Check for updates

Empirical Paper

EUROPEAN JOURNAL OF Personality

European Journal of Personality
2026, Vol. 40(4) 935–952
© The Author(s) 2026

Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/08902070251412958
journals.sagepub.com/home/ejop
Sage

Personality and well-being are genetically associated: Extending previous twin and molecular genetic studies

Marco Deppe[1], Charlotte Katharina Louise Dißelkamp[2], Carlo Maj[3,4], Rana Aldisi[4], Markus Nöthen[2], Martin Diewald[5], Frank Michael Spinath[6], Andreas Josef Forstner[2,7] and Christian Kandler[1,8]

Abstract

Neuroticism, extraversion, and conscientiousness are the most notable personality predictors of subjective well-being (SWB) in phenotypic and behavior genetic studies. We aim to quasi-replicate and extend previous findings. Using data from the German twin family panel *TwinLife*, we analyzed Big Five personality traits and life satisfaction of 3,080 twin pairs from three birth cohorts (born 2003/04, 1997/98, and 1990–93). Prior research has repeatedly provided evidence that genetic variance in personality traits largely explained genetic variance in SWB. Our results replicated this pattern with no significant unique genetic variance in life satisfaction. However, we found significant age cohort differences (e.g., only in ages 17–23 did genetic variance in openness partly explain genetic variance in life satisfaction). Furthermore, we tested personality–SWB associations using polygenic scores (PGSs) for Big Five personality traits and SWB. PGSs were calculated for $N = 5,355$ genotyped twin family members from the *TwinSNPs* study (age range 8–77). PGSs showed genetic association patterns similar to the twin study results, with neuroticism as the most robust predictor (up to $\beta = -.360$) and openness showing near-null associations. Despite low overall explanatory power, phenotype prediction mirrored this as well (e.g., neuroticism PGSs predicted life satisfaction with up to $\beta = -.100$).

Plain Language Summary

Genetic factors responsible for personality are likewise associated with subjective well-being. This is an extension of previous twin studies and molecular genetic studies to better understand if known association patterns replicate based on longitudinal data and across different age cohorts. **Why was the study done?** Personality, when measured in terms of the Big Five typology, has been associated with subjective well-being in previous studies. Neuroticism (or emotional stability), extraversion, and conscientiousness seem to show the strongest links to subjective well-being. Genetically informative studies repeatedly provided evidence that these links are based on genetic factors. Our aim was to see if these findings replicate based on a new and younger data set, to extend previous findings by using longitudinal information collected across six years, and to compare results across different birth cohorts. **What did the researchers do?** We analyzed Big Five personality traits and life satisfaction of 3,080 twin pairs from three birth cohorts (born 2003/04, 1997/98, and 1990–93) based on the German twin family panel *TwinLife*. Furthermore, we tested the associations between personality and subjective well-being using polygenic scores (PGSs). These were available for 5,355 twin family members from the *TwinSNPs* study (age range 8–77). **What did the researchers find?** Genetic factors underlying personality traits fully explained genetic differences in subjective well-being. There were some meaningful age cohort differences (e.g., only in ages 17–23 did genetic differences in openness partly explain genetic differences in life satisfaction). PGSs showed similar results, with neuroticism as the most robust predictor for subjective well-being, and openness being mostly unassociated. The links between personality traits and self-reports of life satisfaction also varied across the lifespan. **What do the findings mean?** Subjective well-being is strongly associated with personality. This holds when considering longitudinal, trait-level data. The associations are mostly based on genetic factors,

[1]Department of Psychology, University of Bremen, Bremen, Germany
[2]School of Medicine, Institute of Human Genetics, University Hospital Bonn, University of Bonn, Bonn, Germany
[3]Center for Human Genetics, University of Marburg, Marburg, Germany
[4]Institute for Genomic Statistics and Bioinformatics, University of Bonn, Bonn, Germany
[5]Faculty of Sociology, Bielefeld University, Bielefeld, Germany
[6]Faculty of Empirical Human Sciences and Economics, Saarland University, Saarbrücken, Germany
[7]Institute of Neuroscience and Medicine (INM-1), Research Center Jülich, Jülich, Germany
[8]Faculty for Psychology and Sports Science, Bielefeld University, Bielefeld, Germany

Corresponding author:
Marco Deppe, Department of Psychology, Institute for Psychology, University of Bremen, Grazer Straße 2a, 28359 Bremen, Germany.
Email: mdeppe@uni-bremen.de

and they can have different meanings across developmental phases and contexts over the lifespan. Molecular genetic results mirror overall patterns based on twin analyses.

Keywords
subjective well-being, life satisfaction, big five, twin study, polygenic scores

Received 3 February 2025; Revised 3 October 2025; accepted 1 December 2025

Introduction

Subjective well-being (SWB) has been linked to a number of core personality traits in previous research with neuroticism, extraversion, and conscientiousness as the most robust correlates. This pattern has been replicated across multiple large-sample studies and multiple psychometric instruments (Anglim et al., 2020). Moreover, personality–SWB associations seem to have a genetic foundation, as inferred from genetically informative studies, such as twin studies (Hahn et al., 2013; Pelt et al., 2024; Røysamb et al., 2018; Weiss et al., 2008) and molecular genetic studies (Baselmans, Jansen, et al., 2019; Weiss et al., 2016). Open questions arise in terms of possible age differences in SWB heritability (Bartels, 2015) and the extent to which quantitative genetic and molecular genetic evidence on this association align. Additionally, most previous studies have relied on single measurements of personality and SWB, which raises the question whether or not their results would replicate when investigating stable traits or set-points across longer time frames. Answering these key questions can shed light on possible context specificity over age or time of genetic (and environmental) influences on personality-mediated differences in SWB (e.g., *genetic innovations* following Kendler et al., 2008).

We ran two studies to investigate the phenotypic and genetic links between core personality traits and SWB aspects within and across different age groups. In a first study, our aim was to (a) quasi-replicate previous findings on the phenotypic and genetic links between personality traits and life satisfaction based on twin studies and (b) extend former studies by examining the genetic and environmental links between six-year stable personality traits and life satisfaction set-points based on a German twin family study. We additionally investigated age cohort differences in these associations. In the second study, we used genotype data from 5,355 individuals to calculate polygenic scores (PGSs) for Big Five personality traits and different SWB facets. We estimated the PGS-based genetic correlations between personality and SWB. In an extension of the previous literature, we also examined the consistency of predictions of life satisfaction set-point and personality trait phenotypes by SWB and personality PGSs, while additionally considering age differences.

Background: Links between subjective well-being and personality traits

Theoretical considerations

Subjective well-being. Theories on the structure of SWB, with a cognitive component, life satisfaction, and affective components, namely, positive and negative affect, have been classified by Diener (1984), among others, into top-down versus bottom-up theories (see also Diener et al., 1999). After four decades of scientific progress, this heuristic still holds. Bottom-up theories assume day-to-day emotions and evaluations of one's life (i.e., fluctuating affect and satisfaction surface levels) to add up to individual differences in general SWB levels. In contrast, top-down approaches typically propose a single higher-order factor accounting for the links between facets of SWB, sometimes referred to as *h*-factor, with "*h*" for happiness (Bjørndal et al., 2023). A specific example for top-down theories is the set-point theory (Headey & Muffels, 2018; Ormel et al., 2017), which assumes SWB to fluctuate around individual set-points that are relatively stable across time and linked to personality differences.

Personality and well-being. The *Big Five* personality traits openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (or inversely, emotional stability; McCrae & Costa, 1991; Soto & John, 2016) are considered predispositions or basic tendencies that account for stable affective, cognitive, and behavioral patterns of an individual over a certain period of time (Kandler et al., 2014). They shape how individuals (re)act in and perceive their environments (Wagner et al., 2020). Thus, personality traits can drive behavior and experiences in ways that might be more or less beneficial for the development of SWB. In a top-down perspective, personality traits might drive individuals' perceptions of their surroundings, shaping their day-to-day affect and satisfaction levels. Reciprocally, day-to-day affect might in sum influence more general SWB levels and associated personality characteristics (e.g., emotional stability).

Genetic and environmental factors. The moderately stable variance in SWB—the so-called SWB set-points—might manifest through stable genetic predispositions (Brown & Rohrer, 2020; Lykken & Tellegen, 1996), rather than potentially changing and mutable environments. Linking set-point theory to the robust finding of personality–SWB associations, broad polygenic personality traits may be promising candidates which can account for stable genetic differences in SWB (Weiss et al., 2008, 2016). However, the relevance of certain genetic factors can change with development across the lifespan via multiple interactions and transactions between genetic and environmental factors. For example, selection into fitting environments and creation or modification of environments to increase person(ality)–environment fit, which is important for well-being (Gebauer et al., 2020; Jokela et al., 2015) are increasingly more feasible in adulthood compared to youth

(Kandler et al., 2019, 2024). Thus, the relevance of genetic differences in certain personality traits driving SWB set-points may increase with age, or differ depending on the investigated time frame.

Current state of research

Phenotypic associations. In their recent meta-analysis, Anglim et al. (2020) found the strongest links between personality traits and SWB to stem from neuroticism, extraversion, and conscientiousness, followed by agreeableness and openness. Short-scale instruments showed somewhat weaker correlations compared to their long-form versions, but the observed pattern remained the same. Personality differences accounted for about half of the variance in SWB.

Associations between personality traits and SWB can manifest through personality-driven behavior. For example, pronounced conscientiousness drives educational success (Hufer-Thamm et al., 2023), which in turn may lead to higher chances for more stable, prestigious, and well-paid career options. Similarly, high conscientiousness predicts health behavior (Gartland et al., 2021). Career success and health are in turn associated with increased well-being (Diener et al., 2017). Pronounced extraversion might lead to a larger social network and increased social participation, which have been shown to positively predict life satisfaction (Rohrer et al., 2018). Pronounced agreeableness drives socially acceptable behavior in interpersonal relations and might thus increase the satisfaction with one's social network (Wilson et al., 2015). The negative association of SWB with neuroticism and the positive link between SWB and extraversion are intuitive. Neuroticism includes facets of negative affectivity, such as anxiety or depressiveness, which are negatively associated with SWB (Fergusson et al., 2015; Stein & Heimberg, 2004), whereas extraversion includes facets of positive emotionality (Soto & John, 2016), which can be understood as the dimension driving positive affect as one aspect of SWB (Diener, 1984).

It seems plausible that the described associations are of varying importance in different stages of development. Given that both personality traits and SWB have been shown to be malleable (Headey & Muffels, 2018; Ormel et al., 2017; Wagner et al., 2020), we expect that their relationship, too, may systematically vary across the lifespan. Previous evidence on such age differences is rare and has been mixed. On the one hand, Magee et al. (2013) and Luo et al. (2023) reported evidence for age differences in the links between personality traits, life satisfaction, and general health. On the other hand, Kokko et al. (2015) and Olaru et al. (2023) found evidence for invariant personality–SWB association patterns across age.

Quantitative genetic associations. Heritability estimates for SWB ranged from about 20% to 60%, with environmental effects accounting for the remaining variance (Bartels, 2015). Similarly, personality trait heritability ranges from 40% to 70%, with higher estimates for measures corrected for random error and systematic rater biases (Kandler et al., 2010; Kandler & Papendick, 2017; Vukasović & Bratko, 2015).

Previous quantitative genetic studies have repeatedly found evidence for substantial genetic overlaps, with considerable proportions of genetic variance in SWB being explained by genetic differences in personality traits. In a first study, Weiss et al. (2008) analyzed 973 twin pairs from a U.S. sample using a multivariate model. They found neuroticism, extraversion, and conscientiousness, along with an overarching genetic self-report factor, to completely account for the genetic variance in life satisfaction. Sadiković et al. (2018) provided similar evidence based on 182 Serbian twin pairs. Hahn et al. (2013) investigated the same constructs based on 1,308 twin pairs and other family members from a German sample. Inferring from a genetically sensitive multigroup design with various unrelated kinship dyads, they found the genetic variance in neuroticism and extraversion to completely explain the genetic variance in life satisfaction. Røysamb et al. (2018) found 65% of the genetic variance in life satisfaction to be explained by genetic variance in neuroticism and extraversion facets, but did not include conscientiousness in their biometric analysis of 758 Norwegian twin pairs. In a study of Dutch twins from 8,232 pairs, Pelt et al. (2024) investigated phenotype- and gender-specificity of the personality–SWB relationship, while highlighting the importance of future examinations of possible age specificity. Neuroticism, extraversion, and conscientiousness likewise showed the largest genetic overlaps with SWB. Life satisfaction, specifically, did not show significant unique trait-specific variance, while other characteristics, such as self-rated health, did show such unique genetic variance components. Overall, twin (family) studies provided consistent evidence for genetic links between personality traits and SWB.

