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Are Some People More Consistent? Examining the Stability and Underlying Processes of Personality Profile Consistency

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Personality traits are relatively consistent across time, as indicated by test–retest correlations. However, ipsative consistency approaches suggest there are individual differences in this consistency. Despite this, it is unknown whether these differences are due to person-level characteristics (i.e., some people are just more consistent) or exogenous forces (i.e., lack of consistency is due to environmental changes). Moreover, it is unclear whether the processes promoting long-term consistency are the same across people. We examine these two questions using item-level profile correlations across four to nine waves of data with four data sets ($N = 21,616$) with multilevel asymptotic growth models. Results indicated that there were, on average, high levels of profile consistency. However, there were notable individual differences in initial profile correlation values as well as in changes in levels of consistency across time, indicating that some people are more *stably* consistent than others. Moreover, the directions of people’s trajectories across increasing time intervals suggest that the mechanisms responsible for reinforcing personality consistency vary across people. These effects were typically moderated by age at 30 years old, maturity-related traits, and education level. Overall, findings indicate some people are more consistent than others, such that this stable level of (in)consistency is a dispositional factor. Additionally, individual differences in profile consistency are shaped by different levels of three processes. On average, stochastic factors are not impactful for most individuals, and transactional processes have an important role in increasing consistency for a sizable amount of people—nuances not previously revealed when focusing on rank-order stability.

Keywords: personality development, Big Five, ipsative consistency, profile correlations, person-centered

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Throughout the lifespan, a general pattern of personality consistency and stability emerges within and across individuals (Asendorpf, 1992; Beck & Jackson, 2020; Donnellan et al., 2007; Roberts et al., 2006). However, personality traits are also adaptable, malleable qualities that can fluctuate over the short-term (Beck & Jackson, 2020) as well as over longer time frames (e.g., Bleidorn et al., 2013; Conley, 1984a). Test–retest correlations are a popular choice to index the amount of consistency in personality traits across

time (Robins et al., 2001). However, using only two time points and aggregating across people with rank-order correlations obscures two open questions about personality consistency.

First, test–retest correlations are typically applied to aggregate levels of between-person, rank-order stability, inevitably masking any individual differences in personality consistency (Aldwin et al., 1989; Lamiell, 1981). In contrast, profile correlations take a person-centered approach in which the consistency of one’s personality profile (i.e., scores on personality traits or items) is relative to one’s past self, not in comparison with others, thus allowing for individual differences to be estimated. While individual differences in profile consistency are well established (e.g., Asendorpf & van Aken, 1991; Ozer & Gjerde, 1989; Terracciano et al., 2010), it is unclear whether these individual differences in consistency persist across time. That is, are some people more or less consistent in general, as some form of a dispositional individual difference? Or are individual differences in profile consistency ephemeral, perhaps due to external circumstances or measurement error?

Second, the pattern of multiple consistency estimates can provide insights into the processes driving consistency more than single test–retest correlations can (Fraleigh & Roberts, 2005). While past work suggests that stochastic, transactional, and enduring factors are all necessary to explain patterns of personality consistency (Anusic & Schimmack, 2016; Fraleigh et al., 2013; Fraleigh & Roberts, 2005), these tests were aggregated across people, making the assumption that the processes are the same for everyone. In contrast, person-centered approaches may identify different patterns of continuity across people (Beck & Jackson, 2020), with different processes

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All code to reproduce analyses, the data codebook, and Supplemental Materials are available at: <https://osf.io/23u9b/>. All data are freely available via application and/or data use agreements at the links specified in each data set’s “Participants” subsection in the Method section. Neither author has any conflicting interests to report. Some findings from this article were presented at the 2021 Association for Research in Personality conference during a data blitz.

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driving consistency. As such, it is unclear whether the processes that drive person-centered consistency are shared across people and if they mirror the processes responsible for between-person stability.

The current article addresses these two questions using multiple waves of person-centered (ipsative) consistency data. Multiple data sets spanning up to 12 years are used to examine longitudinal trends across at least three waves of consistency data. Trajectories in within-person profile consistency are viewed from two perspectives. First, we examine individual differences in levels of personality profile similarity and consistency across sequential waves to examine if those with high or low levels of consistency continue to be highly consistent or inconsistent across subsequent assessments. That is, are people dispositionally stable or unstable in their magnitude of profile consistency? Second, the processes underlying long-term trends of profile consistency from an individual's initial time point are viewed across increasing time intervals. That is, do individuals show similar long-term trajectories of personality profile consistency? These increasing intervals of consistency allow us to ask whether people have similar patterns in their long-term personality consistency trajectories, which inform whether the processes underlying personality consistency are shared across individuals.

Stability and Consistency of Personality

Despite general trends of stability and consistency in personality that emerge between and within people, personality traits are also malleable qualities that can vary over time (Bleidorn et al., 2013; Roberts & Mroczek, 2008). Importantly, there are many ways to conceptualize the ways in which personality can change (Roberts et al., 2008). One helpful way to think about the ways personality can change is in terms of a two-by-two table: If the changes occur at the population or the individual level, crossed by if it is an absolute change or if it changes relative to something else (e.g., another person or another trait; Roberts et al., 2008). Below, we describe each of the four ways personality can change according to this cross-table.

Commonly examined are population mean-level changes. These are absolute changes that reflect normative, or typical, changes in average levels of traits across time (Roberts et al., 2006). Similarly, individual-level and mean-level changes are often examined and reflect absolute changes that occur at the individual level (e.g., Mroczek & Spiro, 2003). These individual differences in change reflect changes in a person's own average levels of a trait that can differ from the normative changes that are observed at the population level.

In contrast to absolute change, relative change is often used to describe the stability and consistency of personality. Rank-order stability, which occurs at the population level and represents the relative ranking of individuals for a single trait, is typically used to demonstrate the consistency of personality across the lifespan (Roberts & DelVecchio, 2000). Less examined is ipsative consistency or person-centered personality consistency. Consistency occurs at the individual level where the configuration of trait indicators within a single person across time is examined, hence *person-centered*. This person-centered approach to personality development can take several forms, such as comparing personality profiles of different individuals/groups (such as different age groups or genders; e.g., De Fruyt et al., 2006; Ozer & Gjerde, 1989), comparing a group of individuals with a profile of certain characteristics to a

group with another distinct profile (e.g., Block, 1971; Gilbert et al., 2021; Meeus et al., 2012; Specht, Luhmann, & Geiser, 2014; Steca et al., 2010), or comparing an individual's own personality profile at different time points (e.g., Ibáñez et al., 2016; Jackson & Beck, 2021; Robins et al., 2001; Terracciano et al., 2010). Notably, out of the four ways outlined above, it is the only perspective of consistency that considers multiple aspects of someone's personality—as opposed to being limited to examining a single trait.

An extension of relative personality change that incorporates absolute change is examining how people tend to change in their level of ipsative consistency across time. That is, are there absolute increases or decreases in levels of person-centered profile consistency or are people stable in their level of profile consistency? Furthermore, the individual differences in these average trends can be examined, such that some individuals may increase in profile consistency, whereas others decrease across time. It is this blend of relative and absolute personality change that our article focuses on.

Indices of Personality Profile Similarity and Consistency

Profile correlations (Q) provide an index of the degree of continuity of a configuration of indicators over time for an individual (Asendorpf, 1992; De Fruyt et al., 2006; Klimstra et al., 2009; Ozer & Gjerde, 1989; Roberts et al., 2008; Robins & Tracy, 2003). That is, they provide a measure of personality profile consistency across two time points. Profile correlations can be calculated at varying levels of breadth and depth, ranging from trait-level (e.g., Robins et al., 2001), facet-level (e.g., De Fruyt et al., 2006), or item-level examinations (e.g., Ozer & Gjerde, 1989). In general, people show moderate-to-high levels of profile consistency with the Big Five traits (De Fruyt et al., 2006; Ibáñez et al., 2016; Robins et al., 2001; Terracciano et al., 2010). Despite these high average profile consistency estimates, there are considerable individual differences around them (Asendorpf & van Aken, 1991; Jackson & Beck, 2021; Ozer & Gjerde, 1989; Terracciano et al., 2010), suggesting some people are very consistent, whereas others are much unlike their previous selves.

Closely related to profile correlations are the D indices proposed by Cronbach and Gleser (1953). These three indices— D^2 , D'^2 , and D''^2 —quantify the degree to which personality profiles change in elevation (i.e., mean-level), scatter (i.e., spread of scores), and shape, respectively. That is, they quantify the degree to which profiles are (dis)similar across two time points. Each of the D indices can be calculated from one another and D''^2 is perfectly inversely related to Q , so similar yet complementary information can be obtained by examining all indices of personality profile similarity and consistency. Past research examining these three D indices has found that, when personality profiles change, most of it tends to be due to changes in elevation and scatter, with typically a smaller proportion of individuals showing changes in profile shapes (De Fruyt et al., 2006; Robins et al., 2001). Although, one study did find the largest proportion of change in their sample being due to changes in shape of profiles (Ibáñez et al., 2016).

Why are some people consistent in their personality profiles while others are inconsistent? In this article, we focus on two potential reasons. First, outside factors may be a driving factor in this heterogeneity. Life experiences are associated with changes in rank-order consistency (Specht et al., 2011), suggesting that experiences may drive individual differences. Engagement in mature social roles such as becoming a parent or starting a career could

facilitate stability in one's personality so long as these roles are maintained across time (Roberts et al., 2003). Evidence for this maturity–stability hypothesis has indeed been found in past work (e.g., Donnellan et al., 2007). Furthermore, the predictability of one's environment (Asendorpf & van Aken, 1991), in addition to the greater likelihood of some people experiencing certain life events more than others (Headey & Wearing, 1989; Magnus et al., 1993), all serve as possible routes by which external factors could bolster or decrease personality consistency across time. Life experiences may also be shaped by health or biological changes (e.g., dementia; Terracciano et al., 2018), thereby mediating the effect between biology and personality continuity.

Second, some people may be inherently more consistent than others (Bem & Allen, 1974). This alternative pattern has not often been discussed as it fails to cleanly align with either of the two predominant schools of thought within personality—dispositionalists versus situationists. Dispositionalists assume relatively constant traits guide behavior, whereas situationists assume behavior is largely guided by the situations we are in (Mischel & Shoda, 1998). However, some people may be more consistent in general, not due to situations per se, but as an inherent individual difference that itself is a stable factor, much like for traits themselves (Anusic & Schimmack, 2016). For example, much like people have trait levels of Neuroticism and Conscientiousness, which remain relatively stable to that person over time, a person's level of personality profile consistency might be another dispositional characteristic. Most work examining whether people are stable in their level of profile consistency has looked at behaviors across short periods of time, such as days or weeks (Epstein, 1979). As such, it is hard to know whether there are stably consistent people over longer periods of time. Some people may be relatively unstable in how much they change their personality profile across the years, whereas others may be quite stable in their profile consistency.

Teasing apart these two perspectives requires multiple ipsative consistency estimates. If people are stable in their level of personality profile (in)consistency, there should be a strong correspondence between ipsative consistency estimates across time. That is, the magnitude of someone's personality profile consistency (as quantified by a profile correlation), regardless of if it is $Q = .30$ or $.80$, would remain similar if calculated at two or more separate occasions. In contrast, if individual differences in personality profile consistency are due to external forces, there should be less correspondence between ipsative consistency estimates across time. That is, the magnitude of a single person's personality consistency could vary from $Q = .60$ to $.30$ across two separate occasions, perhaps due to some environmental change occurring between them, which results in lower profile consistency.

Processes Underlying Patterns of Personality Consistency

The patterns of consistency in personality profiles can also give insights into processes driving the consistency. A single profile correlation cannot describe what the expected test–retest profile correlation should be when time increases, as it only provides a single point estimate. Should it decrease to the minimum value expected by the normativeness of profiles? Should it stay relatively the same over increasing time periods? Most work with longer test–retest intervals (i.e., decades long; Atherton et al., 2021; Jones &

Meredith, 1996; Roberts & DelVecchio, 2000; Terracciano et al., 2006) stems from between-person, rank-order stability. Rank-order stability in personality traits increases throughout early and middle adulthood, peaks in midlife, and decreases again in old age and very old age (Ardelt, 2000; Bleidorn & Hopwood, 2019; Briley & Tucker-Drob, 2014; Lucas & Donnellan, 2011; Roberts & DelVecchio, 2000; Wortman et al., 2012). From this past work on rank-order stability, relatively high levels of profile stability across longer stretches of time might be expected as well. Indeed, as previously noted, there are high levels of profile stability across nearly 20 years (Terracciano et al., 2010). Yet, these studies do not directly examine whether the consistency decreases as a function of time.

Importantly, by examining the patterns of profile consistency, one can gain insight into the processes driving personality consistency. Fraley and Roberts (2005) investigated what drives between-person, rank-order stability by using multiple test–retest estimates aggregated across different studies of young individuals that varied in length of test–retest intervals. They found a pattern whereby stability decreased relatively dramatically and then plateaued to remain stable regardless of the time interval. That is, even when the length of the test–retest interval continued to increase, people were expected to have a similar level of consistency in reference to the original time point. Their trajectory reached an asymptote at a test–retest correlation value of approximately $.25$, suggesting that if personality was assessed many years in the future, the association would at least be $.25$, not zero (Fraley & Roberts, 2005).

Furthermore, they found that three processes are necessary to explain personality stability: stochastic-contextual processes (e.g., Lewis, 1997, 2001; Revelle & Wilt, 2020), developmental constancy factors (e.g., Roberts & Wood, 2006), and person–environment transactions (e.g., Caspi & Bem, 1990; Neyer & Asendorpf, 2001). Each of these three processes was associated with a particular pattern of stability trajectories: Stochastic-contextual processes led to decreasing levels of stability, developmental constancy factors led to stable levels of stability, and person–environment transactions were the only process that could lead to increasing levels of stability. Thus, under the assumption that these three processes reliably lead to these predicted patterns, the direction of observed stability trajectories allows inferences to be made about the processes underlying personality stability.

The first of these mechanisms, stochastic-contextual processes, indicates that a largely influential force in personality consistency is chance—or unpredictable noise—that serves to decrease consistency (Lewis, 1997). For example, a chance run-in with an old coworker while someone is looking for a job could precede both a new employment opportunity and rekindling of an old friendship. These unforeseen experiences result in novel opportunities and environments, the implication being that these random influences lead to decreases in consistency across time. Without these mechanisms at play, the consistency of personality would be quite high.

The second process is developmental constants. In contrast to factors that may largely ebb and flow in importance, there are constancies that promote stability in personality (Roberts & Caspi, 2003). These are most traditionally thought of as genetic factors (Blonigen et al., 2008; McGue et al., 1993; Reiss et al., 2000), though they also may be transformative early life experiences (Fraley et al., 2013) whose impact is constant across the lifespan. These constant factors are assumed to provide a form of long-term

stability. Past work examining the influence of stable factors on test–retest correlations has found that personality traits are slightly less stable than intelligence (Conley, 1984b) but relatively more stable than evaluative individual differences (e.g., self-esteem, life satisfaction; Anusic & Schimmack, 2016; Conley, 1984b). This suggests that, while some individual differences are indeed more subject to fluctuations due to changing factors, personality traits may be strongly influenced by stable factors.

The third and final mechanism is person–environment transactions. Although someone can certainly be shaped by their environment, characteristics of and actions by the individual in that environment can in turn influence the degree to which the environment impacts them (Caspi & Bem, 1990; Caspi & Roberts, 1999). That is, people are not passive receptacles awaiting environmental influence. Rather, individuals are capable of proactively placing themselves in environments that align with their personality (Asendorpf & van Aken, 1991; Caspi & Bem, 1990). To the extent that people are able to actively niche-see and select environments that align with their personality—and thus mitigate random or stochastic processes—personality should remain relatively consistent or even increase in consistency. While transactional processes with the environment do not necessarily *always* lead to increases in consistency, such that there could be no changes or even decreases, they are the only processes of the three that *could* lead to increases.

Fraley and Roberts (2005) concluded that all three processes—developmental constants, stochastic factors, and transactional processes—are necessary to explain patterns of stability in personality. When systematically removing the effect of each of these three processes, though, they found that the removal of stochastic factors had the largest impact on the predicted trajectories, followed by the removal of developmental constants. The removal of transactional processes with the environment had the smallest impact, suggesting these have less of a role in bolstering personality stability compared to the other two processes.

