03
co01	Careless	-.01	-.29	.36	-.50	.06	-.06	.37	.37	.05	-.03	-.10	-.20
co02	Disorganised	.00	.02	.14	-.89	.13	-.07	.37	.36	.05	.00	.01	-.45
co03	Efficient	-.08	.07	.01	.84	.23	.52	-.02	-.01	.44	.08	.01	.33
co04	Inefficient	.12	.03	.27	-.73	-.03	-.06	.38	.38	-.08	.01	.11	-.31
co05	Orderly	.02	.03	.07	.91	.03	.38	.02	.05	.03	-.06	.29	.38
co06	Sloppy	.05	-.11	.23	-.68	.08	-.08	.38	.38	-.03	-.01	.02	-.32
co07	Systematic	.09	-.27	.07	.76	.32	.31	.19	.22	.05	.02	.14	.35
ne01	Calm	.15	.09	-.59	.02	.31	.37	-.09	-.09	.36	.04	.09	.00
ne02	Envious	-.04	.01	.80	.05	-.15	.05	.41	.43	-.12	-.09	.09	.06
ne03	Fretful	.22	.09	.74	-.03	-.01	.04	.43	.42	.03	.11	-.04	-.04
ne04	Jealous	-.01	.02	.83	-.01	-.14	.01	.44	.45	-.02	-.06	-.04	-.02
ne05	Moody	.03	-.06	.85	.03	-.06	-.02	.52	.53	-.13	.02	.00	.06

ne06	Temperamental	-.02	-.12	.81	-.06	-.05	.00	.55	.55	.04	.01	-.12	-.07
ne07	Touchy	.03	.14	.81	.03	-.04	.08	.43	.43	-.02	.01	.07	-.05
op01	Complex	.06	-.28	.36	-.04	.61	.16	.41	.41	.15	.04	-.05	.02
op02	Creative	-.13	.12	.03	-.06	.67	.41	.10	.11	.36	-.02	.08	.03
op03	Deep	.03	.05	.31	.05	.65	.29	.27	.29	.01	-.03	.26	.10
op04	Imaginative	-.17	.11	.00	-.08	.81	.48	.10	.10	.55	-.04	-.04	.01
op05	Intellectual	-.11	-.13	-.03	.14	.69	.39	.14	.16	.28	-.06	.07	.13
op06	Philosophical	.07	-.15	-.05	.01	.76	.31	.29	.30	.10	.01	.16	.12
op07	Traditional	.14	.13	-.08	.27	-.06	.33	.07	.07	.30	.06	.05	.03
Intercorrelations													
f2		-.14					-.03		.08				
f3		.08	-.30						.02	.01			
f4		-.10	.30	-.34					.08	.41	.07		
F5		.00	.16	.14	.08				.04	.14	.02	.22	

Note. The table presents the pattern matrices at the between- and within-person levels from a multilevel exploratory factor analysis of 36 personality items administered at four measurement occasions of the HILDA panel ($N = 22,582$). All loadings equal to or larger than $|\lambda| \geq .30$ are in boldface.

Discussion

An often implicit, though fundamental, assumption of research using personality trait questionnaires is that the cross-sectional factor structure represents both the between- and within-person factor structures. The current analysis of two longitudinal personality datasets, from a Dutch and an Australian panel study, suggested that this assumption might not be valid when using Big Five trait measures such as the 50-item International Personality Item Pool (Goldberg, 1992; Goldberg et al., 2006) and the 36-item Big Five adjective personality inventory (Saucier, 1994). In both panel studies but especially in the Australian panel study, several (but not all) fit indices indicated an unacceptable fit of multilevel CFA models that imposed configural invariance across the two levels. Furthermore, multilevel EFA suggested a different number of factors at the between-person level (five factors) than at the within-person level (two factors). In other words, the CFA and EFA models suggested that configural and thus metric invariance did not hold across between- and within-person levels. This suggests that different constructs were measured across the two levels and that it is necessary to disaggregate the between- and within-person levels not only in the structural part of structural equation models but also in the measurement part (e.g., Hamaker et al., 2017).

Furthermore, the canonical Big Five factor structure clearly emerged at the between-person level but not at the within-person level in the multilevel EFA. In other words, the measured time-invariant differences in personality (i.e., a person's average or typical personality across all measurement occasions) could be well explained/summarized by time-invariant differences in the Big Five personality dimensions, while the measured fluctuations and changes in personality (i.e. a person's deviations from their typical personality) could only be poorly explained/summarized by fluctuations and changes in the Big Five personality dimensions. The multilevel EFA models suggested two rather than five within-person factors to explain/summarize the measured fluctuations and changes.