Molecular genetic associations. Most previous studies on the genetic overlap between personality and SWB relied on twin studies. However, genome-wide association studies (GWASs) are also informative about common genetic variants that are linked to certain phenotypes in a population. GWASs allow for the discovery of single-nucleotide polymorphisms (SNPs) related to specific traits. PGSs based on GWASs can offer molecular genetic estimates of individual polygenic loads associated with particular traits (Andlauer & Nöthen, 2020). Whereas several GWASs on personality and SWB exist (e.g., Baselmans, Jansen, et al., 2019; de Moor et al., 2012), only few studies have systematically investigated the molecular genetic associations between personality and SWB. Okbay et al. (2016) reported a high negative correlation of $r_G = -.75$ between SWB and neuroticism measures. Weiss et al. (2016) found evidence for links between SWB and IRT-based measures of neuroticism and extraversion using PGSs. Both personality PGSs were significantly associated with well-being measures, but the explained variance was very small (<1%). On the other hand, Weiss et al. (2016) did not find any significant associations with SWB based on Big Five trait measures derived from a previous GWAS (de Moor et al., 2012), whereas Baselmans, van de Weijer, et al. (2019) also reported significant genetic associations of neuroticism,

Table 1. Overview of Hypotheses.

Study	#	Hypothesis
Study 1: Genetic links between personality traits and life satisfaction in the TwinLife cohorts	H1	Neuroticism, extraversion, and conscientiousness are linked with life satisfaction due to genetic sources
	H2	Personality traits mediate most of the genetic variance in life satisfaction
Study 2: Polygenic associations between personality and SWB in TwinSNPs	H3a	Life satisfaction PGSs are significantly associated with neuroticism PGSs
	H3b	Life satisfaction PGSs are significantly associated with extraversion PGSs
	H3c	Life satisfaction PGSs are significantly associated with conscientiousness PGSs

Note. H# = Hypothesis, with consecutive enumeration.

extraversion, conscientiousness, agreeableness with SWB based on LD score regression.

In sum, the evidence from molecular genetic studies for genetic links between personality traits and SWB is mixed. One reason may be age specificity of associations between genetic variants and specific phenotypes. Thus, the gene–personality and the gene–SWB link as well as their genetic cross-links may vary across different stages of development. It has been described as a desideratum for molecular genetic research on complex human traits to take a *"life-span approach"* (Freitag & Kelsey, 2023, p. 30), which we follow by investigating PGS-based prediction of stable life satisfaction set-points and personality trait phenotypes in comparison of different age cohorts.

The present research

In the first study, we aimed at quasi-replicating previous findings concerning genetic links between personality traits and life satisfaction set-points. Based on data from a large German twin family panel, which covers longitudinal information on personality traits and life satisfaction, we extended previous studies by analyzing the links between six-year stable components of personality and life satisfaction. We compared these links of valid personality trait and SWB set-point differences between age cohorts, which include different developmental phases from 10 to 30 years of age. In addition to quantitative genetic analyses, PGSs provide molecular genetic estimates of trait associations based on additive genetic effects. Therefore, in the second study, we used PGSs for Big Five personality traits and SWB facets based on genome-wide genotype data. PGS-based genetic correlations of well-being and personality PGSs were estimated. We further examined the consistency of PGS predictions of stable life satisfaction set-point and personality trait phenotypes across different age groups ranging from 8 to 77 years of age.

To our knowledge, this two-study investigation is the first on whether and to what extent the genetic links between stable SWB set-point and personality trait differences are consistent with the existing evidence on single measurements, while additionally considering possible differences across age groups. It adds to the still sparse and mixed evidence on links between Big Five personality traits and facets of well-being on the molecular genetic level. In sum, the current studies aim to quasi-replicate and extend previous findings by answering the following key questions: (1) Are genetic differences in SWB set-points attributable to stable genetic differences in Big Five personality traits? (2) Are there age differences regarding these genetic personality–SWB links? (3) Are patterns of personality–SWB links robust across quantitative and molecular genetic designs? Our hypotheses for both studies are based on previous evidence and are summarized in Table 1.

Study 1: Genetic links between personality traits and life satisfaction in the *TwinLife* cohorts

In the first study, based on data from twins reared together, we aimed at replicating previous findings. In line with previous evidence (Hahn et al., 2013; Pelt et al., 2024; Røysamb et al., 2018; Sadiković et al., 2018; Weiss et al., 2008), we expected that neuroticism, extraversion, and conscientiousness are linked with life satisfaction due to genetic sources (H1) and that these personality traits mediate most of the genetic variance in life satisfaction (H2). We extended previous research by examining the genetic and environmental links of six-year stable personality trait differences and life satisfaction set-point differences. We also explored whether patterns in personality—life satisfaction links are consistent across age cohorts.

Methods

Data. Analyses were based on the German twin family panel study *TwinLife* (Diewald et al., 2023; Mönkediek et al., 2019). The initial sample of 4,096 twin families was representative to the German population by the time of the first panel wave (Lang & Kottwitz, 2017). We used data from the first four face-to-face surveys based on a selection of mono- and dizygotic (MZ/DZ) twins who provided valid zygosity information. The initial sample consists of $N = 6,160$ individuals from 1,475 MZ and 1,605 DZ twin pairs (see Table 2, Tables A4 and A5 and Figure A1 for details—all Table and Figure references with prefix "A" refer to the supplements of Study 1). In the three birth cohorts that were analyzed, by covering four panel waves in total, surveyed biennially, the birth cohorts 2003/04, 1997/98, and 1990–93 cover a mean age range from 11 to 29 years (11–17, 17–23, and 23–29, respectively), for which stable trait differences

Table 2. Initial Twin Sample Description.

Cohort	*N*	n_{MZ}	n_{DZ}	$M_{Initial\ Age}$	% Female
2003–04	2,074	860	1,214	11.00	51.98
1997–98	2,120	1,018	1,102	17.01	57.26
1990–93	1,966	1,072	894	23.04	58.19
Full sample	6,160	2,950	3,210	16.91	55.78

Note. MZ = monozygotic twins; DZ = dizygotic twins. Gender was surveyed in binary form. See Table A4 for a full longitudinal sample description.

can be compared. As SWB and personality traits were only surveyed from age 10 onwards, the youngest *TwinLife* cohort, which ranged in age between 5 and 11 years, was excluded from analyses.

Measures. Life satisfaction was measured with the Satisfaction With Life Scale (SWLS; Diener et al., 1985) and the adapted scale for children (SWLS-C; Gadermann et al., 2010). The SWLS-C was applied when participants were 10–15 years old, and the SWLS for participants of age 16 and older (see Table A1). Data from both instruments were pooled for analysis and checked for measurement invariance (MI) between twin birth cohorts (i.e., between instruments). Partial strict MI could be assumed between twin cohorts (see Tables A10, A11, and A12), suggesting comparability of the SWLS and SWLS-C measures. At least partial strict MI could be assumed across panel waves (see Table A12). Personality traits were measured with a short form of the Big Five Inventory as applied in the German Socio-Economic Panel (BFI-S; Gerlitz & Schupp, 2005; Hahn et al., 2012). See Tables A2 and A8 for details.

Internal consistency was examined for all SWLS(-C) and BFI-S measurements. McDonald's ω ranged from .85 to .89 for SWLS(-C) measures. Internal consistency was acceptable for most of the BFI-S measures, given that short measures were used to capture broad constructs (ranging from $\omega = .45$ for neuroticism in cohort 2003/04 to $\omega = .80$ for extraversion in cohort 1990–93; see Table A6 for all estimates).

Regarding factorial validity, we ran exploratory and confirmatory factor analyses (EFA and CFA) based on first-wave data (2014–16) from the initial sample. EFAs were based on the principal axis method using *varimax* rotation, which was used to maximize explained variance in the expectation of an orthogonal factor structure (Kaiser, 1958). Both EFA and CFA for life satisfaction clearly yielded a one-dimensional solution (see Tables A7 and A9). The EFA of personality items yielded no deviations from the expected five-factor structure (i.e., all items loaded highest on their respective domain with factor loadings ≥ .3, which we assume as sufficient following Costello & Osborne, 2005; see Table A8). Factor scores for personality domains were extracted from EFA as Anderson-Rubin scores (DiStefano et al., 2009). These provide the advantage of uncorrelated personality trait scores, resulting in more specific measures of each personality domain and ensuring factorial independence. With the inclusion of a first-order common method variance factor for the BFI-S measurement (to bind error variance from potential method effects; Podsakoff et al., 2003), CFA likewise showed sufficient fit to the five-factor structure (RMSEA = .045 for life satisfaction and .058 for personality; see Table A9).

Latent state-trait models (Steyer et al., 2012) were then fitted to examine stable variance of life satisfaction set-points and personality traits. These models were based on longitudinal data with additional information from the second (2016–18), third (2018–20), and fourth (2020–22) face-to-face survey of the panel. Factorial independence was considered by fixing covariances between latent personality domains to zero. Both models showed acceptable fit to the data (RMSEA = .036 for life satisfaction and .054 for personality; see Tables A13 and A15). Six-year stable personality trait and life satisfaction set-point scores were extracted as regression scores (DiStefano et al., 2009). Since regression scores retain intercorrelations irrespective of the model-implied covariance structure, trait scores were made orthogonal using the Anderson-Rubin method based on a principal component analysis (Pett et al., 2003), parallel to the procedure used for initial first-wave factor scores. Trait consistency was >50%, with an average of 56.5% for life satisfaction and 66.7% to 79.5% for personality trait measures (see Table A17), indicating higher rank-order stability for personality traits compared to life satisfaction. Personality and SWB differences might be influenced by gender (e.g., Pelt et al., 2024). As gender effects are not the focus of the present study, they were partialed out via regression analyses. The resulting residual scores were used in the following analyses.

Analyses. Genetic and environmental variance in life satisfaction and personality domains were estimated in a classical twin design (CTD) model based on the comparison of MZ and DZ twin correlations. In this model, variance is decomposed into an additive genetic component (*A*), either a shared environmental (*C*; assuming $r_{DZ} = 1$) or a genetic dominance component (*D*; assuming $r_{DZ} = .25$), and environmental variance not shared by twins (*E*), which includes random measurement error (Neale & Maes, 2004). With multivariate Cholesky variance decomposition modeling, genetic and environmental variance components of multiple variables can be analyzed. For any number of variables *n*, the same number of *n* factors are specified for each source of variance, *A*, *C* or *D*, and *E*. In this model, all variables load on the first factor (e.g., A_n), and then, after following a descending order (e.g., A_{n-1}, A_{n-2}, and so forth), the final variable only loads on its own factor (e.g., A_1; Evans et al., 2002; Kohler et al., 2011; Neale & Maes, 2004). In these models, all paths linking personality domains among each other were fixed to zero due to their orthogonal structure based on the factor score calculation.

We started by comparing univariate *ACE*, *ADE*, and *AE* model variants (see Table A24). According to Falconer's (1989) formula, which suggests *C* effects if $r_{MZ} < 2*r_{DZ}$ or *D* effects if $r_{MZ} > 2*r_{DZ}$, *C* effects were suggested for life satisfaction, while *D* effects were suggested for Big Five personality traits. This raised two issues that needed to be resolved: On the one hand, the estimation of *C* and *D* is mutually exclusive in the CTD. While omitting *D* in the presence of non-additive genetic effects inflates *A* with non-additive genetic variance (making *A* an interpretable cumulative genetic factor), omitting *C* in the presence of shared environmental effects would inflate *A* with

environmental variance (making A a hardly interpretable factor representing genetic and environmental variance). On the other hand, the multivariate Cholesky structure in its common application would make the explanation of A factors by D factors impossible (Kohler et al., 2011; Neale & Maes, 2004). Previous studies showed that in the absence of D, in an AE model, $A_G \approx A + D$ applies (Hill et al., 2008). This means that all genetic effects, including non-additive effects from allelic dominance, are confounded and thus estimated along with the A factor, which therefore represents the cumulative genetic variance (hence A_G). This pattern was also evident in our data (see Table A24), and we therefore refer to variance bound in the A factors as genetic variance, summarizing variance components due to both additive and non-additive genetic sources.

