HHS Public Access
Author manuscript
Psychol Aging. Author manuscript; available in PMC 2025 March 01.

Published in final edited form as:
Psychol Aging. 2024 March ; 39(2): 188–198. doi:10.1037/pag0000792.

Associations between personality and psychological characteristics and cognitive outcomes among older adults

Sarah Tomaszewski Farias, PhD[1], **Fransia S. De Leon, BA**[2], **Brandon Gavett, PhD**[1], **Evan Fletcher, PhD**[1], **Oanh L. Meyer, PhD**[1], **Rachel A. Whitmer, PhD**[3], **Charlies DeCarli**[1], **Dan Mungas, PhD**[1]

[1.]Department of Neurology, University of California, Davis

[2.]School of Medicine, University of California, Davis

[3.]Department of Public Health, University of California, Davis

Abstract

Prior research has shown that some personality traits are associated with cognitive outcomes and may confirm risk or protection against cognitive decline. The current study expands on previous work to examine the association between a more comprehensive set of psychological characteristics and cognitive performance in a diverse cohort of older adults. We also examine whether controlling for brain atrophy influences the association between psychological characteristics and cognitive function. A total of 157 older adults completed a battery of psychological questionnaires (openness to experience, conscientiousness, agreeableness, neuroticism, extraversion, positive affect, negative affect- sadness, negative affect-anger, sense of purpose, loneliness, grit, and self-efficacy). Cognitive outcomes were measured across multiple domains: episodic memory, semantic memory, executive function, and spatial ability. Baseline brain (MRI) variables included gray matter, hippocampus, and total white matter hyperintensity volume. Parallel process, multi-level models yielded intercept (individual cognitive domain scores) and linear slope (globally cognitive change) random effects for the cognitive outcomes. Positive affect (β=0.013, SE=0.005, p=0.004) and openness (β=0.018, SE=0.007, p=0.009) were associated with less cognitive change, independent of baseline brain variables and covariates. Greater sadness predicted more cognitive decline, when controlling for covariates but not brain atrophy. A variety of psychological characteristics were associated with the cross-sectional measures of cognition. This study highlights the important impact of positive and negative affect on reducing or enhancing risk of longitudinal cognitive decline. Such findings are especially important given the available efficacious interventions that can improve affect.

Keywords

Dementia; cognition; personality

Corresponding Author: Sarah Tomaszewski Farias, Ph.D., ABPP-CN, University of California, Davis, Department of Neurology, farias@ucdavis.edu.

Introduction

Cognitive decline among older adults is a pressing public health concern as it is associated with a host of negative outcomes including loss of independence and an enhanced need for care (Robinson et al., 2005; Wattmo et al., 2014). Understanding the factors that increase or decrease risk of cognitive decline has the potential to inform intervention strategies (Norton et al., 2014). A limited number of personality or psychological characteristics have been shown to influence cognitive outcomes (Fratiglioni et al., 2020; Luchetti et al., 2016) but little work has considered this in diverse populations or taken into account brain integrity.

Personality traits generally refer to enduring although malleable characteristics including attitudes, values, social behaviors, and habits that manifest across situations. A set of personality traits with substantial empirical support (collectively referred to as "The Big Five") include neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness (McCrae et al., 1992). Several studies have demonstrated an association between cognitive functioning and several of these personality traits, (Terracciano et al., 2014; Luchetti et al., 2016). For instance, higher levels of neuroticism have been associated with poorer concurrent cognitive performance (Boyle et al., 2010), and faster cognitive decline (Crowe et al., 2006), while low levels of conscientiousness have been associated with increased risk of Alzheimer's disease (AD) (Duberstein et al., 2011), and faster cognitive decline (Graham et al., 2021). Openness has also been associated with better cognition (Luchetti et al., 2016; Chapman et al., 2012) and less cognitive decline (Luchetti et al., 2016). The association of extraversion with cognition is inconsistent (Terracciano et al., 2014; Luchetti et al., 2016).

There are a number of pathways through which personality characteristics could influence cognitive and brain health. For example, individuals high on the trait of neuroticism have increased vulnerability to chronic stress, as well as negative affect and depression, the latter being a risk for dementia (Zainal and Newman, 2021; Marchant et al., 2020; Livingston et al., 2020), possibly due to the deleterious effects of cortisol (Terracciano et al., 2011). Although relatively few studies have directly measured the association between personality traits on measures of brain health or integrity, one previous study found higher neuroticism was associated with smaller regional brain volumes, while higher conscientiousness was related to larger brain volumes (Jackson et al., 2011). Examining the association between personality and brain measures helps to address potential mechanistic pathways, if only at a relatively gross level. Additionally, examining whether inclusion of brain atrophy measures reduces associations between personality and cognition may help to account for 'reverse causality' effects (e.g., personality changes are as an early indication of neurodegenerative disease).

Most research in this area has been limited to examining the 'Big Five' personality traits, but it is likely other psychological characteristics also relate to cognitive health. Examining the impact of different, but related, components of these personality constructs may lead to a better understanding of the key features that promote cognitive health. The propensity to experience positive affect has been shown to impact many health outcomes ranging from overall mortality to specific diseases such as cardiovascular disease, diabetes, HIV, and cancer (see Pressman, Jenkins, and Moskowitz, 2019 for a review). However, few studies have examined the impact of positive affect on cognitive trajectories among older adults (Castro-Schilo et al., 2019). The impact of negative affect, particularly in the form of longstanding depression, has been linked to a variety of poor health outcomes (Leger et al., 2018) including risk for cognitive decline (Zainal and Newman, 2021; Marchant et al., 2020). Loneliness, which also has a negative affective valance, has likewise been linked with increased risk for cognitive decline in some studies (Donovan et al., 2017) but not others (Penninkilampi et al., 2018). Alternatively, the tendency to have a strong sense of purpose in life has also been associated with better cognition (Boyle et al., 2012; Kim et al., 2019). Another related psychological characteristic, 'grit', defined as passion and persistence in the pursuit of goals (Duckworth et al., 2007) has been associated with better cognitive and everyday functioning in some clinical populations (i.e., individuals with HIV, Moore et al., 2018) but has not been well studied among older adults. Finally, another related characteristic, self-efficacy, the belief in one's ability to successfully execute various behaviors, is widely known to be a determinant of health behaviors (Sheeran et al., 2016).

The present study expands on previous work by examining a more comprehensive set of psychological characteristics that may have an impact on cognitive function among older adults. In addition to the 'Big Five' personality traits, we also examine positive affect and several other positively valanced, resilience-promoting traits (grit, self-efficacy, and sense of purpose), and several negatively valanced factors (loneliness and two aspects of negative affect: sadness and anger). Importantly, we examine these relationships in a demographically diverse sample of older adults. Cognition was measured cross-sectionally across four specific domains (episodic memory, semantic memory, executive functioning, and visuospatial abilities) and change in a global cognitive composite. Broadly, we hypothesized that psychological characteristics outside of the Big Five traits will be associated with cognition/change in cognition. Further, we also examine whether controlling for degree of brain atrophy (a measure of the presence of neurodegeneration) impacts the relationships between psychological characteristics and cognitive function. Given that multiple mechanistic pathways between psychological characteristics and cognition have been proposed, we hypothesized that inclusion of atrophy would not entirely negate their association.

Methods

Transparency and openness

In the following section, we report how the sample size was determined, and describe data exclusions, inclusions, as well as manipulations and measures. The authors do not have any conflict of interests that would influence how the research was conducted. The study design, hypotheses, and analytic plan, were not preregistered. Analytic methods, code, de-identified data, and materials are available on OSF [osf.io/uytek]. Mplus 8.9, R 4.3.1 were utilized for statistical analyses.