The pattern described by Fraley and Roberts (2005) is thought to extend to all individuals, as the type of change employed captures the population. However, it should be noted that this meta-analytic sample does not include people over the age of 30, making it unclear whether these trends occur for older individuals. Moreover, this assertion was based on population-level, between-person traits, not individual-level, person-centered consistency. As such, it is unknown whether person-centered consistency is guided by similar mechanisms in the same degree. That is, it is unclear if each of these three factors contributes similarly to personality consistency in different individuals, which would be revealed by examining the direction of many individual-level trajectories of person-centered profile consistency. It is likely that people differ on which of and the degree to which these factors are influencing them. If, for example, a person is in a novel environment because they moved to a new city, they may have more stochastic factors affecting consistency relative to their time in their previous city. Moreover, it could be possible that stable trajectories are due to a combination of stochastic factors and transactional processes, such that their decreasing and increasing effects on stability, respectively, cancel each other out and thus no change is observed. When aggregating across many individuals, this pattern of change would be indistinguishable from a purely stable trajectory. However, by examining individual-level trajectories, nuances such as these can be revealed and not lost due to aggregation across people. Overall, the different factors by which

the (in)consistency of personality can be reinforced or elicited give rise to countless ways individuals can be idiosyncratically impacted. That is, these factors do not have to impact everyone similarly nor impact a single person similarly across time. Assuming similar estimates of consistency across individuals who differ in their environments, intrinsic stable tendencies, and the degree to which these factors interact can lead to misleading conclusions about the nature of personality consistency.

Potential Factors Impacting Person-Centered Profile Consistency

The processes influencing personality consistency may differ across people, but other factors may uniquely vary as well. Age is the most routinely examined factor believed to influence personality stability. Personality traits typically become increasingly stable with increasing age, and this stability is thought to plateau in middle to late adulthood, around age 50 (Ardelt, 2000; Bazana & Stelmack, 2004; Roberts & DelVecchio, 2000; Schuerger et al., 1989). Although, the effect of age might be curvilinear such that declines in stability are observed among older adults (Lucas & Donnellan, 2011; Terracciano et al., 2018; Wortman et al., 2012). Cross-age group differences in test–retest correlations have also been found in work on ipsative continuity in young (Donnellan et al., 2007; Roberts et al., 2001; Robins et al., 2001) and middle-aged adults (Terracciano et al., 2010) relative to children and adolescents (De Fruyt et al., 2006; Klimstra et al., 2009). It appears that younger people have lower levels of profile stability, and stability perhaps plateaus around age 30 (McCrae & Costa, 2003; Terracciano et al., 2010).

Additionally, gender differences could be present. In terms of gender differences for individual personality consistency in the Big Five traits, there appear to be inconsistent effects (e.g., Ozer & Gjerde, 1989; Robins et al., 2001), likely a result of methodological and sample differences in past studies (Klimstra et al., 2009). Most studies report no gender differences (Ozer & Gjerde, 1989; Robins et al., 2001), whereas at least one study examining adolescents reported large gender differences in both initial values and trends across time (Klimstra et al., 2009). Roberts et al. (2001) found slight gender differences, with women being slightly more consistent than men.

Furthermore, past work has also found that the traits themselves are important to consider. Single traits can vary with their typical stability estimates across time and can further interact with one another, such that those high or low on some combination of traits at baseline change in similar ways across time compared to individuals who began with different initial levels (Block, 1971; Morizot & Le Blanc, 2005). For example, with single traits, one study found that stability coefficients for Extraversion did not differ with age but were slightly higher in older participants for Neuroticism (Viken et al., 1994). Levels of the traits themselves also appear to have some influential role in the degree to which they change alone or in tandem with other traits across time. For instance, studies of adolescents and young adults have found that lower levels of Conscientiousness and higher levels of Neuroticism, or a somewhat “immature” personality profile, predict lower profile stability across time (Donnellan et al., 2007; Roberts et al., 2001). Traits can also predict exposure to certain experiences or life events that precede or serve as catalysts for personality change (e.g., Kendler et al., 2006),

thus leading to lower stability over time (Costa et al., 2005; McCrae, 1993; Ozer & Benet-Martínez, 2006; Terracciano et al., 2006). Alternatively, it could lead to enhanced stability across time due to increased levels of person–environment fit (Beck & Jackson, 2021a; Caspi & Moffitt, 1993). This could be the case, for example, with traits predicting who goes onto finish their education (Lüdtke et al., 2011), having a degree, which leads someone to a career, and a career turning into a decades-long stabilizing environmental force.

Lastly, another important consideration is the length of the test–retest intervals. Stability estimates will decrease with longer time intervals (Fraleley & Roberts, 2005; Roberts & DelVecchio, 2000; Terracciano et al., 2006). Notably, this factor is important to note not only for comparisons across individuals but also for a single individual. Within individuals, the increased lapse of time between measures also allows for more numerous life events and experiences to be accumulated (Lüdtke et al., 2011). Thus, aside from the general finding of decreased stability estimates across greater lengths of time, there could be individual differences in precisely what occurs during this time that could lead to either enhanced stability, such as the continuation of a lifelong role or stable environment, or decreased stability, such as the loss of a lifelong role or dramatic change in environment.

The Present Study

The consistency of personality has primarily been examined at the group level. However, consistency at the between-person level might not reflect the patterns of personality consistency within those individuals. Instead, ipsative consistency, a neglected aspect of personality development, allows for the examination of an individual's own personality configuration across time. Within this article, we investigate personality development through the lens of individual-level indices of personality profile similarity and consistency for Big Five trait items across multiple waves in four longitudinal panel studies. We address two primary questions.

First, are some people more consistent in their personality profiles? Previous studies identify individual differences in profile consistency, but are these individual differences due to person-level attributes or short-term fluctuations brought on by environmental change? Much like individual differences in slope estimates from growth models provide an estimate of individual differences in people's mean-level changes, we investigate individual differences in profile consistency and similarity. This question cannot be addressed using only two waves of consistency data, as those data do not provide the overall pattern of consistency across time. To investigate this question, we used personality profile similarity and consistency indices calculated across *sequential waves* (i.e., Wave 1 to Wave 2, Wave 2 to Wave 3, etc.).

Second, are the processes promoting long-term personality consistency and change (stochastic, transactions, stable factors) similar for each person? Can the general conclusions based on between-person consistency estimates using younger samples (i.e., Fraley & Roberts, 2005) be ascribed to person-centered consistency, and does the process occur for everyone? To address this question of the processes underlying changes in personality profile consistency, we used profile correlations calculated across *increasing time intervals* (i.e., Waves 1 and 2, Waves 1 and 3, etc.), so that long-term trajectories can be examined.

We hypothesize that the general trajectory of ipsative correlations will be nonlinear in form, decreasing, and asymptote at some modest level (Fraleley & Roberts, 2005; Terracciano et al., 2006). For our first research question, we are noncommittal whether there are meaningful individual trajectories of ipsative consistency across time—that is, whether some people are stably (in)consistent or whether individual differences in ipsative are mostly time-specific error. Further, for the second question, we hypothesize that all three mechanisms—stochastic, transactional, and stable factors—will be important. Evidence of stochastic mechanisms can be found via nonperfect estimates of consistency, whereas evidence of stable factors is the opposite, such that relatively unchanging, nonzero associations are found. Evidence for transactional factors would be observed via increasing ipsative trajectories, as these increases can only be explained by transactional factors.

Method

Participants

In this article, we use data from $N = 21,616$ total participants from four longitudinal panel data sets (Table 1). The number of participants with four waves was 17,311; five waves was 778; six waves was 898; seven waves was 834; eight waves was 1,783; and nine waves was 12. Participants were included in the present study if they had at least four waves of personality data for the Big Five traits. Results from attrition analyses can be found in Supplemental File S1. The institutional review board (IRB) at Washington University in St. Louis deemed this project exempt from IRB approval because it involves accessing publicly available data sets and thus does not meet federal definitions under the jurisdiction of an IRB (IRB ID: 202201080).

German Socioeconomic Panel Study

The German Socioeconomic Panel (GSOEP) study (Socio-Economic Panel, 2018) is an ongoing longitudinal study conducted by the German Institute of Economic Research (DIW Berlin) collecting data on individuals in more than 11,000 German households. Data are freely available by application at <https://www.diw.de/soep>. Data collection began in 1984 and continues annually, with the latest release in 2019. The sample from this data set consisted of $N = 6,771$ individuals.

Household Income and Labour Dynamics in Australia Study

The Household Income and Labour Dynamics in Australia (HILDA) Study (Watson & Wooden, 2012) is an ongoing longitudinal study collecting data on more than 17,000 individuals in Australian households. Data are freely available by application at <https://melbourneinstitute.unimelb.edu.au/hilda/for-data-users>. Data collection began in 2001 and has continued annually, with the latest release in 2020. The sample from this data set consisted of $N = 6,518$ individuals.

Health and Retirement Study

Health and Retirement Study (HRS; Juster & Suzman, 1995) is an ongoing longitudinal study of more than 35,000 individuals from in

Table 1
Descriptive Information by Study

Variable description	GSOEP	HILDA	HRS	LISS	Total
Sample size (<i>N</i>)	6,771	6,518	2,688	5,639	21,616
Age (<i>M</i>)	53.72	50.40	69.40	52.27	54.06
Age (<i>SD</i>)	15.23	16.20	9.48	16.97	16.58
Age (range)	17–100	15–100	30–102	16–97	15–102
Female (%)	53.20	55.00	60.60	53.66	55.00
Years of education (<i>M</i>)	12.80	—	13.35	—	—
Years of education (<i>SD</i>)	2.81	—	2.70	—	—
Years of education (range)	7–18	—	0–17	—	—
Percentage of sample with university degree (%)	21	30	29	44	31
No. of waves of personality data (<i>M</i>)	4.00	4.00	4.00	6.17	4.57
No. of waves of personality data (<i>SD</i>)	0.00	0.00	0.04	1.58	1.25
No. of waves of personality data (range)	4–4	4	4–5	4–9	4–9
Years between waves (<i>M</i>)	4.00	4.00	3.99	1.78	3.16
Years between waves (<i>SD</i>)	0.00	0.00	0.13	0.81	1.19
Length of test–retest interval (in years)	4–12	4–12	2–12	1–12	1–12

Note. HILDA and LISS did not have an explicit variable for years of education and thus these cells do not contain values. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; *M* = mean; *SD* = standard deviation; Age = age across all available waves.

households in the United States. Data are freely available at <https://hrs.isr.umich.edu>. Data collection began in 1992 and continues biennially, with the latest release in 2020. The sample from this data set consisted of *N* = 2,688 individuals.

Longitudinal Studies for the Social Sciences

Longitudinal Studies for the Social Sciences (LISS; Scherpenzeel & Das, 2010) is an ongoing longitudinal study of approximately 8,000 Dutch-speaking individuals from 5,000 households in the Netherlands. Data are freely available through application at <https://statements.centerdata.nl/liss-panel-data-statement>. Data collection began in 2007 and have continued annually, with the latest release in 2021. The sample from this data set consisted of *N* = 5,639 individuals.

Measures

Big Five

The primary variables in this study are Big Five trait items (Goldberg, 1990). All items were scored such that higher scores indicated greater levels of the trait and lower scores indicated lower levels (Neuroticism was keyed as emotional instability¹). The number of items and specific content of items varied across studies (see Supplemental Table S1, for psychometric information per study), but full content for all items per study can be found in Supplemental File S2.

GSOEP. All items were scored on a 1–7 Likert scale (1 = “does not apply” to 7 = “applies fully”). An example item for Extraversion, translated to English, is, “I am sociable”; for Agreeableness, “I am able to forgive”; for Conscientiousness, “I tend to be lazy” (reverse scored); for Neuroticism, “I deal well with stress” (reverse scored); and for Openness, “I have a lively imagination.”

HILDA. All items were scored on a 1–7 Likert scale (1 = “does not describe me at all” to 7 = “describes me very well”). An example item for Extraversion is, “Talkative”; for Agreeableness,

“Sympathetic”; for Conscientiousness, “Orderly”; for Neuroticism, “Calm” (reverse-scored); and for Openness, “Creative.”

HRS. All items asked how well an adjective applied to the participants and were scored on a 1–4 Likert scale (1 = “a lot” to 4 = “not at all”). An example item for Extraversion is, “Talkative”; for Agreeableness, “Sympathetic”; for Conscientiousness, “Organized”; for Neuroticism, “Calm” (reverse-scored); and for Openness, “Creative.”

LISS. All items asked participants to rate how well the description applied to themselves and were scored on a 1–5 Likert scale (1 = “very inaccurate” to 5 = “very accurate”). An example item for Extraversion, translated to English, is, “Am the life of the party”; for Agreeableness, “Feel little concern for others” (reverse scored); for Conscientiousness, “Make a mess of things” (reverse scored); for Neuroticism, “Often feel blue”; and for Openness, “Am not interested in abstract ideas” (reverse scored).

Moderators

We examined the effect of four moderators: gender, age, personality traits, and education level. For all data sets, gender was a dummy variable coded such that 0 = male and 1 = female. Age was calculated from a participant’s date of birth and considered in 1-year increments. For the personality traits, we used the composited Big Five traits (i.e., averaged across the items for each trait) as separate moderators. Last, the level of education variable was operationalized according to if a participant had a college degree from a 4-year

¹ It should be noted that, depending on how the traits are coded, profile correlation values *will* nearly always change. As a *relative* measure of personality consistency, comparisons of raw profile correlation values across different datasets/studies are not advisable because of their dependency on several study-specific factors, such as the direction of how traits are coded. To confirm our results and inferences did not depend on how we coded Neuroticism, the same calculations and baseline models were run for profile correlations where Neuroticism was conceptualized as emotional stability instead. The findings remained unchanged. These results can be found in Supplemental Tables S28–S31.

university (or equivalent) or higher. Having a college degree was coded as 1, whereas not having the degree was coded as 0.

Transparency and Openness

Within this Method section, we report how we determined our final sample size through inclusion criteria, all measures used along with their psychometric properties, and we follow the APA Style Journal Article Reporting Standards (JARS; Kazak, 2018). Data are freely accessible at all links specified in each respective study's "Participants" subsection. All code for all data cleaning, data analysis, and the codebook for each data set are available at <https://osf.io/23u9b/>. Data were analyzed using R, Version 4.0.3 (R Core Team, 2021) and the package brms (Bürkner, 2017). This study's design and its analyses were not preregistered.

Analytic Plan

The analytic plan consisted of first calculating intraindividual indices of personality profile similarity and consistency and then conducting analyses to examine interindividual trends in these values. The indices of personality profile similarity calculated were the three D metrics first proposed by Cronbach and Gleser (1953), which describe the degree to which a personality profile may change in elevation (i.e., mean levels), spread (i.e., scatter of scores around the mean), and shape of the profile. The index of personality profile consistency calculated was the within-person, item-level² profile correlation (Q). To begin, all data were downloaded directly from the data repositories for each study and cleaned/reverse scored as necessary. Cronbach's alpha estimates were calculated using the psych package (Revelle, 2021).

Intraindividual Indices of Personality Profile Similarity and Consistency

D Metrics. Three indices to assess profile similarity are those proposed by Cronbach and Gleser (1953): D^2 , D'^2 , and D''^2 . The first of these, D^2 , is sensitive to differences in elevation, scatter, and shape between two profiles. It can be considered a dissimilarity index, such that larger values indicate more dissimilar profiles and smaller values (with the minimum value being 0) indicate more similar profiles. Mathematically, it quantifies the squared difference between item responses (x_{ij}) across two time points (1 and 2) for all items per person (j). It is calculated using the following formula:

$$D_j^2 = \sum (x_{1ij} - x_{2ij})^2. \quad (1)$$

The second metric, D'^2 , is sensitive to differences in scatter and shape. It quantifies the squared difference between profiles after each item in the profile at the two different time points has been centered around its mean (hence the insensitivity to changes in elevation), summed across all items per person. The same formula as above can be used, but with a slight modification:

$$D_j'^2 = \sum [(x_{1ij} - \bar{x}_{1j}) - (x_{2ij} - \bar{x}_{2j})]^2. \quad (2)$$

The third metric, D''^2 , is sensitive only to differences in shapes of profiles. It quantifies the squared difference between profiles at two

time points after each profile has been standardized, thus removing the influence of the scatter of scores. Again, a similar formula can be used, but this time after substituting standardized scores (z_{ij}) for the centered scores:

$$D_j''^2 = \sum [(z_{1ij}) - (z_{2ij})]^2 \quad (3)$$

Notably, D''^2 is perfectly inversely related to the within-person profile correlation (Q), such that $D_j''^2 = 2(1 - Q_j)$. Similarly, each of the D metrics can be calculated from each other, such that:

$$D_j'^2 = D_j''^2(s_{1s_2}) + \Delta_s^2, \quad (4)$$

$$D_j^2 = D_j'^2 + k\Delta_m^2, \quad (5)$$

whereby, s is the square root of the scatter of scores around the mean at that time point (i.e., the sum of the squared differences), Δ_s^2 is the squared difference between the two scatter quantities at the two time points, k is the number of items, and Δ_m^2 is the squared mean difference between the two time points. From these equations, it becomes clear that these values are not necessarily comparable across data sets, as they are a function of the range of possible response options and the number of items in the measure. Thus, similar to profile correlations, they are a *relative* measure of profile similarity and should only be interpreted relative to the data set from which the values were obtained.