Following this, we compared the model fit between multivariate Cholesky models in their ACE, ADE, and AE variants with the weighted Akaike Information Criterion (wAIC; Wagenmakers & Farrell, 2004) and the Bayesian Information Criterion (Schwarz, 1978), the latter of which more strongly considers model complexity and avoids choosing overfitted models, especially in large sample sizes and models with many indicators such as multivariate behavior genetic models (Markon & Krueger, 2004). The most parsimonious models with smallest BIC were therefore chosen for analysis. This was complemented by additional model variants of the most parsimonious model with statistically insignificant paths dropped from the model, and another one with no A paths unique to life satisfaction, to check whether or not these could be dropped from the model without a significant decline in model fit (see Tables A25, A26, and A27). The described analyses were conducted with initial first-wave factor scores (henceforth: initial scores) and with six-year stable personality trait and life satisfaction set-point scores (henceforth, stable trait and set-point scores).

Results

Zero-order correlations between initial life satisfaction and personality scores were highest for neuroticism, conscientiousness, and extraversion ($r_N = -.21$, $r_C = .19$, and $r_E = .17$; see Table A18). A similar pattern emerged for stable trait and set-point scores, with extraversion switching places with conscientiousness ($r_N = -.28$, $r_E = .21$, and $r_C = .16$; see Table A19). The correlations tended to vary between age cohorts: Initial openness was linked in the youngest cohorts ($r_O = .16$ at age 11), but the associations consecutively decreased with age ($r_O = .09$ at age 17; $r_O = .05$ at age 23). Stable trait openness was likewise only linked to life satisfaction in the younger cohorts (see Figure 1). Neuroticism, extraversion, conscientiousness, and agreeableness stable trait scores showed robust correlations with life satisfaction, while the associations with neuroticism and extraversion tended to increase with age (see Figure 1 and Figure A2).

Twin pair correlations suggested only minor genetic effects and the presence of shared environmental influences on life satisfaction with $r_{MZ} = .47$ and $r_{DZ} = .37$ based on stable life satisfaction set-point scores, while twin correlations suggested relatively strong genetic effects for stable personality trait scores, including those due to allelic dominance (Table A23; see Table A22 for comparable twin correlation patterns of initial scores). This had implications for the multivariate Cholesky models, as described in the methods section. The most parsimonious models, which achieved the best fit to the data according to BIC (Markon & Krueger, 2004; Schwarz, 1978) were $A(C)E$ models, where the shared environment factor C was estimated for life

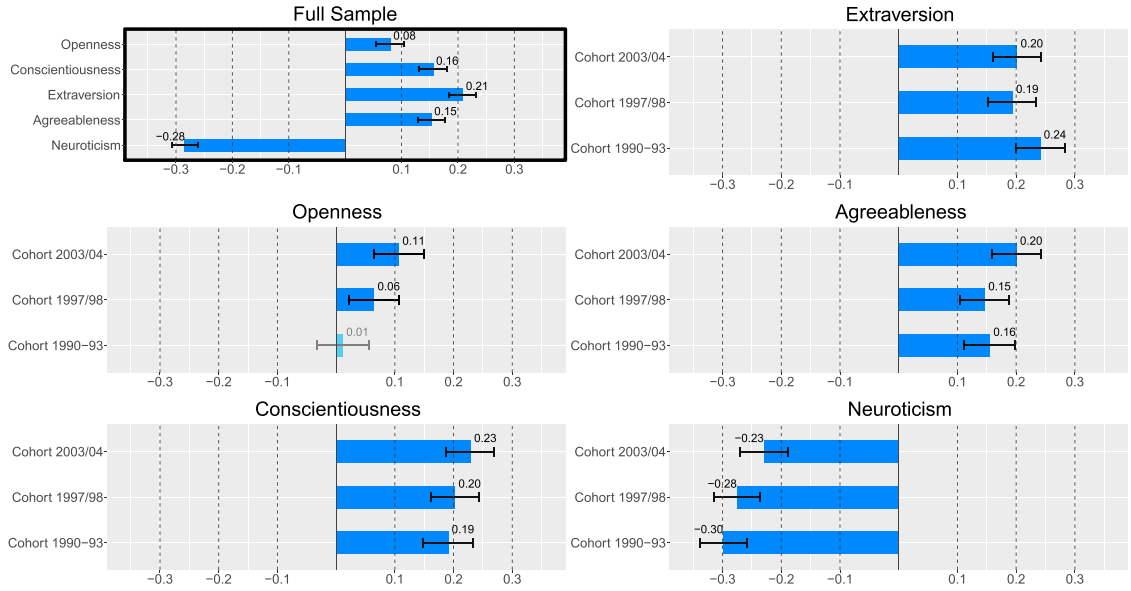


Figure 1. Phenotypic correlations of six-year stable personality traits and life satisfaction set-points. *Note.* Estimates = Pearson's *r*. Insignificant correlations with $p > .01$ in light blue. See Figure A2 for initial first-wave factor score results, which largely mirror this pattern. Whiskers represent 95% confidence intervals. Life satisfaction correlations with conscientiousness were lower in the full sample than in the subsamples due to contrary age cohort rank-order correlations: While moderately positive between the age cohort and conscientiousness, it was moderately negative for life satisfaction ($\rho_C = .26$, while $\rho_{LS} = -.19$).

satisfaction only, while all *C* paths were fixed to zero for personality traits. This resulted in an *ACE* variance decomposition for life satisfaction and an *AE* decomposition for personality traits, where *A* represents a cumulative genetic variance factor (Hill et al., 2008; see Table A24).

The analyses of initial scores showed that in these models, the paths estimating genetic effects unique to life satisfaction could be dropped without significant loss of fit (according to $\Delta BIC \leq 2$; Burnham & Anderson, 2004). Hence, genetic variance in personality scores completely explained genetic variance in life satisfaction (see Tables A28 and A29). Additionally, some age cohort differences emerged. Initial openness was significantly genetically linked only in the middle cohort at age 17, explaining 20% of the genetic variance in life satisfaction. Initial extraversion was not (yet) linked in the youngest cohort at age 11, whereas agreeableness played a greater role, explaining 28.6% of genetic variance in life satisfaction.

Focusing on the analyses based on stable trait and set-point scores, multivariate Cholesky models yielded the strongest genetic links between life satisfaction and the personality traits neuroticism, extraversion, and agreeableness, partially confirming H1. They explained 50.7%, 31.9%, and 8.6% of the genetic variance in life satisfaction, respectively, while conscientiousness only played a minor role with 6.4% explained variance. In the full sample, genetic variance in personality traits fully explained genetic variance in life satisfaction in the context of our analyses, confirming H2. Genetic variance in personality traits accounted for 16% of total variance in life satisfaction (see Figure 2 and Table A30). For all initial and stable trait scores, genetic variance in personality traits completely explained genetic variance in life satisfaction in our data (see Tables A28 to A33), with one exception: In the oldest cohort, genetic variance in life satisfaction stable set-points could not be fully explained by genetic variance in personality traits. This came along with estimates for life satisfaction *C* effects not being significantly different from zero in this group.

Within the youngest cohort (age range 11–17), genetic differences in stable trait extraversion, conscientiousness, neuroticism, and agreeableness explained 29.5%, 27.1%, 26.8%, and 16.6% of the genetic variance in life satisfaction set-point scores, respectively (with genetic and environmental variance in personality traits accounting for 20% of total variance in life satisfaction). For the middle cohort (age range 17–23), genetic differences in stable trait neuroticism, conscientiousness, extraversion, and agreeableness explained 28.8%, 28.3%, 23.1%, and 12.5% of the genetic variance in life satisfaction set-point scores, respectively (with genetic and environmental variance in personality traits accounting for 24% of total variance in life satisfaction). Additionally, openness was genetically linked in this group, but only explained 7.3% of the genetic variance in life satisfaction. In the oldest cohort (age range 23–29), genetic differences in stable trait neuroticism, extraversion, conscientiousness, and agreeableness explained 12.4%, 13.0%, 5.4%, and 4.1% of the genetic variance in life satisfaction set-point scores, respectively. Genetic differences in personality traits accounted for 35% of the genetic variance in life satisfaction in this group, leaving 65% of genetic variance unexplained. Genetic and environmental variance in personality traits accounted for 22.2% of the total variance in life satisfaction in this group.

The environmental variance overlap between life satisfaction and personality traits was only marginal in our data, leaving more than 80% of environmental variance unique to life satisfaction in the context of our analyses, and therefore unexplained by environmental differences in personality. See Figure 2 and Figure A3 for an overview on

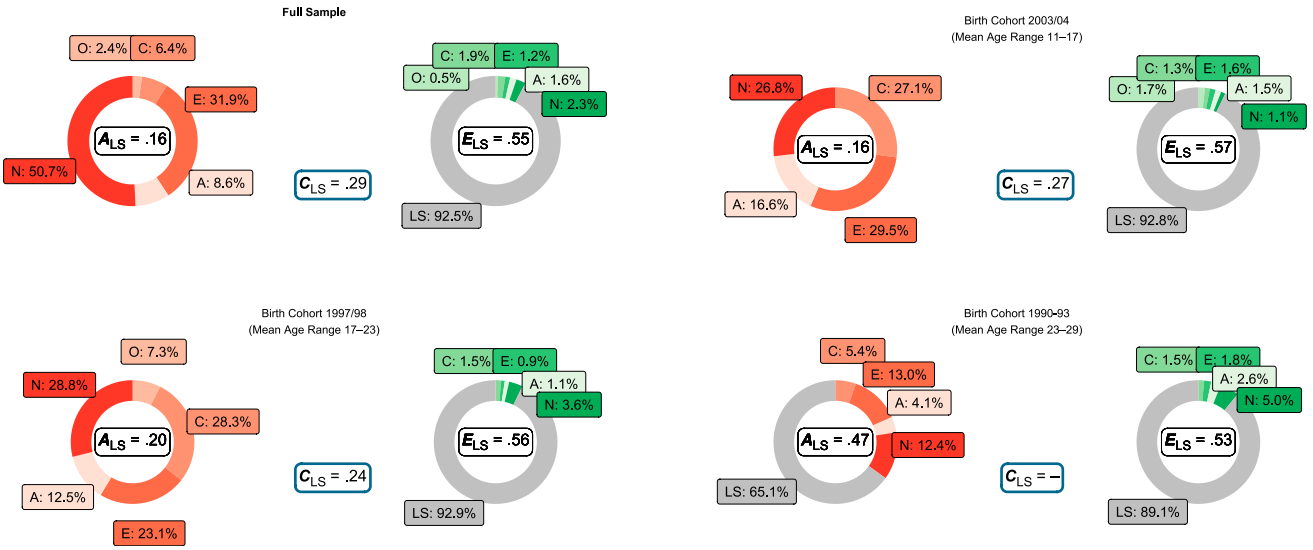


Figure 2. Cholesky decomposition model results for the full sample and different birth cohorts: Six-year stable trait and life satisfaction set-point scores. *Note.* O = Openness; C = Conscientiousness; E = Extraversion; A = Agreeableness; N = Neuroticism; LS = Life satisfaction; *A* = Additive and non-additive genetic effects; *C* = Shared environmental effects (only unique LS paths estimated—personality paths fixed to zero); *E* = Nonshared environmental effects and measurement error; $A/C/E_{LS}$ estimates = total amounts of variance explained by latent *A*/*C*/*E* factors; Percentages = proportions of *A*/*C*/*E* variance explained; Gray segments = variance in life satisfaction not explained by personality. Percentages rounded via largest remainder method. See Figure A3 for results based on initial first-wave scores. The full sample association with conscientiousness was lower than in the subsamples due to contrary age cohort correlations: Rank-order correlation between cohort and conscientiousness was positive, but negative for life satisfaction ($\rho_C = .26$ while $\rho_{LS} = -.19$).

the results based on initial as well as stable trait and set-point scores.

Sensitivity analyses

In addition to our original analyses, we ran a number of sensitivity analyses following suggestions during the review process. Although we can assume partial scalar and partial strict MI between the SWLS and SWLS-C (see Tables A10, A11, and A12), it is possible that the partial measurement non-invariance influenced our results. Since we did not compare mean levels, but associations between variables, metric MI could be considered sufficient (Putnick & Bornstein, 2016). To test whether the partial non-invariance on scalar and strict level meaningfully influenced our results, we conducted sensitivity analyses with life satisfaction scores from a reduced three-item model, for which full strict MI could be assumed (following Cheung & Rensvold, 1998; see Table A12). The resulting scores showed a strong coherence with those from the full five-item model ($r = .96$). Phenotype correlations with Big Five personality traits were essentially the same as those from life satisfaction scores based on the full five-item model (see Table A20). A sensitivity analysis of our behavior genetic analyses likewise produced substantively equivalent results compared to the full five-item model. We therefore opted to stay with the full five-item model to consider all available information and preserve broader content, and report the three-item model results as sensitivity analyses (see Tables A32 and A33). However, the three-item model could be the more conservative choice in terms of measurement invariance, which is a potential limitation future studies could attempt to circumvent.