Design and Participants

The sample comprised 157 participants from the University of California Davis (UCD) Alzheimer's Disease Research Center's (ADRC) Longitudinal Diversity Cohort. Inclusion criteria included age 60 or older at baseline examination and English or Spanish speaking. Exclusion criteria included unstable major medical illness or serious psychiatric disorder. From 1/6/2003 – 3/10/2020, participants received clinical evaluations through the UCD ADRC on an annual basis that included diagnosis, based on standard diagnostic criteria, of normal cognition versus mild cognitive impairment (MCI) versus dementia as well as etiologic diagnosis. All evaluations followed the same protocol and included a detailed medical history and a physical and neurological exam. Diagnosis of cognitive syndrome was made according to standardized criteria based on a consensus conference. Personality data was obtained between 1/25/18 – 2/27/20. All participants signed informed consent, and all human subject involvement was overseen by institutional review boards at University of California (UC) Davis, the Veterans Administration Northern California Health Care System, and San Joaquin General Hospital in Stockton, California. (IRB project title: "Alzheimer's Disease Research Center Diversity Cohort Study"; protocol # 215830, granting institution is UC Davis)

Sample characteristics are presented in Table 1. Roughly two-thirds of the sample was female, average age was 73 years old, and average education was just under a college degree but spanned a wide range from no formal education to a doctoral degree. The sample contained over 40% non-whites. The majority were tested in English (1.3% tested in Spanish). Mean number of annual assessments was about 6 (ranging from 2–15). A majority of the sample was cognitively normal at baseline assessment.

Instruments

Cognitive outcomes.—The cognitive outcomes in this study were from the Spanish and English Neuropsychological Assessment Scales (SENAS). The SENAS has undergone extensive development as a battery of cognitive tests relevant to diseases of aging (Mungas et al., 2004; Mungas et al., 2005). Cognitive domains assessed included: executive function, semantic memory, episodic memory, and spatial ability. Executive function is a composite of IRT measures constructed from component tasks of category fluency (number of animals, fruits, and vegetables named in 60 seconds), phonemic (letter) fluency (words beginning with the /f/ sound, words beginning with the /l/ sound), and working memory (digit-span backward, visual-span backward, list sorting). Semantic memory is a composite of highly correlated IRT measures of verbal (object-naming) and nonverbal (picture- association) tasks. Episodic memory is an IRT score derived from a multi-trial word- list-learning test (Word List Learning 1). Measure development and psychometric characteristics are described in more detail elsewhere (Crane et al., 2008; Mungas et al., 2004; Mungas et al., 2005). SENAS scores are presented in z- score like units where a score of zero corresponds to the mean and differences from the mean are expressed in standard deviation units.

Personality measures.—The Big-Five personality variables, including extraversion (an inclination toward being sociable, assertive, enthusiastic and energetic), neuroticism (the tendency to experience negative emotions such as anxiety, anger and sadness), openness to new experiences (the tendency to be imaginative, unconventional, curious, emotionally and artistically sensitive), agreeableness (an interpersonal dimension defined by altruism, trust, modesty and cooperativeness), and conscientiousness (the tendency to be organized, strong-willed, persistent, reliable, and a follower of rules), were measured via the 44-item version of the Big Five Personality Inventory (John and Srivastava, 1999). Additional psychological characteristics were based on tests from the NIH Toolbox and included sense of purpose in life, self-efficacy, two negative affect variables – sadness and anger, positive affect (feelings that reflect a level of pleasurable engagement with the environment, including both activated (i.e., happiness, joy) as well as unactivated (i.e., serenity, peace) aspects of positive affect), loneliness. Grit was measured using the short (8 item) form of the Duckworth scale (Duckworth and Quinn, 2009).

Baseline brain variables—Cross-sectional MRI measures of brain volumes obtained at baseline were included as independent variables in some models. These measures have been widely shown to relate to cognitive trajectories and included total gray matter volume, hippocampus volume, and total volume of white matter hyperintensities.

Brain volumes—: Structural MR images were processed to remove the skull using an atlas-based method (Aljabar et al., 2009) followed by human quality control to provide generally minor cleanup if needed. Structural MR brain images were then nonlinearly registered to a minimal deformation template (MDT) synthetic brain image (Kochunov et al., 2001) adapted for age range of 60 and above; the registration was performed by a cubic B-spline deformation (Rueckert et al., 2006). Gray, white, and CSF tissues segmentation was performed using automatic tissue class initialization followed by iterated alternating voxel class assignment and tissue class parameter estimation until convergence, in an algorithm designed to enhance accuracy at likely tissue boundaries (Fletcher et al., 2012). Finally, native lobar gray matter volumes were computed by reverse transforming MDT regions of interest (ROIs) into native space using the B-spline registration parameters. The ROIs used in our analyses were defined in MDT space by an experienced neurologist and have been used in a prior publication from our laboratory (Lee et al., 2010).

WMH quantification—: White matter hyperintensities were quantified at baseline using an automated segmentation algorithm using T1 and fluid-attenuated inversion recovery (FLAIR) images in a method our laboratory described previously (DeCarli et al., 2005). Briefly, the technique involves segmenting voxels of the FLAIR image with intensities exceeding 2.5 standard deviations above the FLAIR mean, after this image has been normalized so that the intensity mode is at a standard value. Refinements include mapping WMH probability priors from a pre-determined atlas onto native images in order to better account for likelihoods of WMH occurrences.

Data Analysis

SENAS measures of episodic memory, semantic memory, executive function, and spatial ability were cognitive outcomes. Measures of personality were the independent variables of interest. Covariates included age at baseline evaluation, gender, race/ethnicity, and recruitment source (clinic versus community). Brain variables included MRI measures of total gray matter, hippocampus, and white matter hyperintensity volumes. Total gray matter and hippocampus volumes were residualized for total intracranial volume.

SENAS measures of cognition and MRI brain measures were transformed using the Blom inverse normal rank order transformation to normalize these variables and establish a common scale (mean=0, SD=1). Dichotomous/categorical variables were transformed into indicator variables such that a variable with k response categories was captured by k-1 dichotomous indicator variables. Participant age was centered at 70 years and education at 12 years.

Longitudinal Modeling of Cognitive Trajectories

Mixed effects, parallel process longitudinal analyses were performed using Mplus version 8.2 multilevel modeling (Muthén and Muthén, 2017). Briefly, in the Within part of this model, each of the four cognitive outcomes was regressed on time (years) in study. The Within model generated person-specific intercept and linear slope random effects for each outcome. These random effects then served as dependent variables in the Between part of the model. The Within model included a term to account for practice effects – an indicator variable specifying if there were previous assessments (0 if baseline assessment, 1 for all follow-ups). We compared a series of models to determine whether cognitive intercepts and slopes could be summarized by second order factors. These were unconditional models that did not include covariates or independent variables. The initial model included correlated intercept and slope random effects for each of the four cognitive outcomes. Correlations among intercepts ranged from 0.53–0.77 (mean=0.66) and correlations among slopes ranged from 0.86–0.93 (mean=0.92). We evaluated whether second order latent variables (one with intercepts as indicators, one with slopes) explained the correlations among the random effects. The second order factors were identified by fixing one loading to 1.0 and freely estimating the other loadings. We compared the fit of models with 0, 1, and 2 second order factors using comparative fit indices including the Akaike Information Criterion (AIC) (Bozdogan 1987), the Bayesian Information Criterion (BIC) (Schwarz 1978), and the Sample Size Adjusted Bayesian Information Criterion (aBIC) (Sclove 1987). These indices differ in the relative weighting of model fit and model parsimony with AIC valuing parsimony the least and BIC the most. Lower values on all indices indicate better model fit. The best fit was obtained with the model that had a global slope second order factor but individual intercept random effects.

Modeling Personality and Brain Associations with Cognition Trajectory Components

Personality and other psychological variables were added to the mixed effects longitudinal models as independent variables to explain cognition trajectory components. In Model 1 analyses, individual cognitive intercepts and global slope were regressed on individual personality/affect/behavior variables and covariates. Brain variables were added as independent variables in Model 2 analyses.