The D metrics were calculated across sequential waves for each data set. To interpret the magnitude of the initial empirical D metrics (i.e., the D metrics calculated from the first two waves of personality data per data set), we simulated scores for the Big Five items in each data set for 50,000 individuals that had equivalent levels of elevation, scatter, and shape in their personality profiles across two time points. This approach parallels what has been done in past research (De Fruyt et al., 2006; Ibáñez et al., 2016; Robins et al., 2001). The simulated item scores were constructed such that they had the same means, variances, and reliability from the real data for each data set. Then, the D metrics were calculated from these simulated scores for each data set. To determine if our participants showed meaningful changes in their elevation, scatter, or shape of their profiles across the first two waves of personality data, they were classified as having changed in these three indices if the probability associated with their values for each D metric was less than 5% (i.e., any other changes not beyond this point would be due to measurement error alone), as indicated by the distribution of D metrics calculated from the simulated item scores.

Overall Profile Correlations. Then, individual test–retest profile correlations for all Big Five trait items were calculated within each study. The multicon package (Sherman & Serfass, 2015) in R statistical software was used for calculating all profile correlations. There were two formulas used for calculating profile correlations. First, overall profile correlations were computed; these are “overall” in the sense that the grand mean for each item is not subtracted out from each individual's scores prior to calculating the profile correlations. The formula for calculating an

² Some past research has also calculated profile correlations at the *trait* level, which will lead to different profile correlation values compared to those calculated at the item level. If comparisons of these values are of interest for our data sets, profile correlation values calculated at the trait level are available in Supplemental Tables S32–S33.

overall profile correlation (Q_j) can be represented via the following equation:

$$Q_j = \frac{\sum (x_{ij1} - \bar{x}_{j1})(x_{ij2} - \bar{x}_{j2})}{\sqrt{\sum (x_{ij1} - \bar{x}_{j1})^2 \sum (x_{ij2} - \bar{x}_{j2})^2}}, \quad (6)$$

where, x_{ij1} represents an individual's score for a personality item at one wave; $\bar{x}_{j1}$ represents the average of their scores at that wave; x_{ij2} represents an individual's score for a personality item at a second measurement wave; and $\bar{x}_{j2}$ represents the average of their scores at that second measurement wave.

Importantly, the expected value of an overall profile correlation is not 0 (Cronbach & Gleser, 1953; Ozer & Gjerde, 1989). Thus, to determine if the profile correlation estimates were larger than would be expected by chance, scores on personality profiles were randomly matched for *different* participants for the first and second waves of personality data.

Distinct Profile Correlations. The second formula used for calculating profile correlations was that for distinct profile correlations. These differ from the above overall profile correlations in that everyone's scores for every item are centered around the grand mean for that item, thus capturing unique stability separate from that of the stability to be expected from showing a normative personality profile. These profile correlations should then be smaller in value than overall profile correlations, depending on the degree to which normative profiles inflate the overall profile correlations in each data set. The formula for calculating a distinct profile correlation can be represented via the following equation:

$$Q_j^d = \frac{\sum (x_{ij1} - \bar{x}_{i1} - \bar{x}_{j1})(x_{ij2} - \bar{x}_{i2} - \bar{x}_{j2})}{\sqrt{\sum (x_{ij1} - \bar{x}_{i1} - \bar{x}_{j1})^2 \sum (x_{ij2} - \bar{x}_{i2} - \bar{x}_{j2})^2}}, \quad (7)$$

where, x_{ij1} represents an individual's score for a personality item at one wave; $\bar{x}_{i1}$ represents the grand mean for an item at one wave; $\bar{x}_{j1}$ represents the average of a participant's scores at that wave; x_{ij2} represents an individual's score for a personality item at a second measurement wave; $\bar{x}_{i2}$ represents the grand mean for an item at a second measurement wave; and $\bar{x}_{j2}$ represents the average of a participant's scores at that second measurement wave.

As previously mentioned, with regards to the waves used in the calculation, the profile correlations in our study were computed in two ways. First, test-retest profile correlations were calculated across sequential waves, such that the first correlation was between the item scores for Waves 1 and 2, the second correlation was between the scores for Waves 2 and 3, and so forth. These served to help examine individual differences in average levels of and changes in person-typical personality profile consistency across waves. Second, profile correlations were calculated from the reference point of Wave 1, such that there were always increasing time intervals across waves. For example, the first test-retest correlation for an individual would be between their item scores for Waves 1 and 2, and their second correlation would be between Waves 1 and 3. These allowed us to examine patterns that give insight into the processes underlying patterns of consistency across time. In the rest of the article, we will refer to the first method of obtaining profile correlations as *sequential* and the second method as *increasing intervals*.

Interindividual Differences in Indices of Personality Profile Similarity and Consistency

D Metrics. In addition to evaluating the magnitude of the initial empirical D metrics relative to those calculated from simulated trait item scores, we also examined trends in how the three D metrics changed across sequential waves using Bayesian multilevel models. These models were fit as linear³ multilevel models, with measurements nested within individuals. Separate models were run for each D metric. The generic form of our model specification can be seen with the following:

Level 1

$$Y_{ij} = b_{0j} + b_{1j}time_{ij} + e_{ij}. \quad (8)$$

Level 2

$$b_{0j} = \gamma_{00} + U_{0j} \quad (9)$$

$$b_{1j} = \gamma_{10} + U_{1j} \quad (10)$$

The Y_{ij} is one of the D metrics. The *time* variable was scaled such that a participant's D metric value (always the D metric between a participant's first and second waves of data) had a value of 0. The next set of waves used to calculate the D metric (i.e., the second and third waves of data) had a value of *time* = 1, the following set had a value of *time* = 2 (i.e., the third and fourth waves of data), and so forth. All priors were regularizing priors such that the intercept prior was centered around the average value of each metric for that data set and all other priors were centered around 0.

Profile Correlations. Next, we used a Bayesian multilevel modeling framework to examine the interindividual trends in profile correlations (Q) within each data set. All models were fit as nonlinear⁴ multilevel models, specifically asymptotic nonlinear models, with measurements nested within individuals. We chose asymptotic nonlinear models a priori as these would best model the patterns identified in Fraley and Roberts (2005). The generic form of our model specification can be seen with the following:

Level 1

$$Y_{ij} = a_j - (a_j - b_j) * e^{(-c_j time_{ij})}. \quad (11)$$

Level 2

$$b_j = \gamma_{b0} + U_{bj} \quad (12)$$

$$c_j = \gamma_{c0} + U_{cj} \quad (13)$$

where, a_j is the maximum possible Y_{ij} value (i.e., +1.00); b_j is Y when *time*_{*ij*} = 0 (i.e., the intercept); and c_j is the proportional rate of change in Y_{ij} while *time*_{*ij*} increases. The outcome variable Y_{ij} was

³ Nonlinear models were also run for the D metrics to mirror the model form used for the within-person profile correlations (Q). However, model comparisons indicated the linear models were the superior models for these metrics. Due to the results of model comparisons and the ease of interpreting linear models relative to nonlinear models, these are the only models we include in the article. Both model types yielded similar conclusions.

⁴ We additionally ran linear models to ensure conclusions did not change based on our model form. Results from the linear models can be found in Supplemental Tables S35–S54. However, model comparisons indicated the nonlinear models were the far superior models compared to the linear models (see Supplemental Table S34). Thus, the nonlinear models are the only models we report in the article.

the test–retest profile correlation for each individual across waves. Again, the profile correlations were calculated in two ways: across sequential waves and across increasing time intervals. The *time* variable was scaled such that a participant's first test–retest correlation (always the correlation between a participant's first and second waves of data) had a value of 0. The next set of waves used to calculate the correlations, which varied across our two research questions, had a value of *time* = 1, the following set had a value of *time* = 2, and so forth. The resulting parameters (b_j and c_j) are similar to standard growth model intercept and slope terms, with the main difference that the slope is allowed to be nonlinear and inconstant. All priors were regularizing priors with a Student's t distribution centered around 0, with the degrees of freedom set to 3 and scale parameter set to 2.5.

The effects of potential moderating variables—age, gender, personality traits, and education level—were also tested. Given past research (Lucas & Donnellan, 2011; McCrae & Costa, 2003; Terracciano et al., 2010, 2018; Wortman et al., 2012), the likely effects of age could take multiple forms: linear, curvilinear, or discontinuous. Thus, age was tested in these three ways. The age variable was derived by taking the average age of a participant across all waves and centering it around the average age among all of the participants in their data set. Thus, a participant's age variable was representative of how far they deviated from the average age in their data set across all waves. This particular age variable was tested both linearly and quadratically and will be referred to as *numeric age*. The third way age was operationalized will be considered *dichotomous age*, and this variable was obtained by splitting participants according to their numeric age variable. If their average age was 30 or below, they were coded 1 for this variable; if their average age was above 30, they were coded 0 for this variable. Notably, age was only tested in this manner for three of our four data sets, as no participants in HRS had an average age of 30 or younger. For gender, males were coded 0 and females were coded 1. For education level, participants were coded 1 if they had a college degree from a 4-year university (or equivalent) or higher and were coded 0 if they did not.

Then, the effects of traits were examined two ways. First, a between-person trait variable captured the effect of a person deviating from their sample's average initial levels of each Big Five trait. The initial time point (i.e., baseline) was used instead of the average across all waves so that changes occurring across the study would solely be captured as within-person changes. Second, a within-person trait variable captured those within-person changes. These within-person lag variables captured the difference in a person's own level of each trait between the two waves used to calculate their profile correlation. For example, if we were to determine this value for Wave 3, then for the sequential wave models, a lagged variable for Extraversion would be calculated as the difference between a person's level of Extraversion from Wave 2 to Wave 3, whereas in the increasing interval models, it would be calculated as the difference from Wave 1 to Wave 3.

Results

The D Metrics of Profile Similarity

First, we examined the distributions of the three D indices within our data sets: D^2 , D'^2 , and D''^2 . Descriptive statistics for each of the

empirically derived D metrics for each data set can be found in Supplemental Tables S2–S7 across all sequential waves. To evaluate the magnitude of our empirical D values between the first two waves of personality data, we simulated data for 50,000 individuals based on the initial wave of personality data for each data set. From these simulations, we obtained two waves of simulated personality item data based on the characteristics of each of our data sets (i.e., means, standard deviations, reliability of measures) in which each person's profile had equivalent levels of elevation, scatter, and shape across the two waves. Similar to one study (Ibáñez et al., 2016), we found that most changes occurred at the profile level (D''^2) as opposed to changes in mean levels (D^2) or scatter of scores (D'^2) within profiles (Table 2). The percentage of people showing changes in each of the three indices varied across data sets, with GSOEP having the fewest overall percentage of people change in any index, whereas LISS had the largest percentage of people changing.

Then, to supplement the above simulations, we further examined mean-level trends in each data set for the three D metrics⁵ (Table 3) across all sequential waves. This allowed us to potentially make inferences about how profile similarity, as quantified by the D metrics, was changing across all sequential waves—as opposed to examining only those values calculated from the first two waves of personality data.

For models predicting D^2 , GSOEP, HILDA, and LISS had negative trends in this metric, such that the sum of squared differences in scores from the mean of a person's profile decreased across time (i.e., less of an elevation change in one's profile). HRS, in comparison, had a positive trend in this metric, suggesting that changes in elevation slightly increased across time. However, in the models predicting D (i.e., the square root of D^2), the change in this metric was not meaningful such that its credible interval included 0 (Supplemental Table S7). For models predicting D'^2 , the same pattern emerged such that all data sets except HRS showed negative trends and HRS showed a positive trend. This suggests that changes in the scatter of individuals' profiles decreased across time in GSOEP, HILDA, and LISS, whereas changes in scatter increased across time for individuals in HRS. Lastly, for models predicting D''^2 , GSOEP, HILDA, and LISS, all had slightly negative trends emerge—indicating that changes in the shape of individuals' profiles decreased across time. In comparison, HRS had null changes in this metric across time.

In addition to the mean-level trends in each metric, there were *considerable* individual differences around these average trends (Table 3). These random effects indicate that not only did individuals have very different starting values for each D metric, but that they further greatly varied in how they changed in these metrics across time.

What Are Typical Levels of Within-Person Profile Consistency?

Next, we examined if the initial levels of personality profile consistency, as quantified by within-person, item-level profile correlations (Q), were larger than what would be expected by chance.

⁵ To ensure the skewed distributions expected from squared values did not produce biased results, models predicting the unsquared version of each D metric (i.e., D , D' , and D'') were also run. Results were similar (see Supplemental Table S7).

Table 2

Descriptive Information for the D Metrics Obtained From Simulated Item Scores in Each Data Set

<i>D</i> index	Metric	Data set			
		GSOEP	HILDA	HRS	LISS
D^{n2}	<i>M</i>	0.67	0.42	0.44	0.37
	<i>SD</i>	0.32	0.13	0.17	0.10
	95th percentile value	1.28	0.65	0.75	0.56
	% changed	17.29	41.79	28.27	60.45
D^2	<i>M</i>	46.79	66.79	13.13	28.92
	<i>SD</i>	18.54	16.53	4.00	6.08
	95th percentile value	80.87	96.21	20.40	39.64
	% changed	3.09	19.13	9.56	30.48
D^2	<i>M</i>	50.15	68.70	13.65	29.51
	<i>SD</i>	19.27	16.78	4.10	6.15
	95th percentile value	85.69	98.62	21.09	40.35
	% changed	3.77	20.39	11.5	31.97

Note. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; *M* = mean; *SD* = standard deviation; % changed = the percentage of the sample that had *D* values greater than the value that was the 95th percentile for that data set, indicating significant changes in that metric (i.e., the percentage of people in that data set that had values of that metric that were greater than would be expected by measurement error alone).

The empirical initial overall profile correlation estimates, or the profile correlations between the first and second waves of personality data, are provided in Table 4 (see also Figure 1). Profile correlations have an expected value that is larger than zero. Thus, we calculated the expected profile correlation for each sample by randomly pairing profiles across individuals in each data set for the first two waves of personality data. These values are presented in Table 4 and are marked for each data set via the dashed line in Figure 1. For each data set, the empirical profile correlation was considerably larger than the simulated profile correlation value, suggesting there is, on average, notable consistency in item-level profiles for our participants.

As for the initial distinct profile correlations (Table 4), the values were somewhat smaller in value, similar to a decrease found in past research as well (Klimstra et al., 2009). This is expected to the extent that the magnitudes of the overall profile correlations are inflated due to normative responding. Additionally, it should be noted that because these profile correlations reflect an individual's own unique consistency, separate from any average-level of consistency expected from the normative profile, that the expected value for distinct profile correlations is 0.

Are Some People More Consistent Than Others in Their Personality Profiles?

Overall and distinct item-level profile correlations averaged across all sequential waves are presented in Table 5 for each study. The average overall profile correlation values were moderate to large by conventional standards, with considerable variability around these estimates. Notably, across all data sets, values from -1.00 to $+1.00$ were obtained, indicating that there were both

perfectly opposite patterns of responding as well as perfectly similar patterns of responding. These values indicate that people in general are relatively consistent in their personality profiles.

Next, we used these profile correlations in a series of nonlinear, asymptotic Bayesian multilevel models.⁶ These were used to examine individual differences in the average trends of personality profile consistency in each data set, showing the relative changes across time in person-centered consistency from wave to wave.

Table 6 and Figure 2 describe the results. The intercepts, which reflect average profile consistency at the initial waves, were similar across data sets, ranging from .58 (GSOEP) to .69 (HRS). The slopes, which in these models are the proportional rates of change in the profile correlations across sequential waves, were positive and had nonzero values ranging from .03 (HRS/LISS) to .07 (GSOEP/HILDA). This suggests that, on average, levels of profile consistency were slightly increasing as opposed to individuals maintaining stable levels of consistency (Figure 2A–D). See Supplemental Table S8, for a comparison of results for overall and distinct profile correlations. Notably, these results are consistent with the findings from the mean-level trends in the *D* metrics, such that, on average, changes in profiles decreased across waves (i.e., profile similarity thus increased). Also consistent with the *D* metric models is the magnitude of the changes across time (Table 6), such that HRS and LISS show the smallest amount of change.

To illustrate how to interpret the parameters, we will describe this process for two data sets. The overarching equation guiding the interpretation of these models is $Y_{ij} = 1 - (1 - \text{intercept}_{ij}) * e^{(-\text{slope}_{ij} \times \text{time}_{ij})}$. Since these models do not include other predictors, the additional equations for the intercept and slope calculations are not needed (see the “Analytic Plan” section for full equations). For the average effect for GSOEP, the predicted profile correlation at $\text{time} = 1$ (i.e., the second wave of profile correlations), is thus $1 - (1 - .58) \times e^{(-.07 \times 1)} = .608$ and for $\text{time} = 2$, it is .635. From these calculations, we see that the average difference between the intercept and the second wave of profile correlations is .028 units and the average difference between the second and third waves of profile correlations is .027 units. As for another example, for HILDA, the intercept value is .66, the next predicted profile correlation value at $\text{time} = 1$ is .683 (difference of .023 units), and the following predicted value at $\text{time} = 2$ is .704 (difference of .021 units).