Another addition concerns the analysis of nuances in personality traits at item level (following Mõttus et al., 2024; Mõttus et al., 2017). The short-scale measure for Big Five personality traits that was used (BFI-S; Gerlitz & Schupp, 2005) measures personality domains with only three items per domain (in case of openness: four items). Although such measurements inevitably exhibit low internal consistency, and one could argue that this is desirable and necessary when attempting to capture broad personality domains with only a few items, estimates of $\omega < .70$ are conventionally considered too low (Lance et al., 2006), leading to an increased likelihood of measurement errors. While random error is part of the *E* factor in behavioral genetic variance decomposition (Neale & Maes, 2004), systematic measurement errors can influence the results from aggregated BFI-S measures. A sensitivity analysis on personality nuances can therefore alleviate some of the problems associated with the scale by showing whether the trait aggregation masks associations which are only visible on item level. To this end, we used first-wave nuances based on BFI-S items which were intercorrelated within personality domains, but orthogonal between personality domains. To achieve this, effects of nuances (items) from other personality domains were partialed out via regression analyses, and the residual scores were used for further analyses.

Our analysis of personality nuances produced very similar results to the aggregated personality trait scores. We investigated two variants of personality nuances, parallel to our main analyses: Initial first-wave nuances from the first measurement, and six-year stable personality nuances derived from a structural equation model (see Table A16). Here, we focus our description on the latter. All stable nuances unequivocally pointed into the same direction as the aggregated traits within which they are subsumed. Zero-order correlations of life satisfaction with personality nuances were comparable to those with personality trait domains (see Table A21). In multivariate Cholesky models based on personality nuances (see Table A35), the overlap with life satisfaction was again very similar to the overlap between personality trait domains and life satisfaction. The association was primarily driven by genetic factors. Stable nuances of extraversion and neuroticism were the main predictors (accounting for 29% and 26% of the genetic overlap, respectively), along with stable nuances of openness, agreeableness, and conscientiousness (accounting for 16%, 16%, and 13% of the genetic overlap, respectively). The most important stable nuances were talkativeness (an extraversion nuance), nervousness (a neuroticism nuance), and thoroughness (a conscientiousness nuance). No unique genetic variance remained in life satisfaction, which means that all meaningful proportions of it were explained by genetic variance in personality nuances (see Table A35). Results for the nuances measured in the first wave broadly mirrored the general pattern of the six-year stable nuances (see Table A34).

Study 2: Polygenic associations between personality and SWB in *TwinSNPs*

In the second study based on genotype data from families of the *TwinSNPs* study, including non-twin siblings and parents, we aimed at examining the links between personality traits and SWB using PGSs. In line with previous molecular genetic findings (Baselmans, van de Weijer, et al., 2019; Okbay et al., 2016; Weiss et al., 2016), we expected that PGSs for life satisfaction are significantly associated with PGSs for neuroticism (H3a) and extraversion (H3b). In line with previous twin study findings (Pelt et al., 2024; Sadiković et al., 2018; Weiss et al., 2008), we also expected significant associations with PGSs for conscientiousness (H3c). We further extended previous research by examining whether patterns in PGS–phenotype links across personality traits and SWB measures are consistent across age groups.

Methods

Data. Analyses are based on the *TwinSNPs* study, which genotyped twin family members based on saliva-extracted genomic DNA using Infinium Global Screening Arrays (GSA + MD-24v3.0-Psych-24v1.1, Illumina, San Diego, CA, USA). After filtering, PGS data for the present study were available for $N = 5,355$ individuals ($M_{Age} = 30.37$ [8–77]; $SD_{Age} = 17.12$; 54.88% female). Longitudinal phenotype data were also available for all cases, as participants for *TwinSNPs* were recruited from the *TwinLife* panel study (Rohm et al., 2023). For age group comparisons, the sample was clustered into age quintiles, resulting in five similarly sized groups. These age quintiles cover distinct developmental phases, including childhood

Table 3. Genotype Sample Description.

Sample	*N*	Min_{Age}	M_{Age}	Max_{Age}	% Female
Full sample	5,355	8	30.37	77	54.88
Age Group Quintiles					
8–13	884	8	9.38	13	50.23
14–19	940	14	15.36	19	50.66
20–29	1,316	20	23.85	29	56.29
30–49	1,130	30	42.94	49	64.42
50–77	1,085	50	55.29	77	50.72

Note. Age and gender are based on data from the third face-to-face survey (2018–20), when the first saliva samples were collected. Gender was surveyed in binary form.

(8–13), adolescence (14–19), early adulthood (20–29), middle adulthood (30–49), and late adulthood (50–77 years of age; see Table 3, Tables B3, B4, and Figure B1—all Table and Figure references with prefix "B" refer to the supplements for Study 2).

Measures. A detailed description of sampling, genotyping, quality control, filtering and PGS calculation is provided in Supplement B-I. Briefly, common variants in samples of sufficient quality were imputed to the *1000 Genomes Project* reference panel data (Phase 3; Fairley et al., 2020). Genetic sex checks, relatedness checks, and a population substructure analysis were performed to remove sex/gender and family mismatches, correct reported zygosity data and to limit the analysis to a subsample matching the ancestry profile of the discovery GWASs. PGS data are available from the authors upon request, on condition that a valid data transfer agreement is concluded.

PGSs were computed using PRS-CS (auto-model), a Bayesian regression method applying continuous shrinkage priors to the SNP effects (Ge et al., 2019) derived from GWAS summary statistics (for details on PGS calculation, see Supplement B-I). For the present study, the summary statistics were obtained from Baselmans, Jansen, et al. (2019) and Becker et al. (2021) to generate PGSs for the SWB facets life satisfaction and positive affect, and a general SWB PGS. Summary statistics from de Moor et al. (2012) and Gupta et al. (2024) were used to generate two sets of PGSs for personality traits (see Table B1). For personality PGSs, Anderson-Rubin scores were extracted from EFA (DiStefano et al., 2009) to generate orthogonal scores that are not intercorrelated. To achieve this, the number of factors was forced to the number of PGSs (i.e., two sets of five; see Table B5 for details). Accordingly, EFA was based on the principal axis method using *varimax* rotation, which was used to maximize explained variance in the expectation of an orthogonal factor structure (Kaiser, 1958). PGSs were adjusted for effects from gender and the first ten genetic principal components. We employed *p*-value correction following Benjamini and Hochberg (1995) to deflate the possible increase of Type I or α errors from multiple testing, but also reported uncorrected *p*-values in light of a reciprocal increase of Type II or β errors by *p*-value correction where little explanatory power is to be expected (Barnett et al., 2022), as is still the case with PGS prediction of complex behavioral traits.

Analyses. The study followed a three-step analysis plan: (1) Correlations between SWB and personality PGSs were examined. (2) Genotype-genotype associations were tested considering SWB and personality PGSs in multivariate linear regression models. Effect sizes and explained variance informed about the relationship between SWB and personality PGSs. (3) PGS→phenotype predictions were examined for life satisfaction and personality trait scores from latent state-trait models (Steyer et al., 2012). To test these associations, linear regressions from latent trait scores on PGSs were added to the models. In addition, age groups were compared analogous to Study 1, to detect potential differences across the early lifespan, along with continuous age moderation models. At least partial strict MI could be assumed for phenotypic measures across panel waves and across age groups (see Tables B10 and B11). Since we focused on correlations between variables, metric MI could be considered sufficient (Putnick & Bornstein, 2016). Equivalent to the twin study, we nevertheless performed sensitivity analyses using a reduced three-item model for life satisfaction phenotypes for which full strict MI could be assumed (following Cheung & Rensvold, 1998; see Tables B7 and B11).

Results

Overall, correlations between personality and well-being PGSs were small to moderate. Neuroticism PGSs showed the highest correlations with well-being PGSs, which were consistently negative and statistically significant across all measures. This association was most pronounced in neuroticism PGSs based on the Gupta et al. (2024) GWAS, with $r = -.35$ and $-.36$ in association with positive affect (based on Baselmans, Jansen, et al., 2019) and SWB PGSs (based on Becker et al., 2021). Robust associations also emerged between agreeableness PGSs and life satisfaction PGSs, extraversion PGSs and positive affect PGSs, as well as extraversion, conscientiousness, and agreeableness PGSs with SWB PGSs (see Tables B12 and B13). To test for possible confounding, we ran the same correlations adjusted for family socioeconomic status and in an independent family subset. Both showed only minor differences to the main analysis (see Table B23).

Multivariate associations between well-being and personality PGSs showed similar patterns. All well-being PGSs were primarily predicted by neuroticism PGSs ($\beta = -.087$ to $-.360$), followed by agreeableness ($\beta = .032$ to $.107$) and, with the exception of life satisfaction PGSs, extraversion ($\beta = .082$ to $.168$), providing support for H3a and H3b. Prediction by conscientiousness and openness PGSs was very small ($\beta < .1$). However, the prediction of positive affect and SWB PGSs by conscientiousness PGSs was statistically significant ($p < .001$), providing support for H3c. The explained variance in well-being PGSs by personality PGSs based on the GWAS by de Moor et al. (2012) was generally low, ranging between 1.2% and 2.8%. Personality PGSs based on the more recent GWAS by Gupta et al. (2024) showed strongly increased variance explanation in positive affect and SWB PGSs (>16%; see Figure 3 and Table B14).

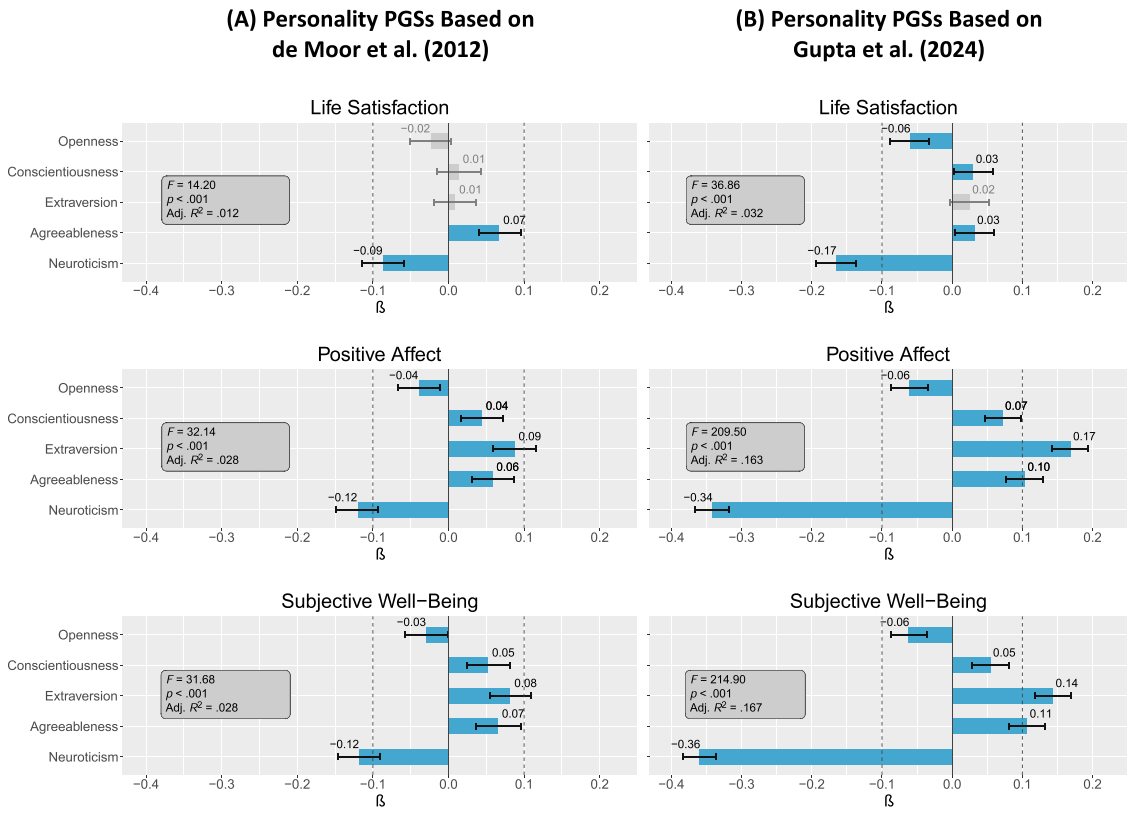


Figure 3. Genotype-genotype prediction of well-being PGSs by personality PGSs. *Note.* F = F-Statistic; Adj. R^2 = Adjusted R^2; β = Standardized regression estimates. All models with 5,349 degrees of freedom, based on N = 5,355. Whiskers represent 95% confidence intervals. Statistically insignificant parameters with $p > .05$ in greyscale.