Bayesian Analysis

In addition to the traditional analyses described above, we also analyzed our data using Bayesian methods. One of the primary advantages of Bayesian analysis is that it allows for pre-existing knowledge to be incorporated with the current data when attempting to estimate population parameters. Rather than rely on the results of a single study in isolation, Bayesian methods allow cumulative scientific knowledge to be quantified and updated as new data are collected (van de Schoot et al., 2014). Previous published meta-analyses relating the Big-5 personality factors to changes in late-life cognition thus provide a valuable source of information to guide expectations about the strength of association between personality and cognitive decline in the current study. Therefore, we replicated some of the Model 1 analyses (excluding brain-based predictors) using Bayesian modeling to incorporate the results of this previous research. Bayesian analysis allows for the specification of priors: expectations about the magnitude and direction of an effect based on existing evidence (Kruschke, 2014). For this study, priors were derived from the meta-analysis performed by Luchetti et al. (2016), which reported effect sizes of −0.010 (95% CI [−0.015, −0.006]) for neuroticism, −0.004 (95% CI [−0.026, 0.018]) for extraversion, 0.007 (95% CI [−0.002, 0.017]) for openness, 0.007 (95% CI [−0.003, 0.017]) for agreeableness, and 0.024 (95% CI [0.016, 0.032]) for conscientiousness, when predicting cognitive decline.

We incorporated these priors – as normal distributions with means equal to the effect sizes and variances derived from the reported 95% confidence intervals – by using the Bayes estimator in Mplus (Muthén & Muthén, 1998; 2017). In particular, these analyses focused on the regressions of global cognitive slope on the Big 5 personality factors, as prior estimates were available for these effects. Because these priors were not derived from a single multivariable model, we incorporated them in five separate univariable (with covariates) models, instead of a single multivariable model, as described in the primary modeling section that immediately precedes this section. The Bayesian analysis produces virtually the same statistical output as maximum likelihood estimation; these results, often referred to as the "posterior" estimates, reflect an update to the priors based on the empirical data. When the evidence provided by the empirical data is highly reliable, the impact of the priors on the parameter estimates is minimized; in contrast, when the empirical evidence is weaker, the priors have a greater influence on the resulting parameter estimates. When using the Bayes estimator, Mplus output includes 95% credible intervals, rather than confidence intervals, which represent the 2.5% and 97.5% quantiles of a Markov Chain Monte Carlo sampling distribution of the estimated parameters' posterior distributions (Kruschke, 2014).

Results

Correlations Among Personality/Psychological and Brain Variables

Figure 1 shows intercorrelations among the personality and other psychological variables. As expected, positively valanced variables were positively correlated with each other, as were negatively valanced variables, whereas positive and negatively valanced variables showed negative correlations. The strongest correlation (r=0.70) was between sense of purpose in life and positive affect but only 2% of the pairwise correlations were higher than 0.60. Twenty-seven percent of the correlations had absolute values in the 0.40–0.60 range (moderate range of association), 46% of absolute values were in the 0.20–0.40 range, 24% fell between −0.20 and +0.20, suggesting fairly low associations. Correlations of personality/psychological variables with total gray matter ranged from −0.12–0.13 (mean absolute value = 0.07), with hippocampus −0.15–0.25 (mean absolute value = 0.10), and with white matter hyperintensity −0.25–0.21 (mean absolute value = 0.16).

Associations of Personality/Psychological Characteristics with Cognition

Table 2 shows associations between each personality and psychological variable with global cognitive slope, independent of covariates (Model 1) and also independent of brain variables (Model 2). Cognitive change was associated with positive affect and openness to experience in both Models (including when controlling for brain atrophy). That is, greater positive affect and greater openness predicted better cognitive outcomes. Conversely, sadness was negatively associated with cognitive trajectories in Model 1, but this relationship was not significant in Model 2. Thus, only when not controlling for brain atrophy did higher levels of sadness predicted greater decline in cognitive function over time.

Table 3 shows associations with cognitive intercepts. Episodic Memory intercept was negatively related to Sadness in both Models and to loneliness in Model 1, and was positively associated with self-efficacy in Model 1. Semantic Memory intercept was not related to any of the variables in either Model. Executive Function intercept was positively associated with openness and negatively associated with sadness in Model 1, but these effects in Model 2 were not significant. Spatial ability intercept was negatively associated with neuroticism and sadness and positively associated with self-efficacy in both Models, conscientiousness in Model 2, and with openness in Model 1.

Because positive affect and openness (which generally have a low correlation with each other) were both associated with global cognitive slope in Model 1 and in Model 2, we performed a secondary analysis to examine their independent effects when entered jointly into Model 2 (covariates plus brain variables). Positive affect was significantly associated with cognitive change in this model (β=0.011, SE=0.005, p=0.018) and the association for openness approached significance (β=0.013, SE=0.007, p=0.070). Both of these effects were 20–25% smaller when entered jointly than when entered individually.

Bayesian Analysis

The results of the Bayesian analysis are shown in Table 4 and Supplementary material Appendix 1, Fig. A1. Notable among these results is the difference – in terms of statistical significance patterns – between the meta-analysis derived priors (Luchetti et al., 2016), the maximum likelihood estimates (derived from the current data), and the posterior estimates (reflecting a blend of the prior estimates with the current data). Despite these differences in statistical significance, the magnitudes of the effects were largely consistent with one another, with the exception of conscientiousness. This discrepancy is easily seen in Supplementary material Appendix 1, Fig. A1, which shows a maximum likelihood estimate close to 0, despite the prior and posterior estimates converging at an effect size around 0.021. In contrast, the empirical extraversion data appeared to have the opposite impact on the results, as Supplementary material Appendix 1, Fig. A1 shows that the posterior estimate deviated from the prior estimate to converge with the maximum likelihood estimate. Altogether, the posterior distributions were credibly different from 0, with 95% probability, for three personality variables, when analyzed in separate univariable models: openness, conscientiousness, and agreeableness.

Discussion

There is a large body of research examining the relationship between personality and related traits and various health outcomes. There is growing evidence psychological factors may also relate to cognitive health in aging, although most of this associated literature has focused on the 'Big Five' personality traits. In the current study we expanded upon previous work by examining other factors broadly related to positively- and negatively-valanced psychological characteristics and patterns of behaving. A particularly novel finding was the impact of positive affect on longitudinal cognitive trajectories wherein greater positive affect was associated with less cognitive decline. Positive affect is generally described as the experience of pleasurable emotions and interactions with the environment. The associated descriptive terms vary, but include happiness, joy, excitement, enthusiasm, a sense of calmness and contentment (Pressman et al., 2019). Alternatively, negative affect reflects the extent to which a person experiences distress and other unpleasant emotions such as sadness or anger. Negative and positive affect are not merely two opposite mood factors on a single continuum but can be better considered as distinct (although still negatively correlated) dimensions (Watson et al., 1988).

Higher levels of positive emotions have been associated with a variety of enhanced health outcomes including reduced risk of adverse cardiovascular events (Sin, 2016; Boehm et al., 2020) and decreased mortality (Pressman et al., 2019). Few previous studies have examined the impact of positive affect specifically on cognitive health in older adults (Hittner et al., 2020). One longitudinal study in older adults showed that baseline positive affect differentiated persons with MCI from controls and predicted stable or improving cognition at follow-up (Dolcos et al., 2012). Alternatively, in a study investigating the impact of positive affect on cognitive change over 12 years in a healthy adult sample, positive affect was not associated with cognitive change (Berk et al., 2016). The reason for the differing results may have to do with sample characteristics (e.g., age in the current sample). In fact, other studies have also found a less beneficial effect of positive affect on younger versus older individuals when examining other health outcomes (Pressman & Cohen 2005; Zhang & Han 2016).

Studies on biological correlates of positive affect and proposed mechanisms for its association with health include reduced activation of neuroendocrine, autonomic, immune, and inflammatory pathways (Steptoe et al., 2009). These same biological processes have also been implicated in brain health and neurodegenerative disorders of aging. In addition, the positive affect dopamine hypothesis suggests that release of dopamine in the brain may facilitate processes such as attention, working memory, and memory consolidation, as well as creative problem solving (Ashby et al., 1999). Experimental designs in which positive affect is induced can also result in improved cognitive performance (Ashby et al., 1999; Isen, 2008). Finally, greater positive affect has also been associated with greater engagement in health behaviors and lifestyles (Okely and Gale, 2016) and relate to a greater propensity to seek medical care when needed. Numerous studies suggest that various health behaviors and modifiable lifestyle factors may mediate the associations between personality traits and health outcomes (Bogg and Roberts, 2004; Guerrero et al., 2016). Hoogwegt et al. (2013), for example, demonstrated that ischemic heart disease patients with higher levels of positive affect were more likely to engage in exercise and have a lower mortality risk during a 5 year follow up, with exercise mediating the relationship between positive affect and mortality (Hoogwegt et al., 2013). Overall, the impact of positive affect on cognition is likely multifactorial and may be one reason why the effect was not eliminated when including a measure of brain integrity (brain volumes). Future studies should consider examining whether lifestyle variables and specific health behaviors, such as engagement in physical activity throughout the lifespan, mediate the observed associations between personality and cognitive trajectories.