These above examples demonstrate a few things. First, the amount of change across waves is proportional to the intercept value, such that slope values of $-.03$ (HRS, LISS) and $-.07$ (GSOEP, HILDA) do not result in the *exact* same magnitude of change between profile correlations across data sets. In general, the larger the intercept value, the more attenuated future change is. Second, the larger the slope value, the larger the changes will be (holding intercept values constant)—in this regard, this is identical to the interpretation of the magnitude of slope parameters in traditional growth models. Third, the magnitude of changes will attenuate over time, such that change is *not* constant across waves. This attenuation is not large but is important to note, as it is one of the key features, along with the proportional rate of change relative

⁶ The conclusions between the overall and distinct profile correlations were similar. Thus, for succinctness, we elaborate on the results for the overall profile correlations in the article, but results for the distinct profile correlations are available in Supplemental Tables S8–S17.

Table 3*Linear Trends in the D Metrics Across Sequential Waves*

Model parameter	GSOEP		HILDA		HRS		LISS	
	Est	CI	Est	CI	Est	CI	Est	CI
D^{n2}								
Person level								
Intercept <i>SD</i>	0.38	[0.37, 0.39]	0.36	[0.35, 0.37]	0.32	[0.31, 0.34]	0.31	[0.30, 0.31]
Time <i>SD</i>	0.18	[0.17, 0.19]	0.13	[0.13, 0.14]	0.14	[0.13, 0.15]	0.05	[0.05, 0.05]
Correlation	-0.53	[-0.56, -0.49]	-0.39	[-0.42, -0.35]	-0.32	[-0.38, -0.26]	-0.32	[-0.36, -0.28]
Sample level								
Intercept	0.83	[0.82, 0.84]	0.67	[0.66, 0.68]	0.61	[0.60, 0.63]	0.71	[0.70, 0.72]
Time	-0.04	[-0.04, -0.03]	-0.03	[-0.03, -0.02]	0.00	[-0.01, 0.01]	-0.01	[-0.01, -0.01]
D^2								
Person level								
Intercept <i>SD</i>	16.46	[16.00, 16.93]	41.70	[40.71, 42.72]	6.10	[5.85, 6.36]	18.46	[18.03, 18.91]
Time <i>SD</i>	7.89	[7.51, 8.26]	17.09	[16.29, 17.88]	2.79	[2.58, 2.99]	2.62	[2.47, 2.77]
Correlation	-0.53	[-0.56, -0.49]	-0.34	[-0.38, -0.31]	-0.36	[-0.42, -0.30]	-0.56	[-0.60, -0.52]
Sample level								
Intercept	30.13	[29.64, 30.61]	69.15	[68.00, 70.31]	11.62	[11.34, 11.89]	36.22	[35.67, 36.76]
Time	-1.53	[-1.82, -1.24]	-1.58	[-2.18, -0.98]	0.23	[0.07, 0.39]	-0.61	[-0.73, -0.49]
D^2								
Person level								
Intercept <i>SD</i>	18.71	[18.19, 19.23]	44.09	[43.05, 45.16]	7.59	[7.27, 7.91]	19.64	[19.18, 20.12]
Time <i>SD</i>	8.80	[8.37, 9.23]	18.27	[17.44, 19.09]	3.73	[3.49, 3.98]	2.78	[2.61, 2.94]
Correlation	-0.54	[-0.57, -0.51]	-0.34	[-0.37, -0.30]	-0.40	[-0.45, -0.33]	-0.57	[-0.61, -0.54]
Sample level								
Intercept	33.90	[33.35, 34.45]	73.29	[72.05, 74.54]	13.15	[12.80, 13.50]	38.04	[37.46, 38.62]
Time	-1.98	[-2.32, -1.66]	-2.07	[-2.75, -1.42]	0.26	[0.04, 0.47]	-0.68	[-0.81, -0.55]

Note. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; Est = the maximum a posteriori (MAP) estimate; CI = 95% credible intervals; *SD* = standard deviation. Bolded values indicate parameter estimates that do not include 0 in the credible intervals.

to the intercept values, that distinguishes these models from linear models.

Furthermore, the average trend of slightly increasing levels of profile consistency across waves masks a large amount of variability in profile consistency. This is evidenced by the random effects for the slope, with values ranging from .08 (LISS) to .23 (GSOEP). For GSOEP, the average of the top 5% of person-level slopes was .36 (95% CI [.04, .70]) and the average of the bottom 5% was -.27 (95% CI [-.56, .01]). For HILDA, the average of the top 5% of person-level slopes was .36 (95% CI [.09, .63]) and the average of the bottom 5% was -.28 (95% CI [-.51, -.06]). For HRS, the average of the top 5% of person-level slopes was .31 (95% CI [.04, .61]) and the average of the bottom 5% was -.33 (95% CI [-.58, -.09]). For LISS, the average of the top 5% of person-level slopes was .13 (95% CI [.02, .24]) and the average of the bottom 5% was -.11 (95% CI [-.20, -.01]). These random effects indicate that some people decreased in their levels of consistency across waves, whereas others increased more than average. In general, these findings indicate that there are individual differences in how consistent personality is *and* how this consistency changes across waves. Some people increase in consistency across time, some people become more inconsistent, and many people are stably consistent (see Figure 2A–D). For the latter, this does not mean that their personality does not change, but the extent to which their personality does or does not change is similar from wave to wave—they are stable in their level of consistency.

Next, we ran a series of models to examine possible moderators of these trends (Table 7; see Supplemental Tables S9–S17, for all moderator results with distinct profile correlations as well). First, we

examined the potential effects of age and gender. In all models where it was included, gender inconsistently moderated intercept values, varying both in direction and magnitude across the data sets, and never had any effect on slopes. In the models with the linear effect of numeric age, there were no effects of age on the intercept values nor slopes, meaning numeric age did not impact average levels of personality profile consistency nor changes in consistency across waves (Table 7; Supplemental Table S9). In the models with the additional quadratic effect of numeric age, there were again no age effects (Table 7; Supplemental Table S10).

In the models including dichotomous age—that is, distinguishing between participants with average ages 30 and younger versus those older than 30—age impacted both the intercept values and the slopes (Table 7; Supplemental Table S11). The effect of age on intercept values indicated that participants aged 30 or younger had lower average values of personality profile consistency, with profile correlations ranging from .05 (GSOEP) to .11 (HILDA/LISS) units lower. For participants with average ages over age 30, slope values ranged from .02 (LISS) to .06 (GSOEP/HILDA). The interaction of age and slope indicated that participants with average ages 30 and under increased at a greater rate in their levels of profile consistency relative to older participants. Specifically, the younger group experienced increases ranging from .03 (LISS) to .08 (GSOEP/HILDA) units.

For the models with personality traits, results of the greatest magnitude and that emerged most frequently across data sets were found for Agreeableness, Conscientiousness, and Neuroticism—traits associated with maturity (Table 7; see Supplemental Tables S12–S16, for all trait results). For Agreeableness and

Table 4

Comparison of Initial Empirical Values and Values Obtained From Randomly Pairing Profiles for Overall and Distinct Item-Level Profile Correlations

Method of calculation	Type of profile correlation					
	Overall			Distinct		
	<i>M</i>	<i>SD</i>	Range	<i>M</i>	<i>SD</i>	Range
GSOEP						
Empirical	0.59	0.25	−0.78 to 1.00	0.44	0.31	−0.77 to 1.00
Random	0.27	0.29	−0.79 to 0.93	0.00	0.32	−0.86 to 0.92
HILDA						
Empirical	0.66	0.21	−0.67 to 0.98	0.51	0.23	−0.56 to 1.00
Random	0.35	0.27	−0.69 to 0.93	0.00	0.26	−0.75 to 0.78
HRS						
Empirical	0.69	0.20	−0.98 to 1.00	0.49	0.24	−0.64 to 1.00
Random	0.40	0.25	−0.74 to 0.96	0.00	0.26	−0.80 to 0.73
LISS						
Empirical	0.65	0.18	−0.32 to 0.95	0.51	0.20	−0.50 to 1.00
Random	0.29	0.23	−0.65 to 0.84	0.00	0.22	−0.70 to 0.79

Note. Empirical profile correlations are those obtained from the actual data sets and calculated between the first and second waves of personality data. Random profile correlations are those obtained from randomly shuffling personality item profiles for the first and second waves of personality data in each data set. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; *M* = mean; *SD* = standard deviation.

Conscientiousness, having higher than average levels at Wave 1 of personality data led to considerably higher levels of initial consistency, whereas the opposite effect was found for Neuroticism. Those individuals that had higher than average initial levels of Agreeableness and sometimes Conscientiousness experienced less of a relative increase in their wave-to-wave profile consistency. In comparison, those who had higher than average levels of Neuroticism experienced greater relative increases in consistency across waves. Last, individuals who increased in Agreeableness and Conscientiousness showed larger increases in their consistency across waves, whereas those who increased in Neuroticism decreased in their consistency across waves.

Last, we examined the effect of education on individual differences in person-typical levels of profile consistency (Table 7; Supplemental Table S17). Across all data sets, having a college degree was associated with higher initial values of profile consistency, ranging from .04 (HRS/LISS) to .06 (GSOEP) units. Then, for all data sets except GSOEP, having a college degree was associated with greater increases in consistency across waves relative to those in the data set that did not have a degree, with effects ranging from .01 (LISS) to .04 (HILDA/HRS) units.

Which Processes Contribute to Personality Consistency?

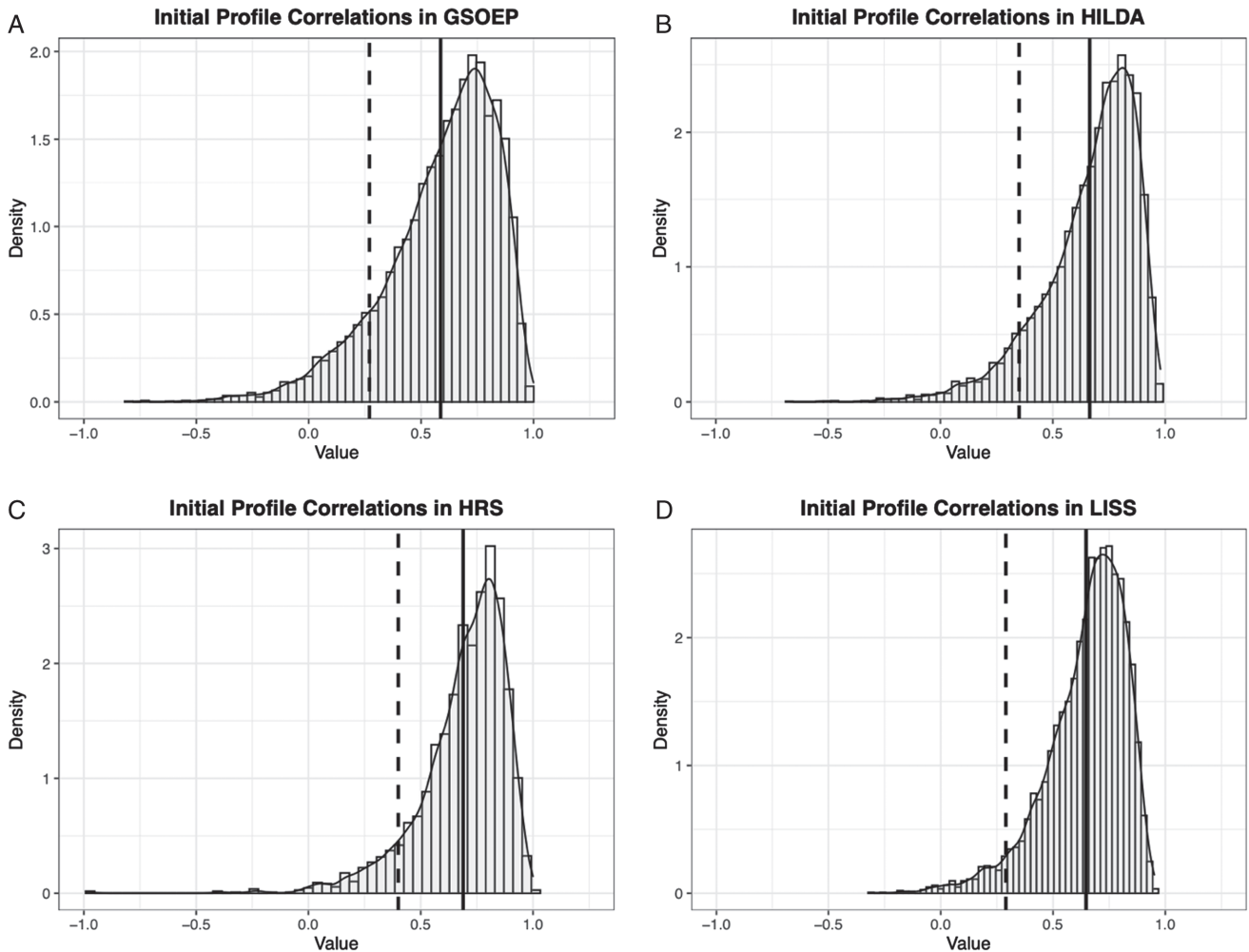
Next, profile correlations were calculated across increasing time intervals. Average item-level profile correlations are presented in Table 8 for overall and distinct correlations for each data set. Average values were lower than the previous profile correlations but still high given they were calculated across much longer time spans.

Then, we again used the above profile correlations in a series of nonlinear, Bayesian multilevel models (Table 9; Figure 3A–D). These models served to examine the interindividual differences in the trends that represent the processes underlying consistency within each data set.

The slopes, which now represent the proportional rate of change in the profile correlations while the length of the test–retest interval always increases, were now negative and had nonzero values ranging from −.05 (HRS) to −.03 (all but HRS). This shows that, on average, levels of profile consistency decreased as this length of time increased, consistent with the idea that stochastic factors accumulate across time. However, the declines were not large, suggesting that people do not drastically drop in their profile correlations within their lifetime, even to the minimum level of expected profile consistency due to profile normativeness. See Supplemental Table S18 for a comparison of results for overall and distinct profile correlations.

There was again variability around the slopes (Figure 3A–D), but to a lesser degree than there was with the sequential wave models, despite the longer time intervals. The standard deviation values around the slope estimates ranged from .04 (LISS) to .16 (HRS), indicating that some people were more greatly decreasing in their level of consistency while others were increasing at more rapid rates across time. To illustrate these differences, we estimated an extreme top and bottom group. For GSOEP, the average value within the top 5% of person-level slopes was .12, whereas the bottom 5% was −.22. Similar findings for the top 5% and bottom 5% of person-level slopes were found for HILDA (.12 and −.22), HRS (.13 and −.28), and for LISS (.02 and −.09), respectively. Surprisingly, many people evidenced positive trajectories. In GSOEP, 29.9% of individuals had positive slopes; 27.9% in HILDA had positive slopes; 23.9% in HRS had positive slopes; and 8.6% in LISS had positive slopes. Importantly, these increasing trajectories can only occur due to transactional processes with the environment, as neither stochastic nor constant factors can lead to increases (Fraleigh & Roberts, 2005). Overall, these differences in trajectories indicate a sizeable amount of people increase, whereas a large number also decrease in consistency. This variability highlights that people differ in the processes that promote personality consistency. Furthermore, the proportion of individuals with positive slopes suggests that transactional factors have a larger role in promoting within-person consistency for some individuals—a nuance not revealed from average findings of between-person consistency.

Then, we examined possible moderators of interindividual differences in the trends representative of the processes underlying profile consistency within each data set (Table 10; see Supplemental Tables S19–S27, for all moderator results with distinct profile correlations as well). The effects of each moderator on intercept values are equivalent to those in the sequential wave models, as the intercept remains the same (i.e., it is always the within-person profile correlation between waves one and two of personality data). Thus, we restrict our discussion of these effects to the impact of the moderators on changes in profile consistency over the longer term stretches of time. Similar to the models with profile correlations calculated across sequential waves, gender never had any effect on the slopes (Table 10). Age effects for the numeric age variables were also similar to the sequential wave models (Supplemental Tables S19–S20). In the models including dichotomous age, there were again effects of age on the slopes, although the effects were now

Figure 1*Density Plots of Initial, Overall Profile Correlations Calculated in Each Data Set*

Note. Average values for the initial, overall profile correlations in each data set are presented on the x axis. The solid line represents the average empirical value in each data set. The dashed line represents the profile correlation value obtained from randomly pairing profiles in each data set (i.e., the expected minimum value due to some degree of normativeness). Panel A is for GSOEP, Panel B for HILDA, Panel C for HRS, and Panel D for LISS. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences.

smaller in magnitude and inconsistently present across data sets (Table 10; Supplemental Table S21). For participants over age 30, slope values ranged from $-.03$ (GSOEP) to $-.02$ (HILDA/LISS), indicating that their levels of consistency slightly decreased as time went on. For HILDA and LISS, younger participants had greater rates of decline in their levels of consistency as time increased relative to older participants.