For genotype-phenotype predictions, the latent state-trait models showed acceptable fit to the data in the full sample (RMSEA = .035 for life satisfaction and .050 for personality). Trait consistency was > 50%, with an average of 63.1% for life satisfaction and 69.4% to 78.7% for personality (see Tables B6 to B9). Based on this, life satisfaction phenotypes were predicted with weak, but statistically significant associations in the full sample from neuroticism, extraversion, agreeableness, and conscientiousness PGSs based on the GWAS by de Moor et al. (2012; $\beta = -.057$, .045, .044, and .037, respectively; see Table B16). PGSs based on the more recent GWAS by Gupta et al. (2024), which showed stronger explanatory power towards well-being PGSs, were associated with life satisfaction phenotypes only via neuroticism and conscientiousness PGSs ($\beta = -.100$ and .040, respectively; see Table B17).

When switching response variables (i.e., the prediction of personality trait phenotypes by well-being PGSs), the only significant associations were found for positive affect and SWB PGSs with neuroticism ($\beta = -.059$ and $-.077$, respectively) and extraversion phenotypes ($\beta = .051$ and .048, respectively). Personality trait prediction by life satisfaction PGSs were mostly null (none of the associations were estimated above $\beta > .1$; see Tables B19, B20, and B21). See Figure 4 for an overview of the results. In age group comparison analogous to Study 1, some differences emerged, but these did not show any systematic patterns. The most robust association across age came from neuroticism PGSs. Besides that, no clear age differences could be observed (see Tables B16 and B17). Consequently, models including continuous age moderation did not show any statistically significant interactions (see Tables B18 and B22). It should be noted that the personality trait phenotype prediction by dedicated personality domain PGSs based on the GWAS by de Moor et al. (2012) was low as well ($\beta < .1$ for extraversion and neuroticism; $\beta < .05$ for openness, agreeableness and conscientiousness), with variance explained $< 1\%$. This was only slightly improved in the personality domain PGSs based on the more recent GWAS by Gupta et al. (2024), with $\beta < .2$ ($Adj.\ R^2 < .3$) for all personality traits besides agreeableness (see Table B15). The sensitivity analysis using a reduced three-item model with full strict MI produced substantively equivalent results in the personality PGS prediction of life satisfaction phenotypes compared to the full five-item model of life satisfaction (see Table B24). We therefore decided to retain the full five-item model in order to consider all available information and preserve broader content. A within-family analysis in dizygotic twin families, working with a stepwise introduction of family-level confounders which approximate effects from population stratification and assortative mating, showed no significant differences after controlling for gender, age, and family affiliation (see Table B25).

Joint discussion

With neuroticism, extraversion, conscientiousness, and agreeableness as robust personality predictors in the CTD, we found strong genetic links between personality domains and life satisfaction. Polygenic associations of different facets of SWB with personality traits showed similar patterns. However, personality–SWB links and respective sources varied across age groups in the twin study results. Openness was only

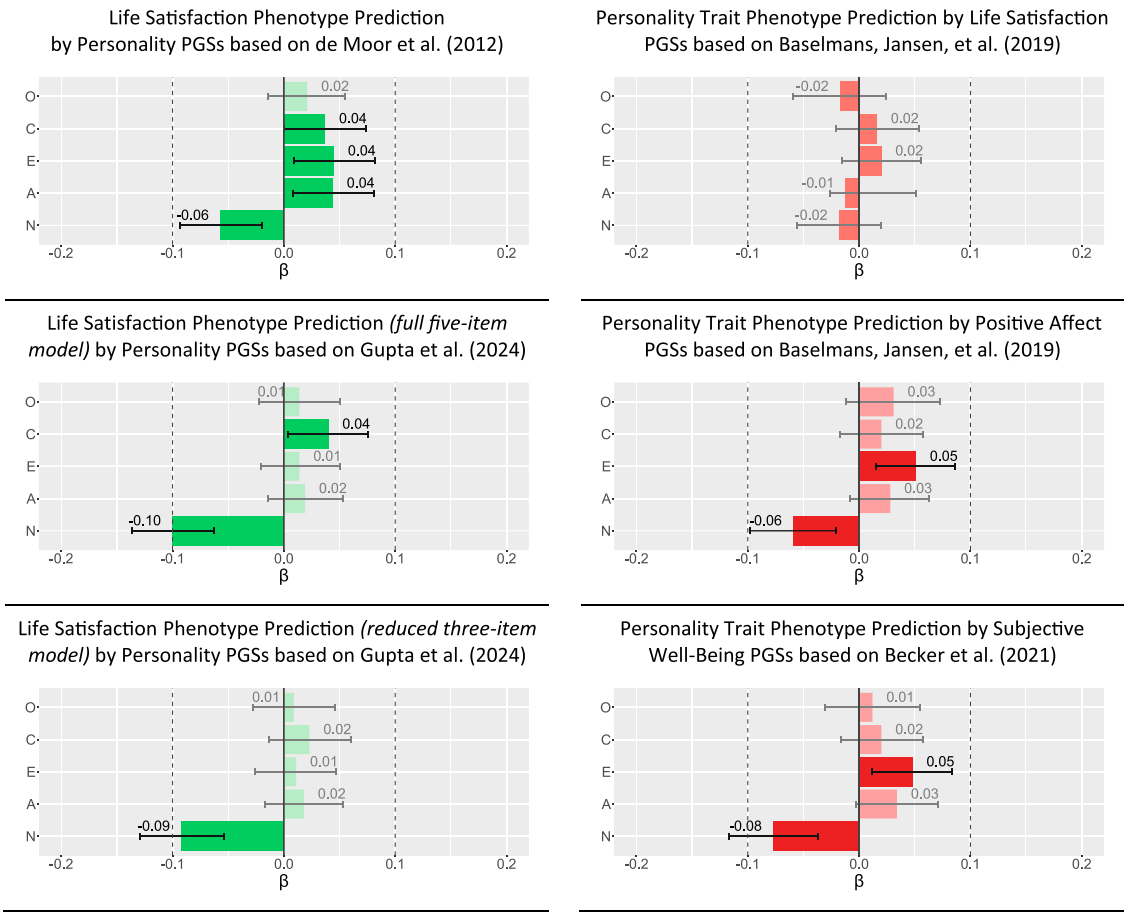


Figure 4. Genotype-phenotype prediction in the full sample. *Note.* O = Openness; C = Conscientiousness; E = Extraversion; A = Agreeableness; N = Neuroticism. Estimates represent standardized regression coefficients from regression paths within structural equation models. Light green/light red/light gray bars denote statistically insignificant coefficients with $p > .05$. Whiskers represent 95% confidence intervals.

linked to SWB in younger age groups, and further but inconsistent age differences in the personality–SWB links appeared in molecular genetic analyses.

Genetic variance in personality explains genetic variance in life satisfaction

In line with Weiss et al. (2008), Hahn et al. (2013), Røysamb et al. (2018), Sadiković et al. (2018), and Pelt et al. (2024), our findings point to neuroticism and extraversion as the most robust personality mediators of genetic variance in SWB set-points, while openness was largely unrelated. Our study adds to the former studies by focusing on the links between six-year stable personality traits and life satisfaction set-points. The observed pattern therefore seems to replicate across different WEIRD (Western, educated, industrialized, rich, and democratic) countries, samples, and measurement occasions. This supports a genetic top-down structure of SWB, in which more generalized (core) personality traits are directly associated with well-being measures.

Our results underline the importance of the analytic differentiation from factorially independent personality trait scores, because intercorrelated personality measures (factor scores and PGSs) could have led to biased links between personality characteristics. For instance, correlations between neuroticism, agreeableness, and conscientiousness might lead to an over- or underestimation of each dimension's role towards SWB if factorial interdependence of theoretically independent personality domains is not accounted for. Intuitive associations of neuroticism and extraversion emerged, which include facets directly related to well-being (e.g., positive affectivity as part of extraversion; anxiety and depression symptoms as part of neuroticism; McCrae & Costa, 1991; Soto & John, 2016). Along with conscientiousness and agreeableness, a high to complete genetic overlap between personality and life satisfaction was observed. Conversely, environmental sources of variance were found to be largely unique to personality and life satisfaction in the context of our analyses. This finding is similar to the results from previous research (Pelt et al., 2024; Røysamb et al., 2018; Weiss et al., 2008). However, it should also be noted that a certain proportion of the unshared variance is due to measurement error. Thus, environmental influences seem to act largely differentially upon personality traits and life satisfaction characteristics and should be the object of dedicated research. For example, individual health trajectories might mediate environmental variance in life satisfaction or moderate its expression (Diener & Chan, 2011; Mroczek et al., 2020). Socioeconomic status and possibly associated differences in job security or daily hassles in the workplace may play a

role (Gottschling et al., 2019; Kesebir & Diener, 2008). Varying partnership trajectories and perceived relationship or friendship network quality are other plausible mediators of environmental differences (Lucas & Dyrenforth, 2006; Stern et al., 2024). In future studies, variables like these may be implemented in a multivariate genetically informative framework like the one we employed here to identify potential sources of variance and mediations. Likewise, they could be used in the analysis of gene-environment interaction (Purcell, 2002) to investigate their potential role in moderating genetic influences and other environmental factors on the links between personality and subjective well-being.

Polygenic associations largely mirror twin study findings

Links between personality and well-being PGSs mirrored the main twin study findings: Neuroticism showed the most robust associations with well-being PGSs. Links of polygenic indices for extraversion were prominent as well. Associations with conscientiousness were only pronounced in PGS–PGS correlations and did not show reliable associations in phenotype prediction, while openness was again only marginally associated with SWB. In genotype-phenotype prediction, neuroticism and extraversion PGSs showed the strongest associations with life satisfaction set-points. Despite some differences in results concerning the other personality PGSs, the pattern with neuroticism and extraversion PGSs as the strongest predictors and openness as the weakest one replicates across both twin study and molecular genetic results. Thus, we see cross-methodological evidence for the pattern of genetic personality–SWB links.

While showing comparable patterns in sum, PGS associations between personality and well-being were generally low when considering personality PGSs based on the relatively dated de Moor et al. (2012) GWAS, with a maximum of 2.8% and < 1% of variance explained in many of the considered constellations. Different from previous results (e.g., Weiss et al., 2016), we did find small but statistically significant associations between well-being measures and personality PGSs based on de Moor et al. (2012). When considering personality PGSs based on the more recent Gupta et al. (2024) GWAS, variance explanation in well-being PGSs increased up to 16.7%. This increase might be partly due to the increased sample overlap between the Gupta et al. (2024) GWAS with the Baselmans, Jansen, et al. (2019) and Becker et al. (2021) GWASs. All three analyzed UK Biobank data, among others, while de Moor et al. (2012) did not. Phenotype prediction from PGSs was still low and remained < 3%. Twin study estimates were much higher: About 18% to 23% of total variance (compared to < 3%) and about 50% to 100% (compared to a maximum of 16.7%) of the genetic variance in life satisfaction was explained by genetic differences in personality traits. This was much larger compared to the predictive power from personality PGSs regarding life satisfaction PGSs or life satisfaction phenotypes, a phenomenon discussed as the *missing heritability* problem (Matthews & Turkheimer, 2022). This term describes the large differences in heritability estimates between twin studies and current molecular genetic studies. These can stem from the limitations inherent to PGS and twin study methodologies, which might result in an under- or overestimation of genetic effects, respectively. Both are discussed further in the limitations section. In sum, while PGSs can mirror overall patterns found in twin studies, we still see wide power margins from current polygenic predictors.

Age differences in the role of personality domains for well-being

Associations between personality traits and SWB varied across age groups in the twin study. Based on the CTD, extraversion was not genetically linked to initial first-wave life satisfaction in the youngest cohort (born 2003/04; $M_{Age} = 11$). Stable genetic differences in openness were only linked with genetic set-point variance in life satisfaction in the middle cohort (born 1997/98; age range 17–23). Stable genetic variance components unique to life satisfaction emerged only in the oldest cohort (born 1990–93; age range 23–29). This might mean that genetic factors underlying differences in openness might be differentially relevant for well-being across developmental phases. For instance, during emerging adulthood, characterized by the leaving of school, entering the job market, possibly moving out of the parental home or relocating, finding new social circles within academic or career settings, openness to experience might be more relevant to achieve outcomes positively associated with SWB. In contrast, the positive maintenance of academic and career trajectories or social circles during later maturation might be comparatively independent from openness to experience.