We also found that one of the negative affective variables, sadness, was related to the rate of cognitive change (greater sadness being associated with greater decline). This is in line with the literature showing that depression is a risk for cognitive decline and dementia (Byers and Yaffe, 2011; Zahodne et al., 2013). In fact, in a recent review, depression has been one of twelve modifiable risk factors that may prevent or delay onset of up to 40% of dementias (Livingston et al, 2020). There are several proposed mechanisms that could help explain the link between depression and dementia risk, including increased glucocorticoids that result in hippocampal atrophy, increased amyloid plaques, pro-inflammatory changes, alterations in nerve growth factors, and vascular disease that results in frontostriatal abnormalities (Byers et al., 2011). Given that our findings show that the impact of sadness on cognitive change was reduced when brain variables were included could mean that its impact is more directly related to brain health/integrity than positive affect, although additional research is needed to address this question.

Of the ‘Big Five’ personality characteristics, only openness to new experience was associated with longitudinal cognitive change in our study. Interestingly, of the Big Five traits, openness was least correlated with positive affect in our sample, suggesting their impacts are likely to be relatively independent (although in a joint model including both variables, the impact of openness was reduced). These findings are consistent with a number of other studies that found openness related to risk of dementia (Terracciano et al., 2014) and cognitive decline (Williams et al., 2013). The trait of openness is generally associated with intellectual curiosity, creativity, and imagination, so individuals high in openness may be more prone to engaging in cognitively stimulating activities, which has also been shown to promote better cognitive aging outcomes (Jackson et al., 2020). Interestingly, similar to positive affect, this effect was not reduced when brain variables were included, suggesting that there may be nonbiological mechanisms or that our biological proxies were not sufficiently sensitive. Along these lines, a recent study found that measures of emotional well-being that included a positive affect component predicted better cognitive function independent of neuropathological change associated with AD (Willwroth et al., 2023). Inconsistent with some previous literature, no statistically significant results in our sample were noted for conscientiousness, extraversion, neuroticism, and agreeableness (similarly, loneliness, grit, purpose in life, and self-efficacy were not statistically significant predictors of cognitive trajectories). However, the results of the Bayesian analyses show mostly good consistency between the prior effect size estimates derived from the literature of the

Big Five characteristics (Luchetti et al., 2016), the sample-derived maximum likelihood estimates, and the posterior effect size estimates, which represent a blend of the prior estimates and the current data. One exception to this was a discrepancy in the effect of conscientiousness on cognitive trajectories in the current study. We found a very small effect (0.001) of conscientiousness on global cognitive decline in our sample, despite a sizeable prior effect size estimate (0.024). Such findings could suggest the current sample may have characteristic differences in some way from those in previous studies, perhaps owing to its diversity. However, as seen in Supplementary material Appendix 1, Fig. A1, the Bayesian posterior estimates for conscientiousness were much more closely aligned with the prior estimates (taken from the Luchetti et al., 2016 meta-analysis) than with the maximum likelihood estimate (derived exclusively from our sample). As such, one benefit of the Bayesian analyses is that it helps properly contextualize the current sample data (based on a relatively small N of 157) within the broader literature; more specifically, the non-significant result in our sample may not be reliable enough to conclude that conscientiousness has a nonzero effect on cognitive decline at the population level.

While the impact of personality and other psychological characteristics on longitudinal cognitive change is perhaps most compelling in the context of cognitive aging, we also examined cross-sectional associations with specific cognitive domains. Results here were more varied, but sadness was a consistent predictor of worse cognitive performance across three of the four cognitive domains. Such findings are, again, consistent with the large literature on the impact of depression on cognitive health (Zahodne et al., 2013). Similarly, feelings of loneliness were associated with worse episodic memory. Self-efficacy was the characteristic with the second most consistent association, related to two of the four cognitive variables. Openness, conscientiousness, neuroticism, and anger were less consistently associated with cognitive functioning across the domains. Interestingly, positive affect was not cross-sectionally related to any of the cognitive domains, suggesting a specific relationship with longitudinal trajectories and possibly more related to underlying brain health. When comparing the models with and without the inclusion of brain variables, the psychologicalical characteristics predicting episodic memory and executive functioning (sadness, loneliness, self efficacy and openness), were all reduced when brain variables were included, suggesting the their impact could be mediated by brain health. Although limited, previous work has linked various psychological characteristics to brain volumes (Wright 2006, 2007). From a neuropathological perspective, neither conscientiousness nor distress proneness traits directly correlated with AD-related neuropathology in work by Wilson et al. (2003, 2007). A better understanding of these mechanisms will be an important avenue for future research.

Among the methodological strengths of this study is the recruitment and enrollment of a demographically diverse sample (over 40% of the sample was from under-represented groups). Also important, we took a more comprehensive approach to measuring psychological traits than previous studies and used rigorous cognitive tests to measure cognitive outcomes. As with all studies, there are limitations. While the Big Five personality traits have been used in diverse populations, some of the other psychological characteristics we studies have not been as well studied in diverse groups and may be influenced by cultural values (Rosenman et al., 2011). Additionally, some previous research has shown that personality traits may change during the prodrome leading up to dementia (Aschenbrenner et al., 2020). While the concern about the influence of prodromal states and reserve causality is lessened to some degree by our longitudinal study design and collection of psychological characteristic data in primarily cognitively normal older adults, measurement of psychological factors in early or midlife would present stronger evidence. One such study that measured personality factors in adolescence to predict late life cognitive trajectories provides further evidence that associations between personality and cognitive aging trajectories are not solely due to prodromal disease (Chapman et al., 2020). Ultimately though, we cannot entirely rule out that reverse causality is playing a role in our findings. Another important limitation is the relatively small sample size. While we were able to identify associations of personality/psychological variables with cognitive change and baseline, this sample size would not support analyses stratifying by important covariates like age, education level, gender, and race.

Conclusion

The present study provides a quantitative analysis of the relationship between cognitive trajectories and both (1) traditional personality characteristics, as represented by the Big Five, and (2) other less commonly assessed psychological traits, among heterogeneous older adults. While we found that several characteristics associated with concurrent cognitive function, most novel to this study is the finding that greater levels of positive affect are associated with better cognitive outcomes in aging. Elucidating the link between personality factors and cognitive trajectories may help guide clinical interventions, thereby reducing the impact of disease related pathology. That is, essentially all of the psychological characteristics examined in this study have been shown to be modifiable, at least to some degree, even personality characteristics which are traditionally viewed as rather stable characteristics (as compared to trait like) (Tang et al., 2009; Jackson et al., 2012). Most germane to our findings, there is growing evidence that positive psychology based interventions (e.g., practicing gratitude, mindfulness and other contemplative techniques) can boost positive affect (Pressman et al,. 2019). While additional research is needed, such interventions could also enhance cognitive and brain health.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors gratefully acknowledge the support provided by grants from the National Institute on Aging (P30 AG072972 and RO1 AG031563). The content is solely the responsibility of the authors and does not necessarily represent the official views of the funding agency. The authors do not have any conflict of interests that would influence how the research was conducted. This study was not preregistered. Analytic methods, code, and de-identified data are available on OSF [osf.io/uytek]. This work was presented at at the AAIC 2021 Annual Meeting, July 26-30, 2021, Denver, USA.