For the models with personality traits, the largest and most frequent results were again found for Agreeableness, Conscientiousness, and Neuroticism (Table 10; see Supplemental Tables S22–S26, for all trait results). Individuals that had higher than average initial levels of Agreeableness and Conscientiousness often bucked the average trend and experienced increases in their consistency across time or showed no changes. Similarly, those who increased in Agreeableness and Conscientiousness relative to their initial values also showed

increases in their long-term levels of personality profile consistency. In comparison, those who had higher than average levels of Neuroticism at Wave 1 and/or increased in Neuroticism relative to their trait level at Wave 1 experienced greater decreases in long-term consistency across time, thus exacerbating the average declining effect. Last, and in contrast to the sequential wave models, there were no effects of having a college degree on longer term changes in consistency (Table 10; Supplemental Table S27).

Discussion

We tested two primary questions using indices of personality profile similarity and consistency across four large-scale data sets. First, are there stable individual differences in levels of personality profile consistency? Results indicated that people

Table 5*Descriptive Information for the Overall/Distinct Item-Level Profile Correlations Calculated Across Sequential Waves in Each Data Set*

Study	Average	Waves used for profile correlation							
		1–2	2–3	3–4	4–5	5–6	6–7	7–8	8–9
GSOEP									
<i>M</i>	.60/.46	.59/.44	.60/.46	.62/.48					
<i>SD</i>	.25/.30	.25/.31	.25/.30	.24/.30					
Range	–.81 to 1.00	–.78 to 1.00	–.75 to .99	–.81 to 1.00					
HILDA									
<i>M</i>	.68/.52	.66/.51	.69/.53	.69/.54					
<i>SD</i>	.21/.23	.21/.23	.21/.23	.21/.23					
Range	–.84 to 1.00	–.67 to 1.00	–.54 to 1.00	–.84 to 1.00					
HRS									
<i>M</i>	.69/.50	.69/.49	.70/.51	.69/.50	.61/.30				
<i>SD</i>	.20/.24	.20/.24	.19/.23	.21/.24	.27/.20				
Range	–.98 to 1.00	–.98 to 1.00	–.66 to 1.00	–.77 to 1.00	.16 to .87				
LISS									
<i>M</i>	.66/.52	.65/.51	.65/.51	.66/.51	.67/.53	.67/.53	.69/.53	.71/.55	.67/.56
<i>SD</i>	.18/.20	.18/.20	.18/.20	.19/.20	.18/.20	.19/.20	.17/.20	.17/.20	.20/.19
Range	–1.00 to 1.00	–.50 to 1.00	–1.00 to 1.00	–.66 to 1.00	–.69 to 1.00	–.63 to 1.00	–.63 to 1.00	–.47 to 1.00	.15 to .87

Note. Average overall and distinct profile correlations calculated across sequential waves are presented for each data set with the standard deviation and range. The averages and standard deviations for the profile correlations are presented such that the overall values are presented first and followed by the distinct values after the/(i.e., overall/distinct). For the ranges, the largest values across both types of profile correlations are presented. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; *M* = mean; *SD* = standard deviation.

were stable in how (in)consistent they are, with some people more greatly changing in their personality, on average, whereas others tend not to change much wave after wave. How consistent someone's personality is differs across people, with some people changing often (and consistently so), whereas others are stably consistent across time. These findings suggest that (in)consistency is best considered as a person-level attribute rather than one that is environmentally induced or due to measurement error.

Second, are the processes promoting long-term personality profile consistency and change (stochastic, transactions, stable factors) similar for each person? Results indicated that there were, on average, high levels of long-term consistency across increasing time intervals. These findings seem to suggest that there are more stable and transactional factors at play rather than stochastic factors, thus differing from the relative impact of each of these factors for between-person consistency (Fraleigh & Roberts, 2005). Moreover, individual differences in the longitudinal profile

consistency trajectories suggest that the processes that promote personality consistency differ across people.

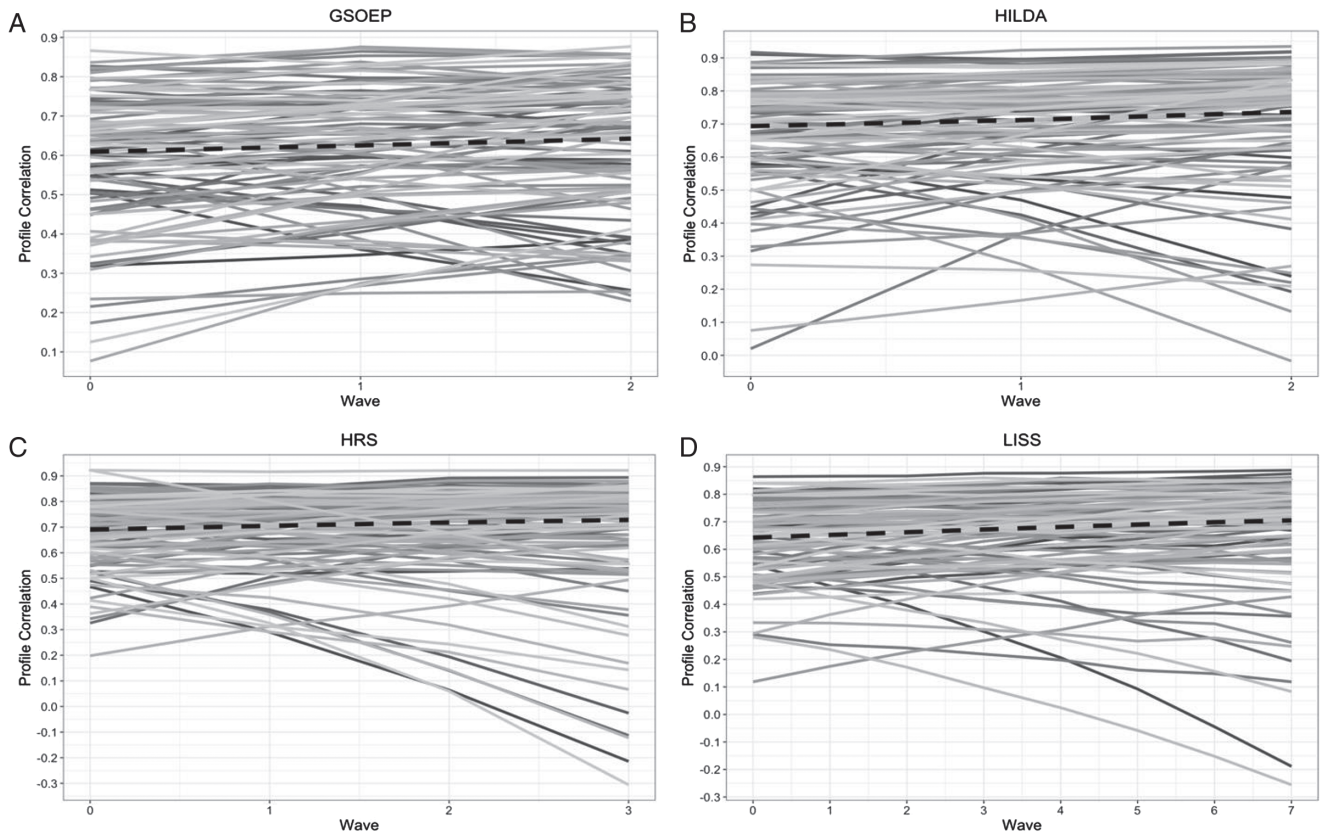
People Differ in Dispositional Personality Profile Consistency

We found profile correlations across time were consistent within a person rather than different across each time period. Although some people may be inherently more consistent than others (i.e., having larger test–retest profile correlations), people in general are *stable in their own person-typical level of consistency*. Those people that are less consistent are less consistent wave-to-wave, and those that are more consistent tend to be highly consistent across waves. Yet, these consistency levels are not set in stone, as changes in them exist such that people can increase and decrease in their consistency levels across time. These findings suggest important features driving personality development.

Table 6*Models for Individual Differences in Personality Consistency Across Sequential Waves*

Model parameter	GSOEP		HILDA		HRS		LISS	
	Est	CI	Est	CI	Est	CI	Est	CI
Person level								
Intercept <i>SD</i>	.19	[.18, .19]	.18	[.18, .19]	.16	[.16, .17]	.15	[.15, .16]
Time <i>SD</i>	.23	[.22, .24]	.21	[.20, .22]	.22	[.21, .23]	.08	[.08, .08]
Correlation	–.41	[–.45, –.37]	–.26	[–.29, –.22]	–.27	[–.32, –.21]	–.19	[–.23, –.15]
Sample level								
Intercept	.58	[.57, .58]	.66	[.65, .66]	.69	[.68, .70]	.64	[.64, .65]
Time	.07	[.06, .08]	.07	[.07, .08]	.03	[.02, .04]	.03	[.02, .03]

Note. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; *Est* = the maximum a posteriori (MAP) estimate; *CI* = 95% credible intervals; *SD* = standard deviation. Bolded values indicate parameter estimates that do not include 0 in the credible intervals.

Figure 2*Sample- and Person-Level Trends in Personality Profile Consistency Across Sequential Waves*

Note. The dashed black line represents the average, sample-level effect. For the person-level trends, a random subset of 100 participants is plotted for *each* data set. The wave number represents the wave of the profile correlation and is centered around 0 such that wave = 0 is the profile correlation between the first and second measurement occasions. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences.

First, given the long timeline of our studies, these findings are some of the strongest to date that identify consistency as an individual difference (cf., Bem & Allen, 1974). There is a rich debate of understanding personality coherence across time frames as short as weeks and up to a year (Beck & Jackson, 2021b), but most research on individual differences in consistency addresses issues stemming from the personality–situation debate (such as consistency across contexts) rather than directly investigating whether some people are more or less consistent over long periods of time. As such, consistency has typically been viewed as being one of two extremes: whether personality is or is not consistent across situations. Viewed this way, situations were the focus of what does or does not contribute to consistency rather than consistency potentially being an intrinsic property of the person. These findings demonstrate that over long swaths of time, some people are more consistent than others in their personality profiles, suggesting that one's level of consistency is a dispositional characteristic. Importantly, these effects do not mean that personality does not change, but rather that the extent that someone's personality does or does not change is similar from wave-to-wave or year-to-year. Some people are more changeable, whereas others are more immutable.

Second, these findings argue against external forces leading to different levels of consistency. The preponderance of two-wave ipsative profile correlation designs in previous investigations of individual level consistency (e.g., Asendorpf & van Aken, 1991; Terracciano et al., 2010) makes it possible that individual differences in consistency are due to differences in environments or random error. Instead, our multiwave findings indicate that internal mechanisms are partially responsible for driving personality consistency, as examining profile correlations across multiple waves across multiple years averages out environmental and transient fluctuations. In any one year or so, different life events could yield changes in personality (Specht et al., 2011), but repeated assessments over roughly a decade suggest that environmental upheaval is less likely to be the root cause of these individual differences. This idea, in conjunction with our above first point, possibly alludes to an idiosyncratic set point of personality consistency for individuals. Set point theories in personality have previously been discussed in the context of the interplay of factors such as genetics, states, traits, and life events (Headey, 2008; Lucas et al., 2003), with life events having only a temporary effect (Roberts, 2018). Our findings align with the idea that environmental influences, if and when present, do

Table 7*Models for Individual Differences in Personality Consistency Across Sequential Waves With Moderators*

Model parameter	GSOEP		HILDA		HRS		LISS	
	Est	CI	Est	CI	Est	CI	Est	CI
Numeric age								
Intercept	.59	[.58, .60]	.63	[.62, .63]	.67	[.66, .68]	.64	[.63, .64]
Num. age	.00	[−.00, .00]	.00	[.00, .00]	.00	[.00, .00]	.00	[.00, .00]
Gender	−.02	[−.03, −.01]	.06	[.05, .07]	.04	[.02, .05]	.01	[.00, .02]
Time	.07	[.06, .08]	.07	[.06, .09]	.03	[.01, .05]	.03	[.02, .03]
Time × Num. age	−.00	[−.00, −.00]	−.00	[−.00, −.00]	−.00	[−.00, −.00]	−.00	[−.00, −.00]
Time × Gender	−.01	[−.02, .01]	−.00	[−.02, .01]	.00	[−.03, .03]	−.00	[−.01, .01]
Numeric age (quadratic)								
Intercept	.59	[.58, .60]	.68	[.67, .68]	.69	[.68, .70]	.67	[.67, .68]
Age	.00	[−.00, .00]	.00	[.00, .00]	.00	[−.00, .00]	.00	[.00, .00]
Age ²	−.00	[−.00, −.00]	−.00	[−.00, −.00]	−.00	[−.00, .00]	−.00	[−.00, −.00]
Time	.06	[.05, .07]	.07	[.06, .08]	.03	[.02, .05]	.03	[.02, .03]
Time × Num. age	−.00	[−.00, −.00]	−.00	[−.00, −.00]	−.00	[−.00, −.00]	−.00	[−.00, −.00]
Time × Num. age ²	.00	[.00, .00]	.00	[−.00, .00]	−.00	[−.00, .00]	−.00	[−.00, .00]
Dichotomous age								
Intercept	.59	[.58, .60]	.64	[.64, .65]			.65	[.64, .66]
Dich. age	−.05	[−.07, −.03]	−.11	[−.12, −.09]			−.11	[−.12, −.09]
Gender	−.02	[−.03, −.01]	.06	[.05, .07]			.01	[−.00, .02]
Time	.06	[.05, .08]	.06	[.05, .08]			.02	[.02, .03]
Time × Dich. age	.08	[.05, .11]	.08	[.06, .10]			.03	[.02, .04]
Time × Gender	−.01	[−.02, .01]	−.00	[−.02, .01]			−.00	[−.01, .01]
Agreeableness								
Intercept	.58	[.57, .59]	.66	[.65, .66]	.69	[.68, .69]	.64	[.64, .65]
Trait T1	.04	[.04, .05]	.10	[.10, .11]	.15	[.14, .17]	.10	[.09, .10]
Time	.07	[.06, .08]	.08	[.07, .08]	.03	[.02, .04]	.03	[.02, .03]
Time × Trait T1	−.03	[−.04, −.02]	−.03	[−.04, −.02]	−.05	[−.07, −.02]	−.02	[−.02, −.01]
Time × Trait lags	.01	[.01, .02]	.03	[.03, .04]	.05	[.04, .07]	.00	[−.00, .01]
Conscientiousness								
Intercept	.58	[.57, .58]	.66	[.65, .66]	.69	[.68, .69]	.64	[.64, .65]
Trait T1	.06	[.05, .06]	.08	[.08, .09]	.16	[.14, .17]	.10	[.09, .11]
Time	.07	[.06, .08]	.08	[.07, .08]	.03	[.02, .05]	.03	[.02, .03]
Time × Trait T1	−.04	[−.05, −.03]	−.02	[−.03, −.01]	.00	[−.02, .03]	−.01	[−.01, −.00]
Time × Trait lags	.03	[.03, .04]	.02	[.01, .02]	.07	[.05, .08]	.01	[.00, .01]
Neuroticism								
Intercept	.58	[.57, .58]	.66	[.66, .66]	.69	[.68, .69]	.64	[.64, .65]
Trait T1	−.05	[−.05, −.04]	−.11	[−.11, −.11]	−.14	[−.15, −.13]	−.10	[−.11, −.09]
Time	.07	[.06, .08]	.08	[.07, .08]	.03	[.02, .04]	.03	[.02, .03]
Time × Trait T1	.02	[.01, .02]	.03	[.03, .04]	.04	[.01, .06]	.01	[.01, .02]
Time × Trait lags	−.02	[−.02, −.01]	−.02	[−.02, −.01]	−.06	[−.07, −.05]	−.01	[−.01, −.01]
Education								
Intercept	.57	[.57, .58]	.65	[.64, .65]	.68	[.67, .69]	.63	[.62, .63]
Education	.06	[.05, .07]	.05	[.04, .06]	.04	[.03, .06]	.04	[.02, .04]
Time	.06	[.05, .07]	.06	[.05, .07]	.01	[−.00, .03]	.02	[.01, .02]
Time × Education	.03	[.00, .05]	.04	[.02, .06]	.04	[.01, .07]	.01	[.01, .02]

Note. To reduce table length, only the sample-level effects (i.e., fixed effects) for each moderator are presented in this table. Please see Supplemental Tables S9–S11, S13–S15, and S17, for full results including the person-level effects (i.e., random effects). GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; Est = the maximum a posteriori (MAP) estimate; CI = 95% credible intervals; Trait T1 = between-person trait variable, indicating the difference between a person's level of a trait at Wave 1 relative to the data set's average level at Wave 1; Trait lags = within-person trait variable, indicating a person's deviation in their level of a trait between the waves used to calculate a profile correlation. Bolded values indicate parameter estimates that do not include 0 in the credible intervals.

not appear to strongly alter individuals' typical personality consistency trajectories (see also Jackson and Beck, 2021).