In the molecular genetic findings, only minor age differences emerged, but there were no systematic patterns between the different PGS predictors or between the PGS and the twin study. The age differences that were found in the twin study, however, could point to genetic variance associated with personality traits to be differentially relevant for life satisfaction throughout the lifespan. For example, genetic variance in conscientiousness showed stronger associations with genetic variance in life satisfaction set-points in the two younger cohort groups. This might mean that genetic loci associated with conscientiousness could be differentially relevant across the lifespan. For instance, conscientiousness facets of achievement-striving and diligence might be especially relevant in formative educational and professional life stages for achieving outcomes positively associated with SWB.

All in all, neuroticism showed the strongest and most robust associations across age cohorts and studies, while openness was unrelated in most (but not all) of the considered constellations. The level of emotional stability therefore seems to be most relevant for overall SWB levels across all ages. At that, neuroticism appears as a constant and significant lifetime predictor of genetic set-point differences in SWB, while other personality characteristics might play mutable roles throughout the lifespan.

Strengths and limitations

The studies at hand provide further evidence towards a growing body of research regarding personality–SWB associations. Our twin study analysis of six-year stable trait scores further adds evidence for younger, less studied ages thus far. Results underscore previous findings and extend them with an examination of age cohort differences. These shed light on some differences across age, whereby we followed recent suggestions on the inclusion of PGSs in the analysis of longitudinal data (Allegrini et al., 2022), although we could not directly disentangle age from birth cohort effects.

While study 2 compared PGS-based associations between personality traits and different well-being facets, as a phenotypic measure, we had to rely on life satisfaction. Thus, the examined associations do not cover all SWB components. Links between personality traits and other facets might manifest differently. It also has to be noted that PGSs have inherent limitations (e.g., biases introduced by ethnicity, social and geographical stratification, and gene-environment interplay), which kept us from referring to them as indicators of "*genetic propensity*", and had us rather describe them as polygenic "*estimates*" (following suggestions of Burt, 2023 and subsequent peer commentary).

This links to the previously mentioned *heritability gap* (Kandler & Instinske, 2025; Matthews & Turkheimer, 2022), which describes the rather strong differences between polygenic and twin study estimation of genetic effects. On the one hand, this might be due to an underestimation of genetic effects from current polygenic methods. On the other hand, this might be due to an overestimation of genetic effects from the CTD. We elaborate on both in the following paragraphs.

GWASs are systematic molecular genetic studies that typically require very large sample sizes to uncover polygenic associations with complex psychological traits. They are based on regressions of phenotype characteristics on many genetic SNPs, and cannot account for the influences of rare genetic variants, copy number variants, epigenetic modifications, or non-additive genetic effects (Matthews & Turkheimer, 2022; Burt, 2023). The latter might be especially relevant here, as our results on twin correlations and from univariate twin models have shown. The legacy GWAS by de Moor et al. (2012) might have been considerably limited regarding sample size, with N = 17,375 and only two found loci with genome-wide significance. While the personality GWAS based on Gupta et al. (2024) had a considerably larger sample size with N = 237,390 to 682,688 and 234 loci with genome-wide significance, its explanatory power towards personality and life satisfaction phenotypes was still very low. More recent developments in personality trait GWASs promise stronger variance explanation in Big Five personality traits, for example, the recent preprint by Schwaba et al. (2025; N = 611,000 to 1,140,000 and 1257 loci with genome-wide significance), for which the summary statistics were not yet publicly available by the time of our analyses. Such increased sample sizes and increased numbers of identified genetic loci might (but do not necessarily) translate into further increases in explanatory power. Future studies should therefore elucidate whether ongoing GWAS developments offer increases in the explanatory power of the Big Five and, by extension, of subjective well-being.

The CTD can only estimate either shared environmental or non-additive genetic effects. However, if both factors play a role, additive genetic effects would be overestimated in the twin model. As a consequence, some of the genetic overlap between personality traits and well-being measures could reflect common environmental factors shared by twins reared together. The CTD also comes with some further limitations stemming from its necessary assumptions. Most prominently, CTDs assume an absence of gene-environment interplay, such as gene-environment correlation (*rGE*) and gene-environment interaction (*GxE*). These assumptions rarely hold and might lead to biased estimations of genetic effects, if present (Kandler et al., 2019). Active or evocative *rGE* (i.e., seeking out environments or receiving reactions from environments that fit heritable characteristics) and *AxC* interaction effects would be confounded with estimates of *A* effects in *ACE* models (Briley et al., 2018; Purcell, 2002). It is plausible that either of these mechanisms could influence both personality and subjective well-being and contribute to their association. For example, a genetic influence on comparatively high neuroticism might elicit more negative environmental reactions, leading to lower subjective well-being (evocative *rGE*). Individuals with a genetic influence on comparatively high extraversion might actively seek out larger, more active, or more stimulating friendship networks, leading to higher subjective well-being (active *rGE*). Parental demands shared by twins might positively accentuate genetic influences on conscientiousness, which can lead to increases in subjective well-being via educational or career trajectories (*AxC* interaction). Furthermore, passive *rGE* would be confounded with *C* estimates, while *AxE* interactions would be confounded with *E* estimates. While our results suggested no evidence for passive *rGE* in personality traits, since *C* was negligible, *AxE* interaction effects could underly the small environmental links between personality traits and life satisfaction. The presence of *rGE* and *GxE* effects, the latter of which are not confounded with PGSs, can act differently across the lifespan which could account for some of the observed age group differences. Particularly, the *GxE* interactions between genetic effects and environmental influences shared between twins reared together, if present, are confounded with estimates of genetic effects. These are comparatively likely in our highly educated and relatively affluent sample. Taken together, these factors might account to some degree for the large gap in explained variance between the twin study and PGS study results.

The BFI-S, which was used for phenotypic measurement of personality, is a very short measure to capture broad personality trait dimensions. Consequently, it shows low internal consistency estimates deemed unacceptable by some standards (i.e., $\omega \geq .70$; Lance et al., 2006). We however argue that strict cutoff criteria like this are often arbitrary and do not consider specifics of certain research situations. The BFI-S has been developed to capture Big

Five traits economically but as broad as possible (Gerlitz & Schupp, 2005). Low internal consistency might be necessary and even desired in such an instrument, while the factorial validity should be and can be considered high (Hahn et al., 2012; see also Credé et al., 2012; Heene et al., 2014; McCrae et al., 2010). Panel studies often have to balance time efficiency with diagnostic precision. Therefore, despite this limitation, the BFI-S is nonetheless a regularly used and valid instrument. As recommended by Hahn et al. (2012), using SEM frameworks is pivotal to deal with the main issue arising from low internal consistency, namely, increased likelihood of measurement error. The SEM-based longitudinal state-trait analyses in Study 1 addressed this issue and showed only minor differences to the results based on initial cross-sectional factor scores. Moreover, twin data regarding personality differences were found to be comparable to those of the general population (Johnson et al., 2002). The limitations regarding bandwidth in the BFI-S may still have produced lower personality–SWB associations than could have been expected with the use of broader measures. Despite these potential limitations and possible resulting underestimation of associations, we still see comparatively strong links between Big Five personality and life satisfaction. Given our findings confirm earlier results based on more informative personality scales (Pelt et al., 2024 analyzed NEO-FFI3 data; Røysamb et al., 2018 analyzed NEO-PI-R data; Weiss et al., 2008 analyzed MIDI data), we conclude that the low internal consistency of the BFI-S can be considered a minor issue.

As one of the first studies to incorporate all Big Five personality traits in quantitative genetic *and* molecular genetic designs to uncover age differences in associations between personality and SWB, our results showed that genetic variance in personality traits can be differentially important across the lifespan to explain variance in SWB levels. Although the main association patterns were consistent across both twin study and PGS results, common patterns of age differences did not show up between studies. This could in part be due to the different age ranges in both studies or due to the described power limitations of PGSs. Nonetheless, future studies could further focus on age differences in genetic variance in personality explaining well-being, as this might point towards systematic differences across the lifespan. Another approach could be to investigate differences in the explained variance between twin studies and molecular genetic designs, taking the limitations of both into account. Future studies could investigate to what extent CTD limitations lead to an overestimation of genetic variance (e.g., by elucidating biases from gene-environment interaction effects) or whether future developments in molecular genetic methodology can correct for a possible underestimation of genetic variance from polygenic information (e.g., increases in sample size and discovery of influences from previously unidentified loci, whole-genome sequencing including rare variants, longitudinal phenotyping, or improved epistasis modeling; Tang et al., 2023). Taken together, these approaches might be able to reduce the heritability gap (Kandler & Instinske, 2025; Matthews & Turkheimer, 2022).

Outlook and conclusion

Our studies provide evidence that genetic differences in well-being are linked to genetic differences in basic personality traits. Association patterns replicate across quantitative and molecular genetic approaches, particularly underscoring the robust link between neuroticism and SWB. Established twin study results on the genetic links between personality traits and well-being could be mirrored based on molecular genetic information. Significant age differences in phenotypic and genetic links between personality traits and well-being were found, with openness, extraversion, and conscientiousness showing the most pronounced age group differences.

As GWASs increase in sample size and precision, a more accurate detection of genetic variants relevant for complex behavioral traits might become possible. Personality PGSs based on forthcoming GWASs might thus yield increases in explanatory power regarding genetic set-points in SWB. Our study has shown that age differences should be considered in the investigation of genetic personality–SWB links. With most of the environmental influences on personality and SWB unique to each construct, the environmental personality–SWB link was estimated as small, but might be meaningful nonetheless, and could also be focused with respect to different age-dependent context variables in future studies.

After all, the observed associations might manifest through differences in personality-driven behavior. Future research could shed light on this by examining possible mediators between personality and SWB (e.g., educational, professional, and health behaviors). Examining other potential mediators, such as experiences related to educational and professional attainment, social inclusion, or susceptibility to external influences, could further enhance our understanding of the associations between personality and SWB. One aim of future research could therefore be to investigate which tangible individual behaviors, choices, and situations (e.g., life stages or environments) might facilitate the found associations between personality domains and well-being (Kandler et al., 2024). In sum, we conclude from our results that well-being is indeed a personality thing (Weiss et al., 2008), at least on the basis of genetic associations, and one that can have different meanings across developmental phases and contexts over the lifespan.

Author contributions

Deppe, Marco, Project administration, conceptualization, methodology, data curation (panel data), software, formal analysis, investigation, validation, visualization, writing – original draft, writing – review & editing. Pahnke, Charlotte Katharina Louise, Conceptualization, methodology, data curation (polygenic scores), software, formal analysis, investigation, writing – review & editing. Maj, Carlo, Data curation (genotype data), resources, methodology, software, formal analysis, investigation, validation, writing – review & editing. Aldisi, Rana, Data curation (genotype data), resources, methodology, software, formal analysis. Nöthen, Markus, Supervision, resources, funding acquisition. Diewald, Martin,

Resources, funding acquisition. Spinath, Frank Michael, Resources, funding acquisition. Forstner, Andreas Josef, Supervision, resources, writing – review & editing. Kandler, Christian, Project administration, conceptualization, methodology, supervision, resources, funding acquisition, writing – review & editing

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Positions of involved researchers, the *TwinLife* project, and molecular genetic analyses are kindly funded by the German Research Foundation (DFG; funding no. 458609264 for the position of M. Deppe, funding no. 428902522 for the position of C. Pahnke and molecular genetic analyses within the *TwinSNPs* project, funding no. 220286500 for the *TwinLife* project).

Open science statement



The phenotype data analyzed in this article are freely available and can be accessed on request via a simple online form at https://search.gesis.org/research_data/ZA6701. Polygenic score data from molecular genetic analyses can currently only be shared with collaboration partners via a valid data transfer agreement, due to data protection laws. The study materials used for this article can be accessed at https://www.twin-life.de/documentation/downloads. https://doi.org/10.17605/OSF.IO/NQH26We decided not to pre-register our analyses, as they mostly cover quasi-replications of previous empirical findings. Phenotype data are publicly available as *TwinLife* Scientific Use File v8.0.0 (https://doi.org/10.4232/1.14331). Materials such as questionnaires are provided with the Scientific Use File(s). Supplemental material and syntax files for statistical software are openly shared via the Open Science Framework: https://doi.org/10.17605/OSF.IO/NQH26.

ORCID iDs

Marco Deppe https://orcid.org/0000-0002-3927-8291
Christian Kandler https://orcid.org/0000-0002-9175-235X

Supplemental Material

Supplemental material for this article is available online.