References

Aljabar P, Heckemann RA, Hammers A, Hajnal JV, & Rueckert D. (2009). Multi-atlas based segmentation of brain images: atlas selection and its effect on accuracy. Neuroimage, 46(3), 726–738. 10.1016/j.neuroimage.2009.02.018 [PubMed: 19245840]

Aschenbrenner AJ, Petros J, McDade E, Wang G, Balota DA, Benzinger TL, … & Dominantly Inherited Alzheimer Network. (2020). Relationships between big-five personality factors and Alzheimer’s disease pathology in autosomal dominant Alzheimer’s disease. Alzheimer’s & Dementia: Diagnosis, Assessment & Disease Monitoring, 12(1), e12038. 10.1002/dad2.12038

Ashby FG, & Isen AM (1999). A neuropsychological theory of positive affect and its influence on cognition. Psychological review, 106(3), 529. 10.1037/0033-295X.106.3.529 [PubMed: 10467897]

Berk L, van Boxtel M, Köhler S, & van Os J. (2016). Positive affect and cognitive decline: a 12-year follow-up of the Maastricht Aging Study. International Journal of Geriatric Psychiatry, 32(12), 1305–1311. 10.1002/gps.4611 [PubMed: 27753153]

Boehm JK, Chen Y, Qureshi F, Soo J, Umukoro P, Hernandez R, Lloyd-Jones D, & Kubzansky LD (2020). Positive emotions and favorable cardiovascular health: A 20-year longitudinal study. Preventive medicine, 136, 106103. doi: 10.1016/j.ypmed.2020.106103.

Bogg T, & Roberts BW (2004). Conscientiousness and health-related behaviors: a meta-analysis of the leading behavioral contributors to mortality. Psychological bulletin, 130(6), 887–919. 10.1037/0033-2909.130.6.887 [PubMed: 15535742]

Boyle LL, Lyness JM, Duberstein PR, Karuza J, King DA, Messing S, & Tu X. (2010). Trait neuroticism, depression, and cognitive function in older primary care patients. The American journal of geriatric psychiatry, 18(4), 305–312. DOI: 10.1097/JGP.0b013e3181c2941b [PubMed: 20220585]

Boyle PA, Buchman AS, Wilson RS, Yu L, Schneider JA, & Bennett DA (2012). Effect of purpose in life on the relation between Alzheimer disease pathologic changes on cognitive function in advanced age. Archives of general psychiatry, 69(5), 499–504. DOI: 10.1001/archgenpsychiatry.2011.1487 [PubMed: 22566582]

Bozdogan H. (1987). Model selection and Akaike’s information criterion (AIC): The general theory and its analytical extensions. Psychometrika, 52(3), 345–370. 10.1007/BF02294361

Byers AL, & Yaffe K. (2011). Depression and risk of developing dementia. Nature reviews. Neurology, 7(6), 323–331. 10.1038/nrneurol.2011.60 [PubMed: 21537355]

Castro-Schilo L, Fredrickson BL, & Mungas D. (2019). Association of positive affect with cognitive health and decline for elder Mexican Americans. Journal of happiness studies, 20(8), 2385–2400. DOI: 10.1007/s10902-018-0053-5 [PubMed: 31798315]

Chapman B, Duberstein P, Tindle HA, Sink KM, Robbins J, Tancredi DJ, Franks P, & Gingko Evaluation of Memory Study Investigators. (2012). Personality predicts cognitive function over 7 years in older persons. The American Journal of Geriatric Psychiatry, 20(7), 612–6. DOI: 10.1097/JGP.0b013e31822cc9cb [PubMed: 22735597]

Chapman B, Huang A, Peters K, Horner E, Manly J, Bennett DA, & Lapham S. (2020). Association between high school personality phenotype and dementia 54 years later in results from a national US sample. JAMA psychiatry, 77(2), 148–154. doi:10.1001/jamapsychiatry.2019.3120 [PubMed: 31617877]

Crane PK, Narasimhalu K, Gibbons LE, Pedraza O, Mehta KM, Tang Y, ... & Mungas DM. (2008). Composite scores for executive function items: demographic heterogeneity and relationships with quantitative magnetic resonance imaging. Journal of the International Neuropsychological Society, 14(5), 746–759. doi:10.1017/0S1355617708081162 [PubMed: 18764970]

Crowe M, Andel R, Pedersen NL, Fratiglioni L, & Gatz M. (2006). Personality and risk of cognitive impairment 25 years later. Psychology and aging, 21(3), 573. 10.1037/0882-7974.21.3.573 [PubMed: 16953718]

DeCarli C, Fletcher E, Ramey V, Harvey D, & Jagust WJ (2005). Anatomical mapping of white matter hyperintensities (wmh) exploring the relationships between periventricular WMH, deep WMH, and total WMH burden. Stroke, 36(1), 50–55. 10.1161/01.STR.0000150668.58689.f2 [PubMed: 15576652]

Dolcos S, MacDonald SW, Braslavsky A, Camicioli R, & Dixon RA (2012). Mild cognitive impairment is associated with selected functional markers: integrating concurrent, longitudinal, and stability effects. Neuropsychology, 26(2), 209. 10.1037/a0026760 [PubMed: 22251311]

Donovan NJ, Wu Q, Rentz DM, Sperling RA, Marshall GA, & Glymour MM (2017). Loneliness, depression and cognitive function in older US adults. International journal of geriatric psychiatry, 32(5), 564–573. 10.1002/gps.4495 [PubMed: 27162047]

Duberstein PR, Chapman BP, Tindle HA, Sink KM, Bamonti P, Robbins J, ... & Franks. (2011). Personality and risk for Alzheimer's disease in adults 72 years of age and older: a 6-year follow-up. Psychology and aging, 26(2), 351–362. 10.1037/a0021377 [PubMed: 20973606]

Duckworth AL, & Quinn PD (2009). Development and validation of the Short Grit Scale (GRIT–S). Journal of personality assessment, 91(2), 166–174. 10.1080/00223890802634290 [PubMed: 19205937]

Duckworth AL, Peterson C, Matthews MD, & Kelly DR (2007). Grit: perseverance and passion for long-term goals. Journal of personality and social psychology, 92(6), 1087. 10.1037/0022-3514.92.6.1087 [PubMed: 17547490]

Fletcher E, Singh B, Harvey D, Carmichael O, & DeCarli C. (2012). Adaptive image segmentation for robust measurement of longitudinal brain tissue change. In 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 5319–5322). IEEE. doi:10.1109/EMBC.2012.6347195

Fratiglioni L, Marseglia A, & Dekhtyar S. (2020). Ageing without dementia: can stimulating psychosocial and lifestyle experiences make a difference?. The Lancet Neurology, 19(6), 533–543. 10.1016/S1474-4422(20)30039-9 [PubMed: 32470425]

Graham EK, James BD, Jackson KL, Willroth EC, Boyle P, Wilson R, ... & Mroczek DK. (2021). Associations between personality traits and cognitive resilience in older adults. The Journals of Gerontology: Series B, 76(1), 6–19. 10.1093/geronb/gbaa135

Guerrero LR, Dudovitz R, Chung PJ, Dosanjh KK, & Wong MD (2016). Grit: A potential protective factor against substance use and other risk behaviors among Latino adolescents. Academic pediatrics, 16(3), 275–281. 10.1016/j.acap.2015.12.016 [PubMed: 26796576]

Hittner EF, Stephens JE, Turiano NA, Gerstorf D, Lachman ME, & Haase CM (2020). Positive affect is associated with less memory decline: Evidence from a 9-year longitudinal study. Psychological Science, 31(11), 1386–1395. 10.1177/0956797620953883 [PubMed: 33090935]

Hoogwegt MT, Versteeg H, Hansen TB, Thygesen LC, Pedersen SS, & Zwisler AD (2013). Exercise mediates the association between positive affect and 5-year mortality in patients with ischemic heart disease. Circulation: Cardiovascular Quality and Outcomes, 6(5), 559–566. doi: 10.1161/CIRCOUTCOMES.113.000158 [PubMed: 24021694]

Isen AM (2008). Some ways in which positive affect influences decision making and problem solving. Handbook of emotions, 3, 548–573.