Third, in addition to the relatively large individual differences in average levels of consistency, there were individual differences in the trajectories of change in consistency across waves. While on average most people are stably consistent in their personality profiles, not everyone showed this pattern. Some people became relatively more consistent to a greater degree while others became relatively less consistent in their personality profiles from wave to wave. These

changes in consistency for the latter individuals may point to the influence of life experiences for those people. It is becoming increasingly clear that life events are not simply the slings and arrows that push around personality consistency. Life events appear to have minimal impact on personality development at the aggregate level (Jackson & Beck, 2021). Instead, it is possible that life experiences may be better viewed as a person-centered issue, one where the effects of events are unique to each person. Those who showed increases of greater magnitude could be growing more accustomed to their

Table 8*Descriptive Information for Overall/Distinct Item-Level Profile Correlations Calculated Across Increasing Intervals*

Waves used for profile correlation									
Study	Average	1–2	1–3	1–4	1–5	1–6	1–7	1–8	1–9
GSOEP									
<i>M</i>	.57/.40	.59/.44	.57/.40	.54/.38					
<i>SD</i>	.26/.31	.25/.31	.26/.32	.26/.32					
Range	–.87 to 1.00	–.78 to 1.00	–.84 to .99	–.87 to 1.00					
HILDA									
<i>M</i>	.65/.48	.66/.51	.64/.48	.63/.46					
<i>SD</i>	.22/.24	.21/.23	.22/.24	.23/.24					
Range	–.72 to 1.00	–.67 to 1.00	–.72 to 1.00	–.71 to 1.00					
HRS									
<i>M</i>	.67/.46	.69/.49	.64/.47	.64/.44	.69/.42				
<i>SD</i>	.21/.24	.20/.24	.20/.24	.22/.25	.17/.35				
Range	–.98 to 1.00	–.98 to 1.00	–.63 to 1.00	–.67 to 1.00	.50 to .93				
LISS									
<i>M</i>	.62/.52	.65/.51	.63/.51	.61/.51	.61/.53	.60/.53	.60/.54	.61/.55	.61/.56
<i>SD</i>	.19/.20	.18/.20	.19/.20	.19/.20	.20/.20	.20/.20	.20/.20	.19/.20	.17/.19
Range	–.84 to 1.00	–.50 to 1.00	–.84 to 1.00	–.66 to 1.00	–.69 to 1.00	–.63 to 1.00	–.47 to 1.00	–.35 to 1.00	.15 to .88

Note. Average overall and distinct profile correlations calculated across increasing time intervals are presented for each data set with the standard deviation and range. The averages and standard deviations for the profile correlations are presented such that the overall values are presented first and followed by the distinct values after the/(i.e., overall/distinct). For the ranges, the largest values across both types of profile correlations are presented. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; *M* = mean; *SD* = standard deviation.

environment, perhaps through niche-seeking, habituation of a routine, or increasing familiarity with an environment. In comparison, those who showed decreases in wave-to-wave consistency could have experienced long-term disruptions in their environment that offset their intrinsic level of consistency. These possibilities highlight the complex relationship between environmental contexts and their reinforcing or detrimental effects on consistency.

Fourth, we found no evidence of numeric age contributing to any meaningful between-person differences in personality profile consistency, despite being associated with between-person estimates of stability (e.g., Bazana & Stelmack, 2004; Roberts & DelVecchio, 2000). However, we did find that those younger than 30 had different profile consistency than those older than 30, again establishing that consistency seems to plateau after age 30 for most people (Terracciano et al., 2010). It is possible that age is more important in younger samples for both profile correlations (e.g., Klimstra et al., 2009) and rank-order correlations (Roberts & DelVecchio, 2000), as

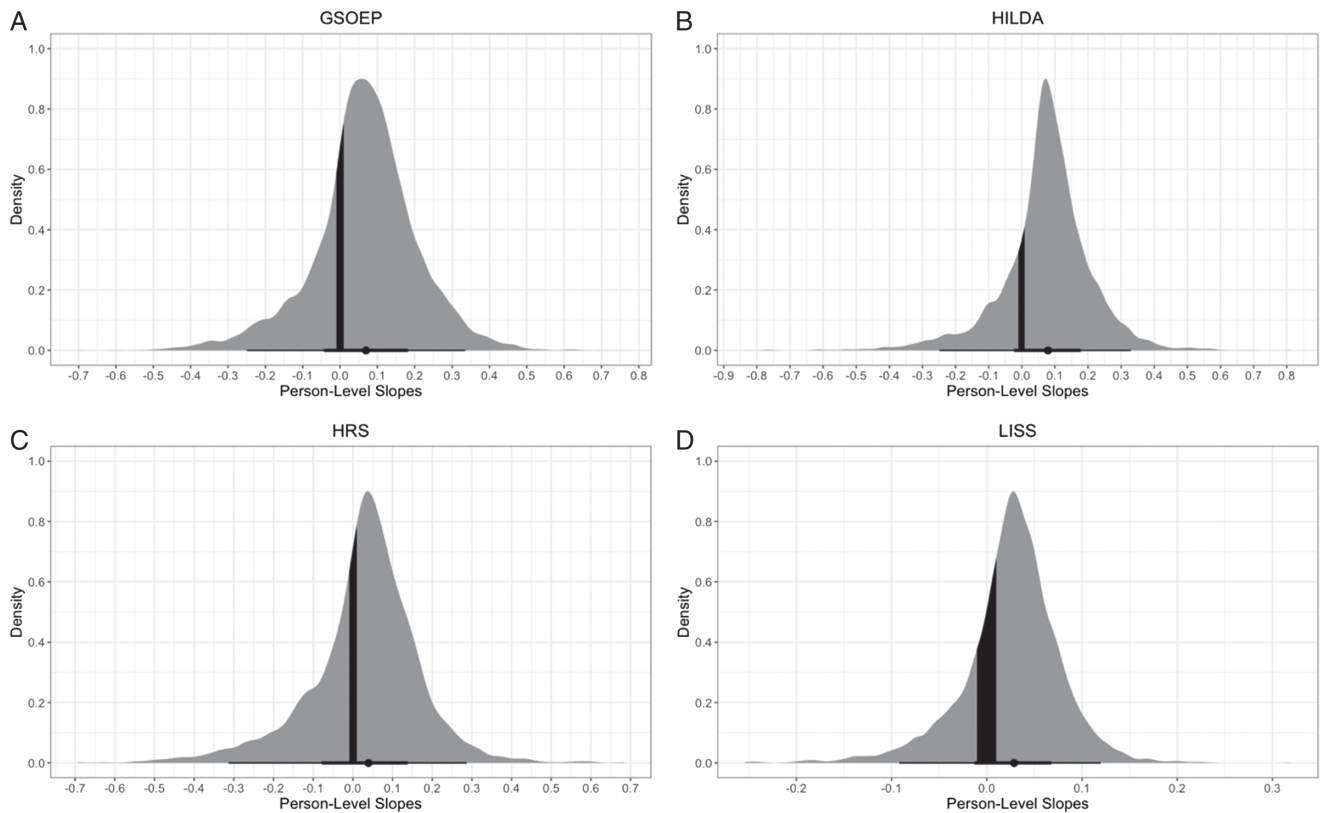
our samples were relatively older. The average age for all of our samples was above the age that personality stability is considered to plateau (i.e., age 30; McCrae & Costa, 2003). Thus, the majority of participants in our samples could have been overwhelmingly “stable” in their personalities—or stably consistent—such that age effects for participants who were outliers for age were masked. It is for this reason that our results should not be interpreted as age never affects profile consistency; rather, at some point, age appears to no longer moderate the degree of consistency in one’s personality profile or the changes in it over time.

Combining the age 30 results with those of the trait results, past work on personality development, particularly that pertaining to the maturity–stability hypothesis (Roberts et al., 2003), can be used to speculate on the reasons both effects emerge. First, “mature” changes in some traits are to be expected with increasing age. Normative age trends found in past research indicate that Agreeableness and Conscientiousness tend to increase with age, whereas

Table 9*Models for Processes Underlying Personality Consistency*

Model parameter	GSOEP		HILDA		HRS		LISS	
	Est	CI	Est	CI	Est	CI	Est	CI
Person level								
Intercept <i>SD</i>	.18	[.18, .19]	.18	[.18, .19]	.16	[.16, .17]	.16	[.15, .16]
Slope <i>SD</i>	.15	[.14, .16]	.13	[.12, .14]	.16	[.15, .17]	.04	[.04, .05]
Correlation	–.21	[–.27, –.15]	–.12	[–.17, –.08]	–.19	[–.25, –.12]	–.07	[–.12, –.02]
Sample level								
Intercept	.58	[.57, .59]	.66	[.65, .66]	.68	[.68, .69]	.64	[.63, .64]
Slope	–.03	[–.04, –.02]	–.03	[–.04, –.02]	–.05	[–.06, –.03]	–.03	[–.03, –.02]

Note. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; Est = the maximum a posteriori (MAP) estimate; CI = 95% credible intervals. Bolded values indicate parameter estimates that do not include 0 in the credible intervals.

Figure 3*Distribution of Person-Level Slope Estimates for Changes in Consistency Across Increasing Intervals*

Note. The posterior distributions for the model-derived, person-level slopes from the models in Table 9 are presented above. The vertical black line constitutes the portion of slopes with values ranging from $-.01 < x < .01$ (i.e., represents .00 with rounding). The black dot represents the median person-level slope estimate, the thicker black horizontal line indicates the 68% quartile interval, and the thin black horizontal line indicates the 95% quartile interval. GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences.

Neuroticism decreases, with these changes likely due to both biological and environmental influences (Lucas & Donnellan, 2011; Terracciano et al., 2005; Wortman et al., 2012). The neosocioanalytic theory highlights the impact of social roles on personality development (Roberts & Wood, 2006). Our younger participants could be transitioning into environments or life roles, such as beginning careers after finishing their education or a starting a family, that are serving to increase their consistency across time by either impacting their levels of relevant personality traits or providing a stable environment. The “investment” in these new social roles offers not only a source of stability for individuals but can also lead to reinforcing changes in relevant traits across time that are associated with the development and maintenance of these mature roles (i.e., the corresponive principle; Denissen et al., 2019; Neyer & Lehnart, 2007; Roberts & Wood, 2006; Specht et al., 2011). Some evidence of this can be seen with the effects of university degree attainment on consistency—participants with higher education levels had higher levels of profile consistency. Importantly, our work extends previous research (see Terracciano et al. 2018, for another similar finding) on the maturity–stability hypothesis by showing it holds in samples other than young adults, as these trait findings were evident in all of our mostly middle-aged

samples (Blonigen et al., 2008; Donnellan et al., 2007; Lönqvist et al., 2008; Roberts et al., 2001).

There Is Variability in the Processes Underlying Personality Consistency

We next examined if the underlying processes driving personality consistency are similar to those observed at the between-person level (i.e., via rank-order consistency) and if there were individual differences in these trends. In our study, when later patterns of responding were compared to people’s initial responses—showing changes in personality consistency across increasing time intervals—we found that people became increasingly less similar from their original selves across time. Moreover, while average trends did emerge across all data sets, there was also variability in terms of the magnitude and direction of absolute changes. This variability in the trajectories of personality consistency suggests that the degree to which these processes matter vary across people (Fraleigh & Roberts, 2005). Importantly, however, our findings further differ in two primary ways from previous between-person investigations of personality consistency (i.e., Fraleigh & Roberts, 2005): (a) a lack of support for stochastic factors having a large

Table 10*Moderators of the Processes Underlying Consistency*

Model parameter	GSOEP		HILDA		HRS		LISS	
	Est	CI	Est	CI	Est	CI	Est	CI
Numeric age								
Intercept	.59	[.58, .60]	.62	[.62, .63]	.66	[.65, .67]	.63	[.62, .64]
Num. age	.00	[−.00, .00]	.00	[.00, .00]	.00	[.00, .00]	.00	[.00, .00]
Gender	−.02	[−.03, −.01]	.06	[.05, .07]	.04	[.02, .05]	.01	[.00, .02]
Time	−.03	[−.04, −.02]	−.02	[−.03, −.01]	−.05	[−.07, −.03]	−.03	[−.03, −.02]
Time × Num. age	−.00	[−.00, .00]	.00	[−.00, .00]	−.00	[−.00, −.00]	.00	[.00, .00]
Time × Gender	.00	[−.01, .02]	−.01	[−.02, .00]	.00	[−.02, .03]	.00	[−.00, .00]
Numeric age (quadratic)								
Intercept	.59	[.58, .60]	.68	[.67, .68]	.68	[.68, .69]	.68	[.67, .69]
Age	.00	[−.00, .00]	.00	[.00, .00]	.00	[−.00, .00]	.00	[.00, .00]
Age ²	−.00	[−.00, −.00]	−.00	[−.00, −.00]	.00	[−.00, .00]	−.00	[−.00, −.00]
Time	−.03	[−.04, −.02]	−.02	[−.02, −.01]	−.04	[−.05, −.03]	−.02	[−.03, −.02]
Time × Num. age	−.00	[−.00, .00]	.00	[−.00, .00]	−.00	[−.00, −.00]	.00	[.00, .00]
Time × Num. age ²	.00	[−.00, .00]	−.00	[−.00, −.00]	−.00	[−.00, .00]	−.00	[−.00, −.00]
Dichotomous age								
Intercept	.59	[.59, .60]	.64	[.63, .65]			.65	[.64, .65]
Dich. age	−.06	[−.08, −.04]	−.11	[−.12, −.10]			−.11	[−.12, −.09]
Gender	−.02	[−.03, −.01]	.06	[.05, .07]			.01	[.00, .02]
Time	−.03	[−.04, −.02]	−.02	[−.03, −.01]			−.02	[−.03, −.02]
Time × Dich. age	.00	[−.02, .03]	−.02	[−.04, −.01]			−.01	[−.02, −.01]
Time × Gender	.00	[−.01, .02]	−.01	[−.02, .00]			−.00	[−.00, .00]
Agreeableness								
Intercept	.58	[.57, .59]	.66	[.65, .66]	.68	[.68, .69]	.63	[.63, .64]
Trait T1	.04	[.04, .05]	.10	[.10, .11]	.15	[.14, .17]	.10	[.09, .11]
Time	−.02	[−.03, −.02]	−.03	[−.03, −.02]	−.04	[−.05, −.02]	−.02	[−.03, −.02]
Time × Trait T1	.03	[.02, .04]	.05	[.04, .05]	.08	[.05, .10]	.02	[.01, .02]
Time × Trait lags	.04	[.04, .05]	.08	[.07, .08]	.16	[.15, .18]	.05	[.04, .05]
Conscientiousness								
Intercept	.58	[.57, .58]	.66	[.65, .66]	.68	[.68, .69]	.64	[.63, .64]
Trait T1	.06	[.05, .06]	.08	[.08, .09]	.16	[.15, .18]	.10	[.09, .11]
Time	−.02	[−.02, −.01]	−.03	[−.04, −.02]	−.03	[−.04, −.02]	−.03	[−.03, −.02]
Time × Trait T1	.04	[.03, .05]	.04	[.03, .04]	.08	[.06, .11]	.02	[.02, .03]
Time × Trait lags	.07	[.06, .07]	.05	[.05, .06]	.15	[.14, .17]	.04	[.04, .04]
Neuroticism								
Intercept	.58	[.57, .59]	.66	[.65, .66]	.68	[.68, .69]	.64	[.63, .64]
Trait T1	−.05	[−.05, −.04]	−.11	[−.11, −.11]	−.14	[−.15, −.13]	−.11	[−.11, −.10]
Time	−.03	[−.04, −.02]	−.03	[−.04, −.02]	−.05	[−.06, −.04]	−.03	[−.03, −.03]
Time × Trait T1	−.02	[−.03, −.01]	−.05	[−.06, −.04]	−.07	[−.09, −.06]	−.02	[−.03, −.02]
Time × Trait lags	−.03	[−.04, −.03]	−.08	[−.09, −.08]	−.12	[−.14, −.11]	−.04	[−.04, −.04]
Education								
Intercept	.57	[.57, .58]	.65	[.64, .65]	.68	[.67, .69]	.62	[.62, .63]
Education	.06	[.05, .07]	.05	[.04, .06]	.04	[.03, .06]	.03	[.03, .04]
Time	−.03	[−.04, −.02]	−.03	[−.04, −.02]	−.06	[−.07, −.04]	−.03	[−.03, −.02]
Time × Education	−.00	[−.02, .02]	.01	[−.01, .02]	.03	[.00, .05]	.00	[−.00, .01]

Note. To reduce table length, only the sample-level effects (i.e., fixed effects) for each moderator are presented in this table. Please see Supplemental Tables S19–S21; S23–S25; and S27, for full results including the person-level effects (i.e., random effects). GSOEP = German Socioeconomic Panel Study; HILDA = Household Income and Labour Dynamics in Australia Study; HRS = Health and Retirement Study; LISS = Longitudinal Studies for the Social Sciences; Est = the maximum a posteriori (MAP) estimate; CI = 95% credible intervals; Trait T1 = between-person trait variable, indicating the difference between a person's level of a trait at Wave 1 relative to the data set's average level at Wave 1; Trait lags = within-person trait variable, indicating a person's deviation in their level of a trait between the waves used to calculate a profile correlation. Bolded values indicate parameter estimates that do not include 0 in the credible intervals.

impact on personality stability and (b) support for transactional processes being impactful and even bolstering consistency.