References

Allegrini, A. G., Baldwin, J. R., Barkhuizen, W., & Pingault, J. B. (2022). Research review: A guide to computing and implementing polygenic scores in developmental research. *The Journal of Child Psychology and Psychiatry and Allied Disciplines*, *63*(10), 1111–1124. https://doi.org/10.1111/jcpp.13611

Andlauer, T. F. M., & Nöthen, M. M. (2020). Polygenic scores for psychiatric disease: From research tool to clinical application. *Medizinische Genetik*, *32*(1), 39–45. https://doi.org/10.1515/medgen-2020-2006

Anglim, J., Horwood, S., Smillie, L. D., Marrero, R. J., & Wood, J. K. (2020). Predicting psychological and subjective well-being from personality: A meta-analysis. *Psychological Bulletin*, *146*(4), 279–323. https://doi.org/10.1037/bul0000226

Barnett, M. J., Doroudgar, S., Khosraviani, V., & Ip, E. J. (2022). Multiple comparisons: To compare or not to compare, that is the question. *Research in Social and Administrative Pharmacy: RSAP*, *18*(2), 2331–2334. https://doi.org/10.1016/j.sapharm.2021.07.006

Bartels, M. (2015). Genetics of wellbeing and its components satisfaction with life, happiness, and quality of life: A review and meta-analysis of heritability studies. *Behavior Genetics*, *45*(2), 137–156. https://doi.org/10.1007/s10519-015-9713-y

Baselmans, B. M. L., Jansen, R., Hill, F. I., van Dongen, J., Abdellaoui, A., van de Weijer, M. P., Bao, Y., Smart, M., Kumari, M., Willemsen, G., Hottenga, J.-J., Boomsma, D. I., de Geus, E. J. C., Nivard, M. G., Bartels, M., & BIOS consortium, Social Science Genetic Association Consortium. (2019). Multivariate genome-wide analyses of the well-being spectrum. *Nature Genetics*, *51*(3), 445–451. https://doi.org/10.1038/s41588-018-0320-8

Baselmans, B. M. L., van de Weijer, M. P., Abdellaoui, A., Vink, J. M., Hottenga, J. J., Willemsen, G., Nivard, M. G., de Geus, E. J. C., Boomsma, D. I., & Bartels, M. (2019). A genetic investigation of the well-being spectrum. *Behavior Genetics*, *49*(3), 286–297. https://doi.org/10.1007/s10519-019-09951-0

Becker, J., Burik, C. A. P., Goldman, G., Wang, N., Jayashankar, H., Bennett, M., Belsky, D. W., Linnér, R. K., Ahlskog, R., Kleinman, A., Hinds, D. A., Caspi, A., Corcoran, D. L., Moffitt, T. E., Poulton, R., Sugden, K., Williams, B. S., Harris, K. M., Okbay, A., & 23 and Me Research Group. (2021). Resource profile and user guide of the polygenic index repository. *Nature Human Behaviour*, *5*(12), 1744–1758. https://doi.org/10.1038%2Fs41562-021-01119-3

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society - Series B: Statistical Methodology*, *B57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Bjørndal, L. D., Nes, R. B., Czajkowski, N., & Røysamb, E. (2023). The structure of well-being: A single underlying factor with genetic and environmental influences. *Quality of Life Research: An International Journal of Quality of Life Aspects of Treatment, Care and Rehabilitation*, *32*(10), 2805–2816. https://doi.org/10.1007/s11136-023-03437-7

Briley, D. A., Livengood, J., & Derringer, J. (2018). Behavior genetic frameworks of causal reasoning for personality psychology. *European Journal of Personality*, *32*(3), 202–220. https://doi.org/10.1002/per.2153

Brown, N. J. L., & Rohrer, J. M. (2020). Easy as (Happiness) pie? A critical evaluation of a popular model of the determinants of well-being. *Journal of Happiness Studies*, *21*(4), 1285–1301. https://doi.org/10.1007/s10902-019-00128-4

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods & Research*, *33*(2), 261–304. https://doi.org/10.1177/0049124104268644

Burt, C. H. (2023). Challenging the utility of polygenic scores for social science: Environmental confounding, downward causation, and unknown biology. *Behavioral and Brain*

Sciences, *46*(e207), 1–66. https://doi.org/10.1017/s0140525x22001145

Cheung, G. W., & Rensvold, R. B. (1998). Cross-cultural comparisons using non-invariant measurement items. *Applied Behavioral Science Review*, *6*(1), 93–110. https://doi.org/10.1016/s1068-8595(99)80006-3

Credé, M., Harms, P., Niehorster, S., & Gaye-Valentine, A. (2012). An evaluation of the consequences of using short measures of the Big Five personality traits. *Journal of Personality and Social Psychology*, *102*(4), 874–888. https://doi.org/10.1037/a0027403

de Moor, M. H., Costa, P. T., Terracciano, A., Krueger, R. F., de Geus, E. J., Toshiko, T., Penninx, B. W., Esko, T., Madden, P. A., Derringer, J., Amin, N., Willemsen, G., Hottenga, J. J., Distel, M. A., Uda, M., Sanna, S., Spinhoven, P., Hartman, C. A., Sullivan, P., … van Duijn, C. M. (2012). Meta-analysis of genome-wide association studies for personality. *Molecular Psychiatry*, *17*(3), 337–349. https://doi.org/10.1038/mp.2010.128

Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, *95*(3), 542–575. https://doi.org/10.1037/0033-2909.95.3.542

Diener, E., & Chan, M. Y. (2011). Happy people live longer: Subjective well-being contributes to health and longevity. Applied Psychology. *Applied Psychology: Health and Well-Being*, *3*(1), 1–43. https://doi.org/10.1111/j.1758-0854.2010.01045.x

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Diener, E., Pressman, S. D., Hunter, J., & Delgadillo-Chase, D. (2017). If, why, and when subjective well-being influences health, and future needed research. *Applied psychology. Health and well-being*, *9*(2), 133–167. https://doi.org/10.1111/aphw.12090

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276–302. https://doi.org/10.1037/0033-2909.125.2.276

Diewald, M., Kandler, C., Riemann, R., Spinath, F. M., Andreas, A., Baier, T., Bartling, A., Baum, M. A., Deppe, M., Eichhorn, H., Eifler, E. F., Gottschling, J., Hahn, E., Hildebrandt, J., Hufer-Thamm, A., Instinske, J., Kaempfert, M., Klatzka, C. H., & Weigel, L. (2023). *TwinLife*. GESIS Data Archive, ZA6701. Data File Version 7.1.0 [dataset]. https://doi.org/10.4232/1.14186

DiStefano, C., Zhu, M., & Mîndrilã, D. (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research and Evaluation*, *14*(1), 20. https://doi.org/10.7275/da8t-4g52

Evans, D. M., Gillespie, N. A., & Martin, N. G. (2002). Biometrical genetics. *Biological Psychology*, *61*(1–2), 33–51. https://doi.org/10.1016/s0301-0511(02)00051-0

Fairley, S., Lowy-Gallego, E., Perry, E., & Flicek, P. (2020). The International Genome Sample Resource (IGSR) collection of open human genomic variation resources. *Nucleic Acids Research*, *48*(D1), D941–D947. https://doi.org/10.1093/nar/gkz836

Falconer, D. S. (1989). *Introduction to quantitative genetics* (3rd ed.). Longman.

Fergusson, D., McLeod, G., Horwood, L., Swain, N., Chapple, S., & Poulton, R. (2015). Life satisfaction and mental health problems (18 to 35 years). *Psychological Medicine*, *45*(11), 2427–2436. https://doi.org/10.1017/S0033291715000422

Freitag, E. W., & Kelsey, C. M. (2023). Taking a lifespan approach to polygenic scores. *Behavioral and Brain Sciences*, *46*(e215), 30–31. https://doi.org/10.1017/S0140525X2200245X

Gadermann, A. M., Schonert-Reichl, K. A., & Zumbo, B. D. (2010). Investigating validity evidence of the Satisfaction with Life Scale adapted for children. *Social Indicators Research*, *96*(2), 229–247. https://doi.org/10.1007/s11205-009-9474-1

Gartland, N., Wilson, A., Lawton, R., & O'Connor, D. B. (2021). Conscientiousness and engagement with national health behaviour guidelines. *Psychology Health & Medicine*, *26*(4), 421–432. https://doi.org/10.1080/13548506.2020.1814961

Ge, T., Chen, C.-Y., Ni, Y., Feng, Y.-C. A., & Smoller, J. W. (2019). Polygenic prediction via Bayesian regression and continuous shrinkage priors. *Nature Communications*, *10*(1), 1776. https://doi.org/10.1038/s41467-019-09718-5

Gebauer, J. E., Eck, J., Entringer, T. M., Bleidorn, W., Rentfrow, P. J., Potter, J., & Gosling, S. D. (2020). The well-being benefits of person-culture match are contingent on basic personality traits. *Psychological Science*, *31*(10), 1283–1293. https://doi.org/10.1177/0956797620951115

Gerlitz, J.-Y., & Schupp, J. (2005). *Zur Erhebung der Big-Five-basierten Persönlichkeitsmerkmale im SOEP*. DIW Research Notes, 4. DIW Berlin. https://www.diw.de/documents/publikationen/73/43490/rn4.pdf

Gottschling, J., Hahn, E., Beam, C. R., Spinath, F. M., Carroll, S., & Turkheimer, E. (2019). Socioeconomic status amplifies genetic effects in middle childhood in a large German twin sample. *Intelligence*, *72*(1), 20–27. https://doi.org/10.1016/j.intell.2018.11.006

Gupta, P., Galimberti, M., Liu, Y., Beck, S., Wingo, A., Wingo, T., Adhikari, K., Kranzler, H. R., Stein, M. B., Gelernter, J., Levey, D. F., & VA Million Veteran Program. (2024). A genome-wide investigation into the underlying genetic architecture of personality traits and overlap with psychopathology. *Nature Human Behaviour*, *8*(11), 2235–2249. https://doi.org/10.1038/s41562-024-01951-3

Hahn, E., Gottschling, J., & Spinath, F. M. (2012). Short measurements of personality – Validity and reliability of the GSOEP Big Five Inventory (BFI-S). *Journal of Research in Personality*, *46*(3), 355–359. https://doi.org/10.1016/j.jrp.2012.03.008

Hahn, E., Johnson, W., & Spinath, F. M. (2013). Beyond the heritability of life satisfaction – The roles of personality and twin-specific influences. *Journal of Research in Personality*, *47*(6), 757–767. https://doi.org/10.1016/j.jrp.2013.07.003

Headey, B., & Muffels, R. (2018). A theory of life satisfaction dynamics: Stability, change and volatility in 25-year life trajectories in Germany. *Social Indicators Research*, *140*(2), 837–866. https://doi.org/10.1007/s11205-017-1785-z

Heene, M., Bollmann, S., & Bühner, M. (2014). Much ado about nothing, or much to do about something? *Journal of Individual Differences*, *35*(4), 245–249. https://doi.org/10.1027/1614-0001/a000146

Hufer-Thamm, A., Starr, A., & Steinmayr, R. (2023). Is there evidence for intelligence-by-conscientiousness interaction in the prediction of change in school grades from age 11 to 15

years? *Journal of Intelligence*, *11*(3), 45. https://doi.org/10.3390/jintelligence11030045

Johnson, W., Krueger, R. F., Bouchard, Jr., T. J., & McGue, M. (2002). The personalities of twins: Just ordinary folks. *Twin Research*, *5*(2), 125–131. https://doi.org/10.1375/1369052022992

Jokela, M., Bleidorn, W., Lamb, M. E., Gosling, S. D., & Rentfrow, P. J. (2015). Geographically varying associations between personality and life satisfaction in the London metropolitan area. *Proceedings of the National Academy of Sciences*, *112*(3), 725–730. https://doi.org/10.1073/pnas.1415800112

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, *23*(3), 187–200. https://doi.org/10.1007/BF02289233

Kandler, C., & Instinske, J. (2025). The polygenic and polyenvironmental nature of personality. *Current Opinion in Psychology*, *65*(1), Article 102068. https://doi.org/10.1016/j.copsyc.2025.102068

Kandler, C., Kühn, S., Mönkediek, B., Forstner, A. J., & Bleidorn, W. (2024). A multidisciplinary perspective on person-environment fit: Relevance, measurement, and future directions. *Current Directions in Psychological Science*, *33*(3), 198–205. https://doi.org/10.1177/09637214241242451

Kandler, C., & Papendick, M. (2017). Behavior genetics and personality development: A methodological and meta-analytic review. In J. Specht (Ed.), *Personality development across the lifespan* (pp. 473–495). Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-804674-6.00029-6