Jackson J, Balota DA, & Head D. (2011). Exploring the relationship between personality and regional brain volume in healthy aging. Neurobiology of aging, 32(12), 2162–2171. 10.1016/j.neurobiolaging.2009.12.009 [PubMed: 20036035]

Jackson JJ, Hill PL, Payne BR, Parisi JM, & Stine-Morrow E. (2020). Linking openness to cognitive ability in older adulthood: The role of activity diversity. Aging & mental health, 24(7), 1079–1087. 10.1080/13607863.2019.1655705 [PubMed: 31446768]

Jackson JJ, Hill PL, Payne BR, Roberts BW, & Stine-Morrow EA (2012). Can an old dog learn (and want to experience) new tricks? Cognitive training increases openness to experience in older adults. Psychology and aging, 27(2), 286. 10.1037/a0025918 [PubMed: 22251379]

John OP, & Srivastava S. (1999). The Big-Five trait taxonomy: History, measurement, and theoretical perspectives. Handbook of personality: Theory and research Vol. 2, 102–138.

Kim G, Shin SH, Scicolone MA, & Parmelee P. (2019). Purpose in life protects against cognitive decline among older adults. The American Journal of Geriatric Psychiatry, 27(6), 593–601. 10.1016/j.jagp.2019.01.01 [PubMed: 30824327]

Kochunov P, Lancaster JL, Thompson P, Woods R, Mazziotta J, Hardies J, & Fox P. (2001). Regional spatial normalization: toward an optimal target. Journal of computer assisted tomography, 25(5), 805–816. [PubMed: 11584245]

Kruschke JK (2014). Doing Bayesian Data Analysis: A tutorial with R, Jags, and Stan 2nd ed.). Academic Press.

Lee DY, Fletcher E, Martinez O, Zozulya N, Kim J, Tran J, ... & DeCarli C. (2010). Vascular and degenerative processes differentially affect regional interhemispheric connections in normal aging, mild cognitive impairment, and Alzheimer disease. Stroke, 41(8), 1791–1797. 10.1161/STROKEAHA.110.582163 [PubMed: 20595668]

Leger KA, Charles ST, & Almeida DM (2018). Let it go: Lingering negative affect in response to daily stressors is associated with physical health years later. Psychological science, 29(8), 1283–12. 10.1177/0956797618763097 [PubMed: 29553880]

Livingston G, Huntley J, Sommerlad A, Ames D, Ballard C, Banerjee S, ... & Mukadam N. (2020). Dementia prevention, intervention, and care: 2020 report of the Lancet Commission. The Lancet, 396(10248), 413–446.10.1016/S0140-6736(20)30367-6

Luchetti M, Terracciano A, Stephan Y, & Sutin AR (2016). Personality and cognitive decline in older adults: Data from a longitudinal sample and meta-analysis. Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 71(4), 591–601. 10.1093/geronb/gbu184 [PubMed: 25583598]

Marchant NL, Lovland LR, Jones R, Pichet Binette A, Gonneaud J, Arenaza-Urquijo EM, ... & PREVENT-AD Research Group. (2020). Repetitive negative thinking is associated with amyloid, tau, and cognitive decline. Alzheimer's & Dementia, 16(7), 1054–1064. 10.1002/alz.12116

McCrae RR, & John OP (1992). An introduction to the five-factor model and its applications. Journal of personality, 60(2), 175–215. 10.1111/j.1467-6494.1992.tb00970.x

Moore RC, Hussain MA, Watson CW, Fazeli PL, Marquine MJ, Yarns BC, ... & Moore DJ. (2018). Grit and ambition are associated with better neurocognitive and everyday functioning among adults living with HIV. AIDS and Behavior, 22(10), 3214–3225. doi:10.1007/s10461-018-2061-1 [PubMed: 29455265]

Mungas D, Farias ST, Fletcher E, Gavett BE, Widaman KF, & De Leon F. (2023, October 11). Personality and Concurrent Cognitive Trajectories Manuscript Retrieved from osf.io/uytek

Mungas D, Reed BR, Crane PK, Haan MN, & Gonzalez H. (2004). Spanish and English Neuropsychological Assessment Scales (SENAS): further development and psychometric characteristics. Psychological Assessment, 16, 347–359. 10.1037/1040-3590.16.4.347 [PubMed: 15584794]

Mungas D, Reed BR, Haan MN, & Gonzalez H. (2005). Spanish and English neuropsychological assessment scales: Relationship to demo- graphics, language, cognition, and independent function. Neuropsychology, 19, 466–475. 10.1037/0894-4105.19.4.466 [PubMed: 16060821]

Muthén B, & Muthén L. (2017). Mplus. In Handbook of item response theory (pp. 507–518). Chapman and Hall/CRC.

Muthén LK, & Muthén BO (1998). Mplus: The comprehensive modeling program for applied researchers: U'er's guide. Muthén & Muthén.

Norton S, Matthews FE, Barnes DE, Yaffe K, & Brayne C. (2014). Potential for primary prevention of Alzheimer's disease: an analysis of population-based data. The Lancet Neurology, 13(8), 788–794. 10.1016/S1474-4422(14)70136-X [PubMed: 25030513]

Okely JA, & Gale CR (2016). Well-being and chronic disease incidence: the English longitudinal study of ageing. Psychosomatic Medicine, 78(3), 335. doi: 10.1097/PSY.0000000000000279 [PubMed: 26569542]

Penninkilampi R, Casey AN, Singh MF, & Brodaty H. (2018). The association between social engagement, loneliness, and risk of dementia: a systematic review and meta-analysis. Journal of Alzheimer's Disease, 66(4), 1619–1633. doi: 10.3233/JAD-180439

Pressman SD, & Cohen S. (2005). Does positive affect influence health?. Psychological bulletin, 131(6), 925. 10.1037/0033-2909.131.6.925 [PubMed: 16351329]

Pressman SD, Jenkins BN, & Moskowitz JT (2019). Positive affect and health: what do we know and where next should we go?. Annual Review of Psychology, 70, 627–650. 10.1146/annurev-psych-010418-102955

Robinson KM, Buckwalter KC, & Reed D. (2005). Predictors of use of services among dementia caregivers. Western journal of nursing research, 27(2), 126–140. 10.1177/019394590427245 [PubMed: 15695566]

Rosenman R, Tennekoon V, & Hill LG (2011). Measuring bias in self-reported data. International Journal of Behavioural and Healthcare Research, 2(4), 320–332. 10.1504/IJBHR.2011.043414 [PubMed: 25383095]

Rueckert D, Aljabar P, Heckemann RA, Hajnal JV, & Hammers A. (2006). Diffeomorphic registration using B-splines. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2006: 9th International Conference, Copenhagen, Denmark, October 1–6, 2006. Proceedings, Part II 9 (pp. 702–709). Springer Berlin Heidelberg. 10.1007/11866763_86

Schwarz G. (1978). Estimating the dimension of a model. The annals of statistics, 6(2), 461–464. http://www.jstor.org/stable/2958889

Sclove SL (1987). Application of model-selection criteria to some problems in multivariate analysis. Psychometrika, 52, 333–343. 10.1007/BF02294360

Sheeran P, Maki A, Montanaro E, Avishai-Yitshak A, Bryan A, Klein WM, ... & Rothman AJ. (2016). The impact of changing attitudes, norms, and self-efficacy on health-related intentions and behavior: A meta-analysis. Health psychology, 35(11), 1178. 10.1037/hea0000387 [PubMed: 27280365]

Sin NL (2016). The protective role of positive well-being in cardiovascular disease: review of current evidence, mechanisms, and clinical implications. Current cardiology reports, 18, 1–10. 10.1007/s11886-016-0792-z [PubMed: 26694723]

Steptoe A, Dockray S, & Wardle J. (2009). Positive affect and psychobiological processes relevant to health. Journal of personality, 77(6), 1747–1776. 10.1111/j.1467-6494.2009.00599.x [PubMed: 19796062]

Tang TZ, DeRubeis RJ, Hollon SD, Amsterdam J, Shelton R, & Schalet B. (2009). Personality change during depression treatment: a placebo-controlled trial. Archives of general psychiatry, 66(12), 1322–1330. doi:10.1001/archgenpsychiatry.2009.166 [PubMed: 19996037]