Although there were average slight decreases in absolute levels of profile consistency across longer stretches of time, the asymptotic values were nowhere near the lowest values found in past meta-analytic research examining these processes in younger samples (i.e., $r = .25-.30$; Fraley & Roberts, 2005), but rather were in line with the larger values previously found in adult samples for both rank-order stability (Atherton et al., 2021; Jones & Meredith, 1996; Terracciano et al., 2006) and within-person ipsative consistency

(Terracciano et al., 2010). As time increases, people's personality profile consistency does not decay quickly, suggesting stable factors (as opposed to changing factors) have an appreciable role in promoting this stability (Anusic & Schimmack, 2016). These findings suggest that stochastic influences, while certainly present to some degree on average, appear to be less important for adult-level personality consistency. Even if it were the case that the stability in trajectories of profile consistency across longer stretches of time is due to a mixture of stochastic and transactional processes rather than due to the sole influence of some constant factor, our results indicate

that these stochastic factors do not greatly outweigh the impact of transactional processes. This could be due to adults being more resilient to the impact of stochastic factors due to ingrained lifestyles/routines or perhaps a stronger sense of self that is not as easily altered compared to younger individuals. That is, even with our up to 12-year test–retest interval, there were no indications that people began to critically decline and asymptote at low values in their profile consistency. Thus, even over longer time spans (i.e., 20–30 years), it is expected that stochastic factors do not accumulate such that people will still mostly maintain their person-centered level of personality profile consistency across time.

Next, our results provide strong evidence of there being developmental constant forces at play, emphasizing the consistency of personality at quite high levels, even over longer time spans (Anusic & Schimmack, 2016). There was an average effect of slight declines in absolute consistency across time, but the points from which people declined varied considerably. This suggests that although constant factors are likely at play to reinforce a person's unique set point of personality consistency, the influence of these need not be the same for everyone. Moreover, it is possible that some individuals showing stable profile consistency trajectories instead had a mixture of stochastic and transactional processes at play, rather than developmental constant processes impacting their long-term stability. That is, stochastic processes leading to decreases in consistency and transactional processes leading to increases in consistency can effectively cancel each other out and result in high levels of consistency. Notably, these possible combinations of processes underlying our observed trajectories of consistency highlight the potentially idiosyncratic nature of this type of personality development. On the one hand, this seems obvious, such that people differ in the processes that promote consistency and change. On the other hand, few designs are capable of addressing this question.

These findings continue to point to taking a person-specific view of change and stability (Beck & Jackson, 2021c). Much of the research done thus far has focused on shared characteristics thought to similarly impact the development of personality for everyone (e.g., life events; Bleidorn et al., 2018). However, the evidence for processes driving change and stability is often nonspecific and discussed in a manner that is applicable to groups or averages rather than individuals. It is important to note that there could be individual differences in these processes, though. For instance, while heritable estimates change over time (Briley & Tucker-Drob, 2013; Plomin & Spinath, 2004), one cannot state that these changes apply to all individuals. Additionally, although an individual's genotype does not vary across time, the influence of those genetic factors may vary and could further be a function of environmental (Reiss et al., 2000) or age-related maturation processes (McCrae & Costa, 2008; Roberts & Jackson, 2008). Similarly, the variable activation or timing of the activity of certain genes across individuals may give rise to individual differences by affecting the extent to which and length of time they exert their influence (Plomin, 1986). This suggests that even this constant factor (i.e., one's genetics) could contribute to within-person variability across time and further differ across individuals. As for a nonbiological example, attachment theories suggest that the early-life mental representations a child develops for themselves and their attachment figures are enduring factors throughout their lives (Bowlby, 1973; Fraley, 2002). Even though this attachment may vary in expression or even in the opportunity to exhibit it at any given time, it is

typically assumed that it serves as an enduring and influential factor in a person's life that itself is largely invariant across time (Fraley & Brumbaugh, 2004; Roisman et al., 2005). However, even this enduring factor can change throughout the course of one's life, with there further being individual differences in the extent to if and what it changes in response to (Fraley et al., 2021).

Lastly, one prominent example in how the processes promoting consistency differ among people is that some people increase in personality profile consistency across longer stretches of time. These increases we found in a substantial proportion of participants indicate the presence of transactional factors at work, as these are the only processes that can lead to increases in consistency and no combination of other processes can mimic their effects (Fraley & Roberts, 2005). Whereas stochastic factors are expected to result in declines in consistency, transactional processes often serve to reinforce and potentially even increase personality consistency across time (Caspi & Roberts, 1999; Fraley & Roberts, 2005). Given that transactional processes with the environment can be still present and not necessarily lead to increases, such that individuals with stable or declining trajectories can also have these, the amount of individuals with positive trajectories is perhaps an underestimate of the number of individuals with these factors at play. However, the positive slopes indicate that, for these individuals, transactional processes not only appear to be the most impactful force, but further that they have a bolstering effect on their consistency—as opposed to serving to help them maintain their person-typical levels. These findings highlight the complex role that environmental factors can have on personality development. Despite the prevalence of transactional theory within the personality development domain (Specht, Bleidorn, et al., 2014), Fraley and Roberts (2005) did not find that the removal of the influence of transactional processes had a detrimental effect on models of personality development. Our findings identify that the impact of transactional effects is very important for some individuals as this is the only process that can lead to increases in consistency (Fraley & Roberts, 2005). Again, this underscores the utility of taking a person-centered approach to understanding personality development.

Limitations

While our study had a number of advantages in terms of a large sample, multiple data sets across different countries, and four to nine waves of data spanning many years, there are still limitations worth considering. First, all data sets were from European-descent countries. Thus, the generalizability of these results to countries that do not fit this criterion could be limited. Second, the average age across our data sets was well above adolescence or even young adulthood. That is, our samples might not have been young enough to, on average, show effects of personality maturation, which is one process thought to drive changes in consistency (Donnellan et al., 2007). It has been found that profile correlations reach a plateau by late adolescence (Branje et al., 2007; Klimstra et al., 2009), suggesting that, at the very least, stark changes should perhaps not be expected in our middle age to older samples. Third, it was indeed the case that individuals who did not qualify for inclusion in our study had lower average levels of profile consistency, as quantified by the within-person profile correlations (Supplemental File S1). While this would have affected the intercept values in our models, likely by decreasing their magnitude to an

extent, our conclusions did not rest on the magnitude of the intercept values. However, we cannot confirm that our conclusions would have held across the excluded individuals, so it should be noted that these inferences may not generalize to individuals with lower-than-average consistency values or that our inferences may have changed if more individuals with lower consistency estimates were included. Fourth, the three processes underlying personality consistency were not directly tested but were inferred based on the direction of the observed long-term trajectories and past work linking these factors with certain directions (Fraley & Roberts, 2005). Future work should incorporate testable factors representing these processes to examine if they have their expected effects and if the assumptions hold. Lastly, the measures used across studies were not equivalent in their exact content, number of items, or psychometric properties. This limits conclusions regarding generalizability to other studies to some degree, as these correlations do vary by these factors (Schmidt & Hunter, 1996), and thus the raw profile correlation values should be compared to other studies with recognition that these factors do perhaps preclude *direct* comparisons. However, the model-derived conclusions drawn across our four data sets were extremely similar, suggesting the different measures did not affect the study's main findings.

Conclusion

This study showed that there were considerable individual differences in levels of person-typical personality consistency and, to a slightly lesser extent, changes in these levels across time, indicating that some people are more *stably* consistent in their personality profiles than others. Individual differences in profile consistency are not short-term perturbations but rather inherent properties of an individual, such that some people are more stable in their personality than others. Our findings also highlight that, at the individual level, the processes underlying personality consistency need not affect everyone to the same degree nor equivalently impact a single person to the same extent across time. Between-person investigations can conceal these nuanced individual differences and give too much weight to any single process being associated with one trend for all individuals. This person-centered investigation of personality consistency highlights the benefit of taking a within-person approach.

References

- Aldwin, C. M., Spiro, A., Levenson, M. R., & Bossé, R. (1989). Longitudinal findings from the normative aging study: 1. Does mental health change with age? *Psychology and Aging*, 4(3), 295–306. <https://doi.org/10.1037/0882-7974.4.3.295>
- Anusic, I., & Schimmack, U. (2016). Stability and change of personality traits, self-esteem, and well-being: Introducing the meta-analytic stability and change model of retest correlations. *Journal of Personality and Social Psychology*, 110(5), 766–781. <https://doi.org/10.1037/pspp0000066>
- Ardelt, M. (2000). Still stable after all these years? Personality stability theory revisited. *Social Psychology Quarterly*, 63(4), 392–405. <https://doi.org/10.2307/2695848>
- Asendorpf, J. B. (1992). Beyond stability: Predicting inter-individual differences in intra-individual change. *European Journal of Personality*, 6(2), 103–117. <https://doi.org/10.1002/per.2410060204>
- Asendorpf, J. B., & van Aken, M. A. (1991). Correlates of the temporal consistency of personality patterns in childhood. *Journal of Personality*, 59(4), 689–703. <https://doi.org/10.1111/j.1467-6494.1991.tb00927.x>
- Atherton, O. E., Grijalva, E., Roberts, B. W., & Robins, R. W. (2021). Stability and change in personality traits and major life goals from college to midlife. *Personality and Social Psychology Bulletin*, 47(5), 841–858. <https://doi.org/10.1177/0146167220949362>
- Bazana, P. G., & Stelmack, R. M. (2004). Stability of personality across the life span: A meta-analysis. In R. M. Stelmack (Ed.), *On the psychobiology of personality: Essays in honor of Marvin Zuckerman* (pp. 113–144). Elsevier Science. <https://doi.org/10.1016/B978-008044209-9/50009-9>
- Beck, E. D., & Jackson, J. J. (2020). Consistency and change in idiographic personality: A longitudinal ESM network study. *Journal of Personality and Social Psychology*, 118(5), 1080–1100. <https://doi.org/10.1037/pspp0000249>
- Beck, E. D., & Jackson, J. J. (2021a). Idiographic personality coherence: A quasi experimental longitudinal ESM study. *European Journal of Personality*, 36(3), 391–412. <https://doi.org/10.1177/08902070211017746>
- Beck, E. D., & Jackson, J. J. (2021b). Within-person variability. In J. F. Rauthmann (Ed.), *The handbook of personality dynamics and processes* (pp. 75–100). Elsevier Academic Press. <https://doi.org/10.1016/B978-0-12-813995-0.00004-2>
- Beck, E. D., & Jackson, J. J. (2021c). Detecting idiographic personality change. *Journal of Personality Assessment*, 104(4), 467–483. <https://doi.org/10.1080/00223891.2021.1984246>
- Bem, D. J., & Allen, A. (1974). On predicting some of the people some of the time: The search for cross-situational consistencies in behavior. *Psychological Review*, 81(6), 506–520. <https://doi.org/10.1037/h0037130>
- Bleidorn, W., & Hopwood, C. J. (2019). Stability and change in personality traits over the lifespan. In D. P. McAdams, R. L. Shiner, & J. L. Tackett (Eds.), *Handbook of personality development* (pp. 237–252). Guilford Press.
- Bleidorn, W., Hopwood, C. J., & Lucas, R. E. (2018). Life events and personality trait change. *Journal of Personality*, 86(1), 83–96. <https://doi.org/10.1111/jopy.12286>
- Bleidorn, W., Klimstra, T. A., Denissen, J. J., Rentfrow, P. J., Potter, J., & Gosling, S. D. (2013). Personality maturation around the world: A cross-cultural examination of social-investment theory. *Psychological Science*, 24(12), 2530–2540. <https://doi.org/10.1177/0956797613498396>
- Block, J. (1971). *Lives through time*. Bancroft Books.
- Blonigen, D. M., Carlson, M. D., Hicks, B. M., Krueger, R. F., & Iacono, W. G. (2008). Stability and change in personality traits from late adolescence to early adulthood: A longitudinal twin study. *Journal of Personality*, 76(2), 229–266. <https://doi.org/10.1111/j.1467-6494.2007.00485.x>
- Bowlby, J. (1973). *Attachment and loss: Volume II: Separation, anxiety and anger* (pp. 1–429). Basic Books.
- Branje, S. J. T., van Lieshout, C. F. M., & Gerris, J. R. M. (2007). Big Five personality development in adolescence and adulthood. *European Journal of Personality*, 21(1), 45–62. <https://doi.org/10.1002/per.596>
- Briley, D. A., & Tucker-Drob, E. M. (2013). Explaining the increasing heritability of cognitive ability across development: A meta-analysis of longitudinal twin and adoption studies. *Psychological Science*, 24(9), 1704–1713. <https://doi.org/10.1177/0956797613478618>
- Briley, D. A., & Tucker-Drob, E. M. (2014). Genetic and environmental continuity in personality development: A meta-analysis. *Psychological Bulletin*, 140(5), 1303–1331. <https://doi.org/10.1037/a0037091>
- Bürkner, P. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, 80(1), 1–28. <https://doi.org/10.18637/jss.v080.i01>
- Caspi, A., & Bem, D. J. (1990). Personality continuity and change across the life course. In L. A. Pervin (Ed.), *Handbook of personality: Theory and research* (pp. 549–575). Guilford Press.
- Caspi, A., & Moffitt, T. E. (1993). When do individual differences matter? A paradoxical theory of personality coherence. *Psychological Inquiry*, 4(4), 247–271. https://doi.org/10.1207/s15327965pli0404_1