Kandler, C., Riemann, R., Spinath, F. M., & Angleitner, A. (2010). Sources of variance in personality facets: A twin study of self-self, peer-peer, and self-peer (dis-)agreement. *Journal of Personality*, *78*(5), 1565–1594. https://doi.org/10.1111/j.1467-6494.2010.00661.x

Kandler, C., Waaktaar, T., Mõttus, R., Riemann, R., & Torgersen, S. (2019). Unravelling the interplay between genetic and environmental contributions in the unfolding of personality differences from early adolescence to young adulthood. *European Journal of Personality*, *33*(3), 221–224. https://doi.org/10.1002/per.2189

Kandler, C., Zimmermann, J., & McAdams, D. P. (2014). Core and surface characteristics for the description and theory of personality differences and development. *European Journal of Personality*, *28*(3), 231–243. https://doi.org/10.1002/per.1952

Kendler, K. S., Gardner, C. O., & Lichtenstein, P. (2008). A developmental twin study of symptoms of anxiety and depression: Evidence for genetic innovation and attenuation. *Psychological Medicine*, *38*(11), 1567–1575. https://doi.org/10.1017/S003329170800384X

Kesebir, P., & Diener, E. (2008). In pursuit of happiness: Empirical answers to philosophical questions. *Perspectives on Psychological Science*, *3*(2), 117–125. https://doi.org/10.1111/j.1745-6916.2008.00069.x

Kohler, H.-P., Behrman, J. R., & Schnittker, J. (2011). Social science methods for twins data: Integrating causality, endowments, and heritability. *Biodemography and Social Biology*, *57*(1), 88–141. https://doi.org/10.1080/19485565.2011.580619

Kokko, K., Rantanen, J., & Pulkkinen, L. (2015). Associations between mental well-being and personality from a life span perspective. In M. Blatný (Ed.), *Personality and well-being across the life-span* (pp. 134–159). Palgrave Macmillan. https://doi.org/10.1057/9781137439963_8

Lance, C. E., Butts, M. M., & Michels, L. C. (2006). The sources of four commonly reported cutoff criteria. What did they really say? *Organizational Research Methods*, *9*(2), 202–220. https://doi.org/10.1177/1094428105284919

Lang, V., & Kottwitz, A. (2017). *The sampling design and sociodemographic structure of the first wave of the TwinLife panel study: A comparison with the Microcensus. TwinLife Technical Report Series, 03*. Universität Bielefeld/Universität des Saarlandes.

Lo, M. T., Hinds, D. A., Tung, J. Y., Franz, C., Fan, C.-C., Wang, Y., Smeland, O. B., Schork, A., Holland, D., Kauppi, K., Sanyal, N., Escott-Price, V., Smith, D. J., O'Donovan, M., Stefansson, H., Bjornsdottir, G., Thorgeirsson, T. E., Stefansson, K., McEvoy, L. K., … Andreassen, O. A. (2017). Genome-wide analyses for personality traits identify six genomic loci and show correlations with psychiatric disorders. *Nature Genetics*, *49*(1), 152–156. https://doi.org/10.1038/ng.3736

Lucas, R. E., & Dyrenforth, P. S. (2006). Does the existence of social relationships matter for subjective well-being? In K. D. Vohs & E. J. Finkel (Eds.), *Self and relationships: Connecting intrapersonal and interpersonal processes* (pp. 254–273). The Guilford Press.

Luo, J., Zhang, B., Graham, E. K., & Mroczek, D. K. (2023). Does personality always matter for health? Examining the moderating effect of age on the personality-health link from life span developmental and aging perspectives. *Journal of Personality and Social Psychology*, *125*(5), 1189–1206. https://doi.org/10.1037/pspp0000485

Lykken, D., & Tellegen, A. (1996). Happiness is a stochastic phenomenon. *Psychological Science*, *7*(3), 126–190. https://doi.org/10.1111/j.1467-9280.1996.tb00355.x

Magee, C. A., Miller, L. M., & Heaven, P. C. L. (2013). Personality trait change and life satisfaction in adults: The roles of age and hedonic balance. *Personality and Individual Differences*, *55*(6), 694–698. https://doi.org/10.1016/j.paid.2013.05.022

Markon, K. E., & Krueger, R. F. (2004). An empirical comparison of information-theoretic selection criteria for multivariate behavior genetic models. *Behavior Genetics*, *34*(6), 593–610. https://doi.org/10.1007/s10519-004-5587-0

Matthews, L. J., & Turkheimer, E. (2022). Three legs of the missing heritability problem. *Studies in History and Philosophy of Science*, *93*(1), 183–191. https://doi.org/10.1016/j.shpsa.2022.04.004

McCrae, R. R., & Costa, P. T. (1991). Adding Liebe und Arbeit: The full Five-Factor Model and well-being. *Personality and Social Psychology Bulletin*, *17*(2), 227–232. https://doi.org/10.1177/014616729101700217

McCrae, R. R., Kurtz, J. E., Yamagata, S., & Terracciano, A. (2010). Internal consistency, retest reliability, and their implications for personality scale validity. *Personality and Social Psychology Review*, *15*(1), 28–50. https://doi.org/10.1177/1088868310366253

Mroczek, D. K., Weston, S. J., & Willroth, E. C. (2020). A lifespan perspective on the interconnections between personality, health, and optimal aging. In P. L. Hill & M. Allemand (Eds.), *Personality and healthy aging in adulthood* (pp. 191–202). Springer. https://doi.org/10.1007/978-3-030-32053-9_12

Neale, M. C., & Maes, H. H. (2004). *Methodology for genetic studies of twins and families*. Kluwer.

Okbay, A., Baselmans, B. M. L., De Neve, J.-E., Turley, P., Nivard, M. G., Alan, M. A., Meddens, S. F. W., Linnér, R. K., Rietveld,

C. A., Derringer, J., Gratten, J., Lee, J. J., Liu, J. Z., de Ivaming, R., Ahluwaila, T. S., Buchwald, J., Cavadino, A., Frazier-Wood, A. C., Furlotte, N. A., & LifeLines Cohort Study. (2016). Genetic variants associated with subjective well-being, depressive symptoms, and neuroticism identified through genome-wide analyses. *Nature Genetics*, *48*(6), 624–633. https://doi.org/10.1038/ng.3552

Olaru, G., van Scheppingen, M. A., Bleidorn, W., & Denissen, J. J. A. (2023). The link between personality, global, and domain-specific satisfaction across the adult lifespan. *Journal of Personality and Social Psychology*, *125*(3), 590–606. https://doi.org/10.1037/pspp0000461

Ormel, J., VonKorff, M., Jeronimus, B. F., & Riese, H. (2017). Set-point theory and personality development: Reconciliation of a paradox. In J. Specht (Ed.), *Personality development across the lifespan* (pp. 117–137). Academic Press. https://doi.org/10.1016/B978-0-12-804674-6.00009-0

Pelt, D. H. M., de Vries, L. P., & Bartels, M. (2024). Unraveling the relation between personality and well-being in a genetically informative design. *European Journal of Personality*, *38*(1), 99–119. https://doi.org/10.1177/08902070221134878

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). Interpreting factors and generating factor scores. In M. A. Pett, N. R. Lackey, & J. J. Sullivan (Eds.), *Making sense of factor analysis* (pp. 207–225). Sage. https://doi.org/10.4135/9781412984898.n7

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Purcell, S. (2002). Variance components models for gene–environment interaction in twin analysis. *Twin Research and Human Genetics*, *5*(6), 554–571. https://doi.org/10.1375/136905202762342026

Putnick, D. L., & Bornstein, M. H. (2016). Measurement invariance conventions and reporting: The state of the art and future directions for psychological research. *Developmental Review*, *41*(1), 71–90. https://doi.org/10.1016/j.dr.2016.06.004

Rohm, T., Andreas, A., Deppe, M., Eichhorn, H., Instinske, J., Klatzka, C. H., Kottwitz, A., Krell, K., Mönkediek, B., Paulus, L., Piesch, S., Ruks, M., Starr, A., Weigel, L., Diewald, M., Kandler, C., Riemann, R., & Spinath, F. M. (2023). Data from the German TwinLife Study: Genetic and social origins of educational predictors, processes, and outcomes. *Journal of Open Psychology Data*, *11*(1), 1–15. https://doi.org/10.5334/jopd.78

Rohrer, J. M., Richter, D., Brümmer, M., Wagner, G. G., & Schmukle, S. C. (2018). Successfully striving for happiness: Socially engaged pursuits predict increases in life satisfaction. *Psychological Science*, *29*(8), 1291–1298. https://doi.org/10.1177/0956797618761660

Røysamb, E., Nes, R. B., Czajkowski, N. O., & Vassend, O. (2018). Genetics, personality and wellbeing. A twin study of traits, facets and life satisfaction. *Scientific Reports*, *8*(1), Article 12298. https://doi.org/10.1038/s41598-018-29881-x

Sadiković, S., Smederevac, S., Mitrović, D., & Milovanović, I. (2018). Behavioral genetics foundations of relations between personality traits and satisfaction with life. *Primenjena Psihologija*, *11*(4), 487–502. https://doi.org/10.19090/pp.2018.4.487-502

Schwaba, T., Clapp Sullivan, M. L., Akingbuwa, W. A., Ilves, K., Tanksley, P. T., Williams, C. M., Dragostinov, Y., Liao, W., Ackerman, L. S., Fealy, J. C. M., Hemani, G., de la Fuente, J., Gupta, P., Stein, M. B., Gelernter, J., Levey, D. F., Võsa, U., Ausmees, L., Realo, A., … Tucker-Drob, E. M. (2025). Robust inference and widespread genetic correlates from a large-scale genetic association study of human personality. *bioRxiv: The Preprint Server for Biology*, 648988. https://doi.org/10.1101/2025.05.16.648988

Schwarz, G. E. (1978). Estimating the dimension of a model. *Annals of Statistics*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Soto, C. J., & John, O. P. (2016). The next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology*, *113*(1), 117–143. https://doi.org/10.1037/pspp0000096

Stein, M. B., & Heimberg, R. G. (2004). Well-being and life satisfaction in generalized anxiety disorder: Comparison to major depressive disorder in a community sample. *Journal of Affective Disorders*, *79*(1–3), 161–166. https://doi.org/10.1016/S0165-0327(02)00457-3

Stern, J., Krämer, M. D., Schumacher, A., MacDonald, G., & Richter, D. (2024). Differences between lifelong singles and ever-partnered individuals in big five personality traits and life satisfaction. *Psychological Science*, *35*(12), 1364–1381. https://doi.org/10.1177/09567976241286865

Steyer, R., Geiser, C., & Fiege, C. (2012). Latent state-trait models. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf, & K. J. Sher (Eds.), *APA handbook of research methods in psychology, Vol. 3. Data analysis and research publication* (pp. 291–308). American Psychological Association. https://doi.org/10.1037/13621-014

Tang, D., Freudenberg, J., & Dahl, A. (2023). Factorizing polygenic epistasis improves prediction and uncovers biological pathways in complex traits. *The American Journal of Human Genetics*, *110*(11), 1875–1887. https://doi.org/10.1016/j.ajhg.2023.10.002

Vukasović, T., & Bratko, D. (2015). Heritability of personality: A meta-analysis of behavior genetic studies. *Psychological Bulletin*, *141*(4), 769–785. https://doi.org/10.1037/bul0000017

Wagner, J., Orth, U., Bleidorn, W., Hopwood, C. J., & Kandler, C. (2020). Towards an integrative model of sources of personality stability and change. *Current Directions in Psychological Science*, *29*(5), 438–444. https://doi.org/10.1177/0963721420924751

Weiss, A., Baselmans, B. M. L., Hofer, E., Yang, J., Okbay, A., Lind, P. A., Miller, M. B., Nolte, I. M., Zhao, W., Hagenaars, S. P., Hottenga, J. J., Matteson, L. K., Snieder, H., Faul, J. D., Hartman, C. A., Boyle, P. A., Tiemeier, H., Mosing, M. A., Pattie, A., … Bartels, M. (2016). Personality polygenes, positive affect, and life satisfaction. *Twin Research and Human Genetics*, *19*(5), 407–417. https://doi.org/10.1017/thg.2016.65

Weiss, A., Bates, T. C., & Luciano, M. (2008). Happiness is a personal(ity) thing: The genetics of personality and well-being in a representative sample. *Psychological Science*, *19*(3), 205–210. https://doi.org/10.1111/j.1467-9280.2008.02068.x

Wilson, R. E., Harris, K., & Vazire, S. (2015). Personality and friendship satisfaction in daily life: Do everyday social interactions account for individual differences in friendship satisfaction? *European Journal of Personality*, *29*(2), 173–186. https://doi.org/10.1002/per.1996