The first of the two within-person factors reflected positivity bias because the items with positive loadings were positively worded extraversion, agreeableness, conscientiousness, and openness items with socially desirable item content. The second within-person factor reflected neuroticism or negativity bias because the items with positive loadings were neuroticism items and negatively worded items with socially undesirable content from the other four Big Five domains. These two within-person factors appear to reflect intraindividual fluctuations and changes in positive and negative attitudes towards the self potentially induced by positive and negative affect—although the agreeableness items loaded more strongly on the “positivity factor” (Tables 2 and 3) than would be expected on the basis of the associations between agreeableness and positive affect found in past research (e.g., Wilson et al., 2017).

One reason for the absence of the Big Five factor structure at the within-person level might be that the used Big Five items were unable to reliably and validly assess changes in the personality nuances, facets, and traits they were supposed to assess. For instance, rather than changes and fluctuations in conscientiousness, the positively worded conscientiousness items appeared to indicate changes and fluctuations in positivity bias and the negatively worded conscientiousness items appeared to indicate changes and fluctuations in neuroticism or negativity bias. Positive affect or self-esteem boosting events that happened a few hours or days prior to a measurement occasion might have affected how desirable the person perceived themselves regarding a wide range of personality aspects. This could explain why social desirable conscientiousness items covaried with socially desirable non-conscientiousness and why a positivity bias factor rather than a conscientiousness factor emerged in the multilevel EFA at the within-person level. Although positivity and negativity bias could be considered to be aspects of personality (e.g., Anusic et al., 2009), researchers interested in changes in conscientiousness might argue that changes and fluctuations in positivity bias and neuroticism/negativity bias are not of substantial interest and contaminate conscientiousness

trait measures. If existing Big Five items are indeed poor indicators of changes in the personality aspects they are supposed to measure and instead reflect mainly fluctuations and changes in positive and negative attitudes towards the self, this would be concerning because trait measures like the ones used in the LISS and HILDA panel are frequently used to study changes in the Big Five (for reviews see, e.g., Anusic & Schimmack, 2016; Bleidorn et al., 2022). Past research using these measures to study the development and changes of the Big Five would be to some extent questionable. For example, the previously observed increase in agreeableness and conscientiousness and decrease in neuroticism with age, termed the maturity principle (e.g., Caspi et al., 2005; Brandes et al., 2021), might then be a consequence of changes in positive and negative attitudes toward the self rather than changes in agreeableness, conscientiousness, and neuroticism per se. Researchers interested in how the aspects of the Big Five change and their within-person factor structure would need to find or develop personality measures that reliably and validly assesses changes in all aspects of the Big Five rather than only changes in positivity and negativity bias.

An alternative reason for the absence of the Big Five at the within-person level might be that the two within-person factors found in the current study suffice to explain/summarize personality differences at the within-person level (i.e., fluctuations and changes in personality within a person over time). What could explain that the two factors suffice? Environmental influences and events might temporary affect positive and negative attitudes towards the self and the positive and negative attitude, in turn, might each affect a large number of cognitions, feelings, and behaviors from several Big Five domains. For example, the positive attitude towards the self of a person might strongly impact how enthusiastic, cooperative, efficient, imaginative etc. that person is. As a consequence, all the personality nuances affected by changes in positive attitude towards the self might covary and load on the same factor at the within-person level. However, the interpretation that the two found within-person factors suffice to explain/summarize actual personality changes is at odds with the finding that

positively and negatively worded items that arguably measured the same personality nuance loaded on different factors at the within-person level. For example, in the HILDA panel, the item “efficient” loaded positively on the positivity bias factor but not on the negativity bias factor while the item “inefficient” loaded positively on the negativity bias factor but not on the positivity bias factor (Table 3). If the item scores of these two items reflected actual change in effectiveness rather than merely changes in positive and negative attitudes towards the self, the two items should have covaried and loaded on the same factor. Thus, the found within-person factors probably reflected only changes in positive and negative attitudes towards the self but not changes in the personality nuances that the items intended to assess.

Furthermore, the within-person factor structure might vary from individual to individual. In this case, the fixed within-person structure observed in the current study would resemble the average within-person-factor structure. That is, although the within-person factor structures would vary, the within-person factor structure of most panelists would presumably contain a factor for positivity bias and a factor for neuroticism/negative bias. Future research might want to investigate individual differences (e.g., Beck & Jackson, 2020; Hamaker et al., 2007; Lee & Little, 2012). If there are individual differences in the within-person factor structure, researchers interested in personality change would want to assess and study changes in the personalized within-person factors rather than changes in the factors of the average structure (e.g., positivity and negativity bias).