Terracciano A, Lobina M, Piras MG, Mulas A, Cannas A, Meirelles O, ... & Schlessinger D. (2011). Neuroticism, depressive symptoms, and serum BDNF. Psychosomatic medicine, 73(8), 638. doi:10.1097/PSY.0b013e3182306a4f [PubMed: 21949427]

Terracciano A, Sutin AR, An Y' O'Brien RJ., Ferrucci L., Zonderman AB., & Resnick SM. (2014). Personality and risk of Alzheimer's disease: new data and meta-analysis. Alzheimer's & Dementia, 10(2), 179–186. 10.1016/j.jalz.2013.03.002

van de Schoot R, Kaplan D, Denissen J, Asendorpf JB, Neyer FJ, & van Aken MAG (2014). A gentle introduction to bayesian analysis: Applications to developmental research. Child Development, 85(3), 842–860. 10.1111/cdev.12169 [PubMed: 24116396]

Watson D, Clark LA, & Carey G. (1988). Positive and negative affectivity and their relation to anxiety and depressive disorders. Journal of abnormal psychology, 97(3), 346. 10.1037/0021-843X.97.3.346 [PubMed: 3192830]

Wattmo C, Londos E, & Minthon L. (2014). Solitary living in Alzheimer's disease over 3 years: Association between cognitive and functional impairment and community-based services. Clinical interventions in aging, 1951–1962. 10.2147/CIA.S71709

Williams PG, Suchy Y, & Kraybill ML (2013). Preliminary evidence for low openness to experience as a pre-clinical marker of incipient cognitive decline in older adults. Journal of Research in Personality, 47(6), 945–951.doi:10.1016/j.jrp.2013.09.006

Willroth EC, James BD, Graham EK, Kapasi A, Bennett DA, & Mroczek DK (2023). Well-being and cognitive resilience to dementia-related neuropathology. Psychological Science, 34(3), 283–297. 10.1177/09567976221119828 [PubMed: 36473124]

Wilson RS, Evans DA, Bienias JL, De Leon CM, Schneider JA, & Bennett DA (2003). Proneness to psychological distress is associated with risk of Alzheimer's disease. Neurology, 61(11), 1479–1485. https://doi.org/10.1212 [PubMed: 14663028]

Wilson RS, Schneider JA, Arnold SE, Bienias JL, & Bennett DA (2007). Conscientiousness and the incidence of Alzheimer disease and mild cognitive impairment. Archives of general psychiatry, 64(10), 1204–1212. doi:10.1001/archpsyc.64.10.1204 [PubMed: 17909133]

Author Manuscript
Author Manuscript
Author Manuscript

Wright CI, Williams D, Feczko E, Barrett LF, Dickerson BC, Schwartz CE, & Wedig MM (2006). Neuroanatomical correlates of extraversion and neuroticism. Cerebral cortex, 16(12), 1809–1819. 10.1093/cercor/bhj118 [PubMed: 16421327]

Wright CI, Feczko E, Dickerson B, & Williams D. (2007). Neuroanatomical correlates of personality in the elderly. Neuroimage, 35(1), 263–272. 10.1016/j.neuroimage.2006.11.039 [PubMed: 17229578]

Zahodne LB, Gongvatana A, Cohen RA, Ott BR, Tremont G, & Alzheimer's Disease Neuroimaging Initiative. (2013). Are apathy and depression independently associated with longitudinal trajectories of cortical atrophy in mild cognitive impairment?. The American Journal of Geriatric Psychiatry, 21(11), 1098–1106. doi:10.1016/j.jagp.2013.01.043 [PubMed: 23636003]

Zainal NH, & Newman MG (2021). Larger increase in trait negative affect is associated with greater future cognitive decline and vice versa across 23 years. Depression and anxiety, 38(2), 146–160. doi: 10.1002/da.23093 [PubMed: 32840954]

Zhang Y, & Han B. (2016). Positive affect and mortality risk in older adults: A meta-analysis. PsyCh journal, 5(2), 125–138. doi: 10.1002/pchj.129 [PubMed: 27113246]

Public Significance Statement:

This study elucidates the importance of positive and negative affect on modifying the risk of longitudinal cognitive decline. Given the many currently available efficacious interventions that modify affect, such findings may be used to guide clinical practice.

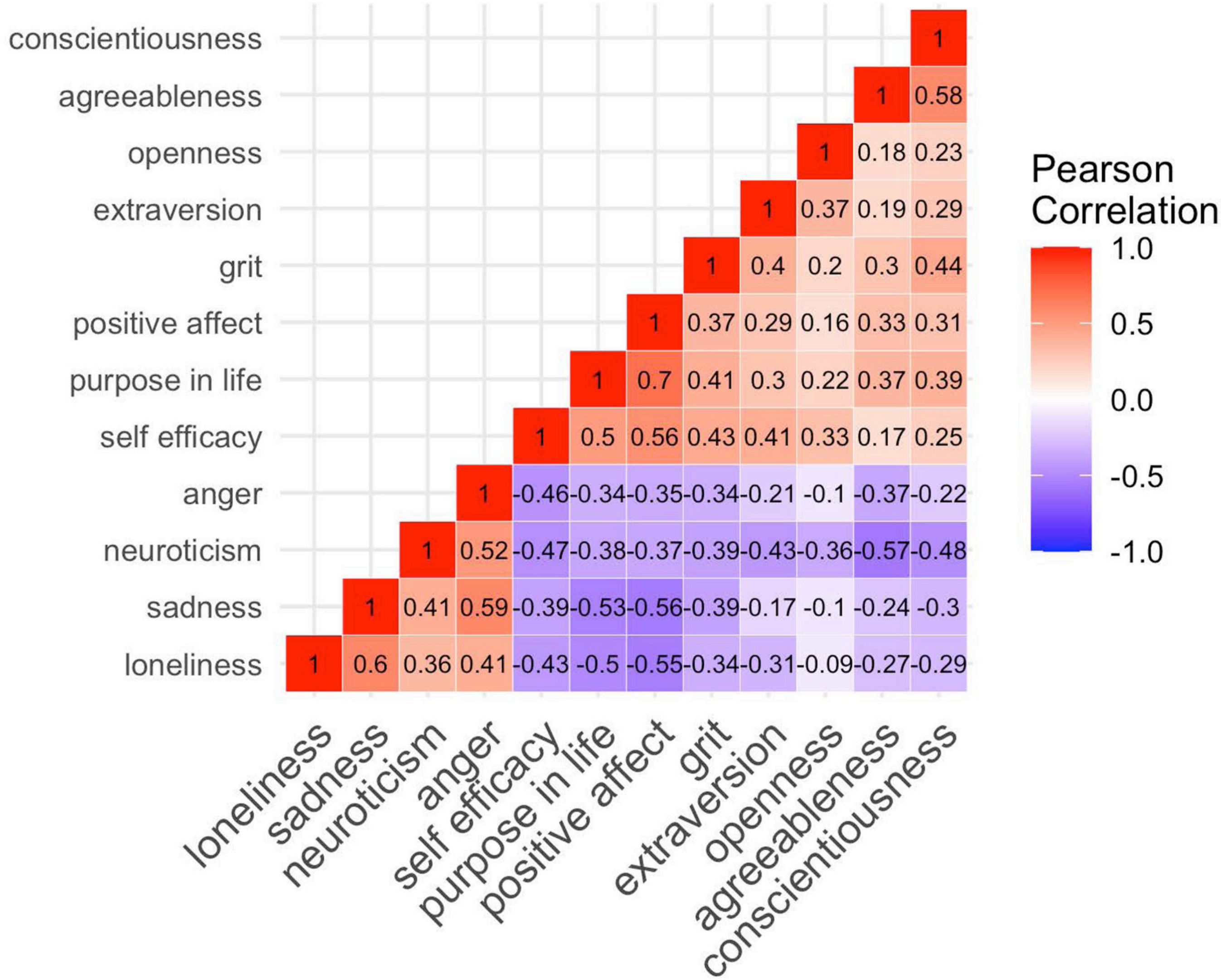

Figure 1.
Correlation among Personality/Affect/Behavior Variables

Author Manuscript

Author Manuscript

Author Manuscript

Table 1.