- Caspi, A., & Roberts, B. W. (1999). Personality continuity and change across the life course. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (Vol. 2, pp. 300–326). Guilford Press.
- Conley, J. J. (1984a). Longitudinal consistency of adult personality: Self-reported psychological characteristics across 45 years. *Journal of Personality and Social Psychology*, 47(6), 1325–1333. <https://doi.org/10.1037/0022-3514.47.6.1325>
- Conley, J. J. (1984b). The hierarchy of consistency: A review and model of longitudinal findings on adult individual differences in intelligence, personality and self-opinion. *Personality and Individual Differences*, 5(1), 11–25. [https://doi.org/10.1016/0191-8869\(84\)90133-8](https://doi.org/10.1016/0191-8869(84)90133-8)
- Costa, P. T., Jr., Bagby, R. M., Herbst, J. H., & McCrae, R. R. (2005). Personality self-reports are concurrently reliable and valid during acute depressive episodes. *Journal of Affective Disorders*, 89(1–3), 45–55. <https://doi.org/10.1016/j.jad.2005.06.010>
- Cronbach, L. J., & Gleser, G. C. (1953). Assessing similarity between profiles. *Psychological Bulletin*, 50(6), 456–473. <https://doi.org/10.1037/h0057173>
- De Fruyt, F., Bartels, M., Van Leeuwen, K. G., De Clercq, B., Decuyper, M., & Mervielde, I. (2006). Five types of personality continuity in childhood and adolescence. *Journal of Personality and Social Psychology*, 91(3), 538–552. <https://doi.org/10.1037/0022-3514.91.3.538>
- Denissen, J. J. A., Luhmann, M., Chung, J. M., & Bleidorn, W. (2019). Transactions between life events and personality traits across the adult lifespan. *Journal of Personality and Social Psychology*, 116(4), 612–633. <https://doi.org/10.1037/pspp0000196>
- Donnellan, M. B., Conger, R. D., & Burzette, R. G. (2007). Personality development from late adolescence to young adulthood: Differential stability, normative maturity, and evidence for the maturity–stability hypothesis. *Journal of Personality*, 75(2), 237–263. <https://doi.org/10.1111/j.1467-6494.2007.00438.x>
- Epstein, S. (1979). The stability of behavior: I. On predicting most of the people much of the time. *Journal of Personality and Social Psychology*, 37(7), 1097–1126. <https://doi.org/10.1037/0022-3514.37.7.1097>
- Fraley, R. C. (2002). Attachment stability from infancy to adulthood: Meta-analysis and dynamic modeling of developmental mechanisms. *Personality and Social Psychology Review*, 6(2), 123–151. https://doi.org/10.1207/S15327957PSPR0602_03
- Fraley, R. C., & Brumbaugh, C. C. (2004). A dynamical systems approach to conceptualizing and studying stability and change in attachment security. In W. S. Rholes & J. A. Simpson (Eds.), *Adult attachment: Theory, research, and clinical implications* (pp. 86–132). Guilford Publications.
- Fraley, R. C., Gillath, O., & Deboeck, P. R. (2021). Do life events lead to enduring changes in adult attachment styles? A naturalistic longitudinal investigation. *Journal of Personality and Social Psychology*, 120(6), 1567–1606. <https://doi.org/10.1037/pspi0000326>
- Fraley, R. C., & Roberts, B. W. (2005). Patterns of continuity: A dynamic model for conceptualizing the stability of individual differences in psychological constructs across the life course. *Psychological Review*, 112(1), 60–74. <https://doi.org/10.1037/0033-295X.112.1.60>
- Fraley, R. C., Roisman, G. I., Booth-LaForce, C., Owen, M. T., & Holland, A. S. (2013). Interpersonal and genetic origins of adult attachment styles: A longitudinal study from infancy to early adulthood. *Journal of Personality and Social Psychology*, 104(5), 817–838. <https://doi.org/10.1037/a0031435>
- Gilbert, K., Whalen, D. J., Jackson, J. J., Tillman, R., Barch, D. M., & Luby, J. L. (2021). Thin slice derived personality types predict longitudinal symptom trajectories. *Personality Disorders*, 12(3), 275–285. <https://doi.org/10.1037/per0000455>
- Goldberg, L. R. (1990). An alternative “description of personality”: The Big Five factor structure. *Journal of Personality and Social Psychology*, 59(6), 1216–1229. <https://doi.org/10.1037/0022-3514.59.6.1216>
- Headey, B. (2008). Life goals matter to happiness: A revision of set-point theory. *Social Indicators Research*, 86(2), 213–231. <https://doi.org/10.1007/s11205-007-9138-y>
- Headey, B., & Wearing, A. (1989). Personality, life events, and subjective well-being: Toward a dynamic equilibrium model. *Journal of Personality and Social Psychology*, 57(4), 731–739. <https://doi.org/10.1037/0022-3514.57.4.731>
- Ibáñez, M. I., Viruela, A. M., Mezquita, L., Moya, J., Villa, H., Camacho, L., & Ortet, G. (2016). An investigation of five types of personality trait continuity: A two-wave longitudinal study of Spanish adolescents from age 12 to age 15. *Frontiers in Psychology*, 7, Article 512. <https://doi.org/10.3389/fpsyg.2016.00512>
- Jackson, J. J., & Beck, E. D. (2021). Personality development beyond the mean: Do life events shape personality variability, structure, and ipsative continuity? *The Journals of Gerontology: Series B*, 76(1), 20–30. <https://doi.org/10.1093/geronb/gbaa093>
- Jones, C. J., & Meredith, W. (1996). Patterns of personality change across the life span. *Psychology and Aging*, 11(1), 57–65. <https://doi.org/10.1037/0882-7974.11.1.57>
- Juster, F. T., & Suzman, R. (1995). An overview of the Health and Retirement Study. *The Journal of Human Resources*, 30, S7–S56. <https://doi.org/10.2307/146277>
- Kazak, A. E. (2018). Editorial: Journal article reporting standards. *American Psychologist*, 73(1), 1–2. <https://doi.org/10.1037/amp0000263>
- Kendler, K. S., Gatz, M., Gardner, C. O., & Pedersen, N. L. (2006). Personality and major depression: A Swedish longitudinal, population-based twin study. *Archives of General Psychiatry*, 63(10), 1113–1120. <https://doi.org/10.1001/archpsyc.63.10.1113>
- Klimstra, T. A., Hale, W. W., III, Raaijmakers, Q. A. W., Branje, S. J. T., & Meeus, W. H. J. (2009). Maturation of personality in adolescence. *Journal of Personality and Social Psychology*, 96(4), 898–912. <https://doi.org/10.1037/a0014746>
- Lamiell, J. T. (1981). Toward an idiographic psychology of personality. *American Psychologist*, 36(3), 276–289. <https://doi.org/10.1037/0003-066X.36.3.276>
- Lewis, M. (1997). *Altering fate: Why the past does not predict the future*. Guilford Press.
- Lewis, M. (2001). Issues in the study of personality development. *Psychological Inquiry*, 12(2), 67–83. https://doi.org/10.1207/S15327965PLI1202_02
- Lönnqvist, J.-E., Mäkinen, S., Paunonen, S. V., Henriksson, M., & Verkasalo, M. (2008). Psychosocial functioning in young men predicts their personality stability over 15 years. *Journal of Research in Personality*, 42(3), 599–621. <https://doi.org/10.1016/j.jrp.2007.08.006>
- Lucas, R. E., Clark, A. E., Georgellis, Y., & Diener, E. (2003). Reexamining adaptation and the set point model of happiness: Reactions to changes in marital status. *Journal of Personality and Social Psychology*, 84(3), 527–539. <https://doi.org/10.1037/0022-3514.84.3.527>
- Lucas, R. E., & Donnellan, M. B. (2011). Personality development across the life span: Longitudinal analyses with a national sample from Germany. *Journal of Personality and Social Psychology*, 101(4), 847–861. <https://doi.org/10.1037/a0024298>
- Lüdtke, O., Roberts, B. W., Trautwein, U., & Nagy, G. (2011). A random walk down university avenue: Life paths, life events, and personality trait change at the transition to university life. *Journal of Personality and Social Psychology*, 101(3), 620–637. <https://doi.org/10.1037/a0023743>
- Magnus, K., Diener, E., Fujita, F., & Pavot, W. (1993). Extraversion and neuroticism as predictors of objective life events: A longitudinal analysis. *Journal of Personality and Social Psychology*, 65(5), 1046–1053. <https://doi.org/10.1037/0022-3514.65.5.1046>
- McCrae, R. R. (1993). Moderated analyses of longitudinal personality stability. *Journal of Personality and Social Psychology*, 65(3), 577–585. <https://doi.org/10.1037/0022-3514.65.3.577>
- McCrae, R. R., & Costa, P. T., Jr. (2003). *Personality in adulthood: A five-factor theory perspective* (2nd ed.). Guilford Press. <https://doi.org/10.4324/9780203428412>
- McCrae, R. R., & Costa, P. T., Jr. (2008). The five-factor theory of personality. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality: Theory and research* (pp. 159–181). Guilford Press.

- McGue, M., Bacon, S., & Lykken, D. T. (1993). Personality stability and change in early adulthood: A behavioral genetic analysis. *Developmental Psychology*, 29(1), 96–109. <https://doi.org/10.1037/0012-1649.29.1.96>
- Meeus, W., van de Schoot, R., Keijsers, L., & Branje, S. (2012). Identity statuses as developmental trajectories: A five-wave longitudinal study in early-to-middle and middle-to-late adolescents. *Journal of Youth and Adolescence*, 41(8), 1008–1021. <https://doi.org/10.1007/s10964-011-9730-y>
- Mischel, W., & Shoda, Y. (1998). Reconciling processing dynamics and personality dispositions. *Annual Review of Psychology*, 49(1), 229–258. <https://doi.org/10.1146/annurev.psych.49.1.229>
- Morizot, J., & Le Blanc, M. (2005). Searching for a developmental typology of personality and its relations to antisocial behavior: A longitudinal study of a representative sample of men. *Journal of Personality*, 73(1), 139–182. <https://doi.org/10.1111/j.1467-6494.2004.00307.x>
- Mroczek, D. K., & Spiro, A., III (2003). Modeling intraindividual change in personality traits: Findings from the normative aging study. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 58(3), 153–165. <https://doi.org/10.1093/geronb/58.3.P153>
- Neyer, F. J., & Asendorpf, J. B. (2001). Personality–relationship transaction in young adulthood. *Journal of Personality and Social Psychology*, 81(6), 1190–1204. <https://doi.org/10.1037/0022-3514.81.6.1190>
- Neyer, F. J., & Lehnart, J. (2007). Relationships matter in personality development: Evidence from an 8-year longitudinal study across young adulthood. *Journal of Personality*, 75(3), 535–568. <https://doi.org/10.1111/j.1467-6494.2007.00448.x>
- Ozer, D. J., & Benet-Martínez, V. (2006). Personality and the prediction of consequential outcomes. *Annual Review of Psychology*, 57(1), 401–421. <https://doi.org/10.1146/annurev.psych.57.1.401>
- Ozer, D. J., & Gjerde, P. F. (1989). Patterns of personality consistency and change from childhood through adolescence. *Journal of Personality*, 57(2), 483–507. <https://doi.org/10.1111/j.1467-6494.1989.tb00490.x>
- Plomin, R. (1986). Behavioral genetic methods. *Journal of Personality*, 54(1), 226–261. <https://doi.org/10.1111/j.1467-6494.1986.tb00394.x>
- Plomin, R., & Spinath, F. M. (2004). Intelligence: Genetics, genes, and genomics. *Journal of Personality and Social Psychology*, 86(1), 112–129. <https://doi.org/10.1037/0022-3514.86.1.112>
- R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <http://www.R-project.org/>
- Reiss, D., Neiderhiser, J., Mavis, E., Hetherington, E. M., & Plomin, R. (2000). *The relationship code: Deciphering genetic and social influences on adolescent development*. Harvard University Press.
- Revelle, W. (2021). *psych: Procedures for psychological, psychometric, and personality research* (R package Version 2.1.3). Northwestern University. <https://CRAN.R-project.org/package=psych>
- Revelle, W., & Wilt, J. (2020). The dynamics of personality. In J. F. Rauthmann (Ed.), *Handbook of personality dynamics and processes* (1st ed.). Elsevier.
- Roberts, B. W. (2018). A revised sociogenomic model of personality traits. *Journal of Personality*, 86(1), 23–35. <https://doi.org/10.1111/jopy.12323>
- Roberts, B. W., & Caspi, A. (2003). The cumulative continuity model of personality development: Striking a balance between continuity and change in personality traits across the life course. In R. M. Staudinger & U. Lindenberger (Eds.), *Understanding human development: Lifespan psychology in exchange with other disciplines* (pp. 183–214). Kluwer Academic. https://doi.org/10.1007/978-1-4615-0357-6_9
- Roberts, B. W., Caspi, A., & Moffitt, T. E. (2001). The kids are alright: Growth and stability in personality development from adolescence to adulthood. *Journal of Personality and Social Psychology*, 81(4), 670–683. <https://doi.org/10.1037/0022-3514.81.4.670>
- Roberts, B. W., & DelVecchio, W. F. (2000). The rank-order consistency of personality traits from childhood to old age: A quantitative review of longitudinal studies. *Psychological Bulletin*, 126(1), 3–25. <https://doi.org/10.1037/0033-2909.126.1.3>
- Roberts, B. W., & Jackson, J. J. (2008). Sociogenomic personality psychology. *Journal of Personality*, 76(6), 1523–1544. <https://doi.org/10.1111/j.1467-6494.2008.00530.x>
- Roberts, B. W., & Mroczek, D. (2008). Personality trait change in adulthood. *Current Directions in Psychological Science*, 17(1), 31–35. <https://doi.org/10.1111/j.1467-8721.2008.00543.x>
- Roberts, B. W., Robins, R. W., Caspi, A., & Trzesniewski, K. (2003). Personality trait development in adulthood. In J. Mortimer & M. Shanahan (Eds.), *Handbook of the life course* (pp. 579–598). Kluwer Academic. https://doi.org/10.1007/978-0-306-48247-2_26
- Roberts, B. W., Walton, K. E., & Viechtbauer, W. (2006). Patterns of mean-level change in personality traits across the life course: A meta-analysis of longitudinal studies. *Psychological Bulletin*, 132(1), 1–25. <https://doi.org/10.1037/0033-2909.132.1.1>
- Roberts, B. W., & Wood, D. (2006). Personality development in the context of the neo-socioanalytic model of personality. In D. K. Mroczek & T. D. Little (Eds.), *Handbook of personality development* (pp. 11–39). Lawrence Erlbaum.
- Roberts, B. W., Wood, D., & Caspi, A. (2008). The development of personality traits in adulthood. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality: Theory and research* (pp. 375–398). Guilford Press.
- Robins, R. W., Fraley, R. C., Roberts, B. W., & Trzesniewski, K. H. (2001). A longitudinal study of personality change in young adulthood. *Journal of Personality*, 69(4), 617–640. <https://doi.org/10.1111/1467-6494.694157>
- Robins, R. W., & Tracy, J. L. (2003). Setting an agenda for a person-centered approach to personality development. *Monographs of the Society for Research in Child Development*, 68(1), 110–122. <https://doi.org/10.1111/j.1540-5834.2003.06801012.x>
- Roisman, G. I., Collins, W. A., Sroufe, L. A., & Egeland, B. (2005). Predictors of young adults' representations of and behavior in their current romantic relationship: Prospective tests of the prototype hypothesis. *Attachment and Human Development*, 7(2), 105–121. <https://doi.org/10.1080/14616730500134928>
- Scherpenzeel, A. C., & Das, M. (2010). “True” longitudinal and probability-based internet panels: Evidence from the Netherlands. In M. Das, P. Ester, & L. Kaczmarek (Eds.), *Social and behavioral research and the internet: Advances in applied methods and research strategies* (pp. 77–104). Taylor and Francis.
- Schmidt, F. L., & Hunter, J. E. (1996). Measurement error in psychological research: Lessons from 26 research scenarios. *Psychological Methods*, 1(2), 199–223. <https://doi.org/10.1037/1082-989X.1.2.199>
- Schuerger, J. M., Zarrella, K. L., & Hotz, A. S. (1989). Factors that influence the temporal stability of personality by questionnaire. *Journal of Personality and Social Psychology*, 56(5), 777–783. <https://doi.org/10.1037/0022-3514.56.5.777>
- Sherman, R. A., & Serfass, D. G. (2015). The comprehensive approach to analyzing multivariate constructs. *Journal of Research in Personality*, 54, 40–50. <https://doi.org/10.1016/j.jrp.2014.05.002>
- Socio-Economic Panel. (2018). *Socio-Economic Panel (SOEP) data for years 1984–2018* (Version 35).
- Specht, J., Bleidorn, W., Denissen, J. J., Hennecke, M., Hutteman, R., Kandler, C., Luhmann, M., Orth, U., Reitz, A. K., & Zimmermann, J. (2014). What drives adult personality development? A comparison of theoretical perspectives and empirical evidence. *European Journal of Personality*, 28(3), 216–230. <https://doi.org/10.1002/per.1966>
- Specht, J., Egloff, B., & Schmukle, S. C. (2011). Stability and change of personality across the life course: The impact of age and major life events on mean-level and rank-order stability of the Big Five. *Journal of Personality and Social Psychology*, 101(4), 862–882. <https://doi.org/10.1037/a0024950>
- Specht, J., Luhmann, M., & Geiser, C. (2014). On the consistency of personality types across adulthood: Latent profile analyses in two large-scale panel studies. *Journal of Personality and Social Psychology*, 107(3), 540–556. <https://doi.org/10.1037/a0036863>

- Steca, P., Alessandri, G., & Caprara, G. V. (2010). The utility of a well-known personality typology in studying successful aging: Resilients, undercontrollers, and overcontrollers in old age. *Personality and Individual Differences*, 48(4), 442–446. <https://doi.org/10.1016/j.paid.2009.11.016>
- Terracciano, A., Costa, P. T., & McCrae, R. R. (2006). Personality plasticity after age 30. *Personality and Social Psychology Bulletin*, 32(8), 999–1009. <https://doi.org/10.1177/0146167206288599>
- Terracciano, A., McCrae, R. R., Brant, L. J., & Costa, P. T., Jr. (2005). Hierarchical linear modeling analyses of the NEO-PI-R scales in the Baltimore Longitudinal Study of Aging. *Psychology and Aging*, 20(3), 493–506. <https://doi.org/10.1037/0882-7974.20.3.493>
- Terracciano, A., McCrae, R. R., & Costa, P. T., Jr. (2010). Intra-individual change in personality stability and age. *Journal of Research in Personality*, 44(1), 31–37. <https://doi.org/10.1016/j.jrp.2009.09.006>
- Terracciano, A., Stephan, Y., Luchetti, M., & Sutin, A. R. (2018). Cognitive impairment, dementia, and personality stability among older adults. *Assessment*, 25(3), 336–347. <https://doi.org/10.1177/1073191117691844>
- Viken, R. J., Rose, R. J., Kaprio, J., & Koskenvuo, M. (1994). A developmental genetic analysis of adult personality: Extraversion and neuroticism from 18 to 59 years of age. *Journal of Personality and Social Psychology*, 66(4), 722–730. <https://doi.org/10.1037/0022-3514.66.4.722>
- Watson, N., & Wooden, M. (2012). The HILDA Survey: A case study in the design and development of a successful Household Panel Study. *Longitudinal and Life Course Studies*, 3(3), 369–381. <https://doi.org/10.14301/llcs.v3i3.208>
- Wortman, J., Lucas, R. E., & Donnellan, M. B. (2012). Stability and change in the Big Five personality domains: Evidence from a longitudinal study of Australians. *Psychology and Aging*, 27(4), 867–874. <https://doi.org/10.1037/a0029322>

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