The results of the current study were arguably influenced by the time spans of the longitudinal panel data. The longer the interval between the first and the last measurement occasion, the more personality changes there are over the course of the study, thus, the smaller the variance there is at the between-person level and the larger the variance there is at the within-person level. That said, the variance at the between-person level should *not* approach zero in the limit as the time span increases because previous studies suggest that personality stability has a non-zero asymptote (e.g., Anusic & Schimmack, 2016; Fraley &

Roberts, 2005). In the current study with its 13-year (LISS) and 12-year (HILDA) time spans, the between-person variance captured the fixed system of the revised sociogenomic model (i.e., the portion of personality that is largely due to an enduring signal from DNA variation; Roberts, 2018). In addition to the fixed system, the revised sociogenomic model (Roberts, 2018) proposes a pliable, elastic, and short-term fluctuating system. The pliable system pertains to permanent modifications above and beyond stable genetic factors. For example, a traumatic childhood experience might lead to permanent personality changes. If these permanent modifications happened prior to the first measurement occasion, then they should be located at the between-person level in the current study. If not, then they should be located at the within-person level. The elastic system comprises nonpermanent personality changes that stay in place for some weeks or months. Examples for the elastic system are episodes of depression, panic, or anxiety that run over weeks and months. Given the long time spans of the LISS and HILDA studies, the elastic system should be located at the within-person level in the current study. The short-term fluctuating system should be also located at the within-person level because it reflects short-lived personality changes in response to changes in one's environment (i.e., moment-to-moment fluctuations in thoughts, feelings, and behaviors; Roberts, 2018). If Roberts's revised sociogenomic model is valid, then the current within-person personality differences and corresponding factor structures (Tables 2 and 3) could turn out to be a blend of the pliable, elastic, and short-term fluctuating systems. This argument points to the fact that the current analysis and results do not inform us to what extent the fluctuations and changes at the within-person-level last for hours, weeks, months, or even years. Future studies might want to investigate the factor structure of personality measures at more than two levels. To do so, study designs are needed that combine a panel data design with an intensive longitudinal design. Personality would need to be assessed daily to distinguish the short-term fluctuating system from the elastic system, and personality would need to be assessed for a long time (10 years or more) to distinguish the fixed system from the

pliable and the elastic system. Hopefully, future research will be able to investigate whether a further partitioning of the variance is required.

Limitations and Future Directions

Although the current study was based on rich longitudinal panel data and utilized statistical and computational advances (e.g., Asparouhov & Muthén, 2007; Hamaker et al., 2017), there are several limitations of a methodological and statistical nature. For example, the guidelines for interpreting fit indices to determine whether invariance holds or how many factors to retain were developed in the context of single-level CFA and EFA models with cross-sectional data rather than multilevel CFA and EFA models with longitudinal data (e.g., Chen, 2007; Fabrigar & Wegener, 2012; Schermelleh-Engel et al., 2003). This might, for example, explain why almost all factor solutions met the recommended RMSEA standard for a good model fit ($RMSEAs < .050$) and almost none of the differences in RMSEAs were marginally meaningful ($\Delta RMSEAs < .010$; Table 1). That said, the scree test and Hull method appeared to work for the multilevel EFAs similarly well as they do for single-level EFAs. Nevertheless, future methodological research might want to conduct simulation studies in order to propose guidelines for determining whether invariance holds or how many factors to retain on the basis of fit indices of multilevel CFA and EFA models.

Conclusion

Previous research with personality trait measures has distinguished time-invariant from changing aspects of personality in the structural part of the analysis (e.g., Fetvadjev & He, 2019; Anusic & Schimmack, 2016) and in theories (e.g., Fraley & Roberts, 2005; Roberts, 2018). The current analysis of two large longitudinal data sets suggests that it might be also worth distinguishing time-invariant from changing aspects in the measurement part of the analysis. Time-invariant interpersonal personality differences were characterized by a different factor structure than intrapersonal personality fluctuations and changes. In particular, the within-person factor structure was characterized by positivity and negativity bias rather

than the canonical Big Five structure. Therefore, the current study suggests that it would be valuable for personality researchers to focus their efforts on how to measure and model personality change.

Data Accessibility Statement

I am not allowed to publicly share the data. Researchers can apply for access to the data at <https://www.lissdata.nl/> and <https://dataverse.ada.edu.au/dataverse.xhtml?alias=hilda>.

The R code, Mplus output files, and supplemental tables and figures for the current study are available on the OSF project page at

https://osf.io/e9mkx/?view_only=699861f6ea264290ae4dbce57f9a53e1.

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