Sample Characteristics

	Overall
Gender	
Male	54 (35.1%)
Female	100 (64.9%)
Age (years)	
Mean (SD)	73.3 (6.43)
Median [Min, Max]	73.0 [60.0, 92.0]
Education (years)	
Mean (SD)	15.7 (3.00)
Median [Min, Max]	16.0 [0, 20.0]
Race/Ethnicity	
Black	34 (22.1%)
Latino	19 (12.3%)
Other	11 (7.1%)
White	90 (58.4%)
Spanish Test Administration	
English	152 (98.7%)
Spanish	2 (1.3%)
Number of Assessments	
Mean (SD)	6.32 (3.91)
Median [Min, Max]	5.00 [2.00, 15.0]
Follow-up Time (years)	
Mean (SD)	6.38 (4.81)
Median [Min, Max]	4.81 [0.972, 15.7]
Recruitment Source	
Clinic	18 (11.7%)
Community	128 (83.1%)
Syndrome Diagnosis	
MCI	18 (11.7%)
Normal	136 (88.3%)

Table 2.

Associations of personality, affect, and behavior variables with global cognitive slope in models with and without adjustment for brain variables.

Personality/Affect/Behavior Variable	Model 1	Model 2
Grit	0.002 (0.004)	0.002 (0.004)
Openness	0.015 (0.007) *	0.018 (0.007) **
Conscientiousness	0.001 (0.005)	0.001 (0.004)
Extraversion	0.006 (0.006)	0.007 (0.006)
Neuroticism	−0.008 (0.005)	−0.005 (0.005)
Agreeableness	0.004 (0.005)	0.006 (0.005)
Sadness	−0.013 (0.006) *	−0.011 (0.006) °
Anger	−0.004 (0.005)	−0.005 (0.005)
Purpose in Life	0.008 (0.005)	0.006 (0.005)
Self Efficacy	0.008 (0.006)	0.004 (0.006)
Loneliness	−0.006 (0.006)	−0.005 (0.006)
Positive Affect	0.014 (0.005) **	0.013 (0.005) **

°(p<0.10

* p<0.05

** p<0.01

*** p<0.001)

Table 3.

Associations of personality, affect, and behavior variables with cognitive intercepts in models without (Model 1) and with (Model 2) adjustment for brain variables.

Dependent Variable	Personality/Affect/Behavior Variable	Model 1	Model 2
Episodic Memory	Grit	0.041 (0.051)	0.002 (0.054)
Episodic Memory	Openness	0.047 (0.045)	0.072 (0.048)
Episodic Memory	Conscientiousness	0.039 (0.051)	0.031 (0.056)
Episodic Memory	Extraversion	0.044 (0.048)	0.048 (0.056)
Episodic Memory	Neuroticism	−0.073 (0.051)	−0.049 (0.056)
Episodic Memory	Agreeableness	0.033 (0.046)	0.017 (0.050)
Episodic Memory	Sadness	−0.150 (0.047)***	−0.109 (0.051)*
Episodic Memory	Anger	−0.101 (0.053)$^{\circ}$	−0.077 (0.053)
Episodic Memory	Purpose in Life	0.093 (0.055)$^{\circ}$	0.067 (0.056)
Episodic Memory	Self Efficacy	0.149 (0.054)**	0.104 (0.060)$^{\circ}$
Episodic Memory	Loneliness	−0.123 (0.055)*	−0.098 (0.061)
Episodic Memory	Positive Affect	0.077 (0.050)	0.048 (0.053)
Semantic Memory	Grit	0.036 (0.047)	0.009 (0.054)
Semantic Memory	Openness	0.068 (0.051)	0.033 (0.059)
Semantic Memory	Conscientiousness	−0.044 (0.046)	−0.024 (0.052)
Semantic Memory	Extraversion	0.018 (0.050)	−0.036 (0.056)
Semantic Memory	Neuroticism	−0.076 (0.048)	−0.058 (0.056)
Semantic Memory	Agreeableness	0.005 (0.055)	−0.048 (0.059)
Semantic Memory	Sadness	−0.075 (0.049)	−0.074 (0.054)
Semantic Memory	Anger	−0.038 (0.051)	−0.017 (0.051)
Semantic Memory	Purpose in Life	0.004 (0.048)	−0.016 (0.052)
Semantic Memory	Self Efficacy	0.091 (0.047)$^{\circ}$	0.054 (0.052)
Semantic Memory	Loneliness	−0.091 (0.057)	−0.070 (0.063)
Semantic Memory	Positive Affect	0.007 (0.050)	−0.001 (0.053)
Executive Function	Grit	0.082 (0.053)	0.067 (0.059)
Executive Function	Openness	0.094 (0.043)*	0.079 (0.047)$^{\circ}$
Executive Function	Conscientiousness	0.032 (0.052)	0.050 (0.061)
Executive Function	Extraversion	0.008 (0.046)	−0.028 (0.054)
Executive Function	Neuroticism	−0.028 (0.046)	−0.009 (0.053)
Executive Function	Agreeableness	0.021 (0.051)	−0.029 (0.056)
Executive Function	Sadness	−0.097 (0.047)*	−0.063 (0.052)
Executive Function	Anger	−0.089 (0.054)$^{\circ}$	−0.072 (0.057)
Executive Function	Purpose in Life	0.048 (0.056)	0.021 (0.062)
Executive Function	Self Efficacy	0.090 (0.053)$^{\circ}$	0.055 (0.061)
Executive Function	Loneliness	−0.095 (0.060)	−0.055 (0.071)
Executive Function	Positive Affect	0.032 (0.054)	0.000 (0.062)

Dependent Variable	Personality/Affect/Behavior Variable	Model 1	Model 2
Spatial Ability	Grit	0.098 (0.056)[°]	0.107 (0.061)[°]
Spatial Ability	Openness	0.100 (0.056)[°]	0.115 (0.066)[°]
Spatial Ability	Conscientiousness	0.076 (0.051)	0.115 (0.054)[+]
Spatial Ability	Extraversion	0.065 (0.048)	0.079 (0.051)
Spatial Ability	Neuroticism	−0.116 (0.054)[*]	−0.138 (0.060)[*]
Spatial Ability	Agreeableness	0.019 (0.057)	−0.036 (0.057)
Spatial Ability	Sadness	−0.108 (0.050)[*]	−0.115 (0.054)[*]
Spatial Ability	Anger	−0.116 (0.054)[*]	−0.127 (0.059)[*]
Spatial Ability	Purpose in Life	0.040 (0.051)	0.040 (0.054)
Spatial Ability	Self Efficacy	0.114 (0.052)[*]	0.119 (0.056)[*]
Spatial Ability	Loneliness	−0.082 (0.055)	−0.075 (0.062)
Spatial Ability	Positive Affect	−0.003 (0.048)	−0.001 (0.053)

[°](p<0.10

[*]p<0.05

[**]p<0.01

[***]p<0.001)

Table 4.

Regression of Global Cognitive Slope on Personality Variables: Comparison of Bayesian Estimates (Posterior) to Prior Meta-Analytic Results and Maximum Likelihood Estimates.

Personality Variable	Prior [95% CI]	ML Estimate [95% CI]	Posterior [95% CrI]
Openness	0.007 [−0.002, 0.017]	**0.015 [0.001, 0.030]**	**0.011 [0.003, 0.019]**
Conscientiousness	**0.024 [0.016, 0.032]**	0.001 [−0.008, 0.010]	**0.018 [0.011, 0.025]**
Extraversion	−0.004 [−0.026, 0.018]	0.004 [−0.007, 0.016]	0.003 [−0.009, 0.015]
Neuroticism	0.007 [−0.003, 0.017]	0.005 [−0.004, 0.014]	0.006 [−0.002, 0.013]
Agreeableness	**−0.010 [−0.015, −0.006]**	−0.009 [−0.019, 0.001]	**−0.010 [−0.014, −0.006]**

Note. Bold font represents estimates whose 95% confidence or credible intervals do not overlap 0 (“statistically significant” at $\alpha = .05$). Prior estimates were taken from Luchetti et al. (2016). ML = maximum likelihood; ML estimates are slightly different from those reported in Table 2 because these results are based on separate univariable analyses for each personality variable. CI = confidence interval; CrI = credible interval.