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Personality traits and cognitive reserve—High openness benefits cognition in the presence of age-related brain changes

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ABSTRACT

Cognitive reserve explains differential susceptibility of cognitive performance to neuropathology. We investigated whether certain personality traits underlie cognitive reserve and are accordingly associated with better cognition and less cognitive decline in the presence of age-related brain changes. We included healthy adults aged 19–80 years for cross-sectional (N=399) and longitudinal (N=273, mean follow-up time=5 years, SD=0.7 years) analyses. Assessment of the BIG5 personality traits openness, conscientiousness, extraversion, agreeableness, and neuroticism was questionnaire-based. Each cognitive domain (perceptual speed, memory, fluid reasoning, vocabulary) was measured with up to six tasks. Cognitive domain-specific brain status variables were obtained by combining 77 structural brain measures into single scores using elastic net regularization. These brain status variables explained up to 43.1% of the variance in cognitive performance. We found that higher openness was associated with higher fluid reasoning and better vocabulary after controlling for brain status, age, and sex. Further, lower brain status was associated with a greater decline in perceptual speed only in individuals with low openness. We conclude that high openness benefits cognitive reserve.

1. Introduction

Life expectancy has dramatically increased over the past decades, with the global life expectancy increasing by 5 years between 2010 and 2016 (Gulland, 2016). Since age represents a key risk factor for dementia (Niu et al., 2017), it has been estimated that the global dementia prevalence will almost triple within the next 30 years (Nichols et al., 2022). Alzheimer's disease (AD) is the most common form of dementia (Alzheimer's Association, 2022; Barker et al., 2002) and is characterized by ß amyloid deposition, pathologic tau, and neurodegeneration in the brain (Jack et al., 2018). Surprisingly, post-mortem brain examinations revealed that about one quarter of individuals whose brains have severe AD pathology were not diagnosed with AD during their lifetime (Riley et al., 2002; Roe et al., 2007). Since dementia represents a major challenge for societies all over the world (Nichols et al., 2022), it is essential to better understand what makes some individuals resistant to the negative effects of brain pathology on clinical outcomes.

The concept that describes differential susceptibility to age- and disease-related brain pathology has been termed cognitive reserve (CR) (Stern, 2009). According to this concept, individuals with higher CR can withstand more brain pathology, such as cortical thinning, volume loss or accumulation of amyloid plaques and tau tangles, before experiencing cognitive impairment. The underlying neural mechanisms may be that individuals with higher CR have neural networks with greater efficiency and/or capacity and/or they are better in compensating for brain pathology by using alternate brain networks (Stern and Barulli, 2019). Among the best-studied factors underlying CR are high educational and occupational attainment, intelligence, as well as participation in leisure activities of intellectual or social nature (Opdebeeck et al., 2016; Tucker and Stern, 2011). To test whether a factor underlies CR, the rigorous CR-test outlined by the "Reserve and Resilience" collaboratory (http://reserveandresilience.com/) can be used. The collaboratory's CR test states that factors associated with CR should explain variance in cognitive performance beyond the variance explained by brain status

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and/or moderate the brain status-cognition relationship (Stern et al., 2023, 2020). Since personality may influence leisure behavior, e.g., the extent to which somebody pursues intellectual or social leisure activities or takes advantage of new learning opportunities, personality may also underlie CR (Ihle et al., 2019; Trapp et al., 2019). If so, personality should explain variance in cognitive performance beyond the variance explained by brain status and/or moderate the brain status-cognition relationship.

Personality can be described by the 5 factors (BIG5) openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Costa and McCrae, 1992). A recent meta-analysis on personality-cognition relationships, which included data from millions of individuals from 1976 independent samples, found that openness and some facets of conscientiousness and extraversion were positively associated with several cognitive abilities, while neuroticism was negatively associated with most cognitive abilities (Stanek and Ones, 2023). Agreeableness showed very weak associations with cognition (Stanek and Ones, 2023). Further, higher openness to experience, higher conscientiousness, lower extraversion, and lower neuroticism have been found to be related to less cognitive decline over time (Luchetti et al., 2016). Additionally, previous studies reported that individuals with AD have a distinctive personality profile compared to healthy controls, as expressed by higher scores on the neuroticism scale (D'Iorio et al., 2018; Wilson et al., 2006) and lower scores on the conscientiousness (Wilson et al., 2007), extraversion and openness scales (D'Iorio et al., 2018). However, the question whether personality is a factor underlying CR has been addressed in few studies so far (Colombo et al., 2020; Graham et al., 2021; Tautvydaitė et al., 2017; Terracciano et al., 2013). Studies on the relationship between personality and cognition provide an important basis for this question, but they do not take into account brain status. Thus, only the question of whether personality traits underlie CR can shed light on whether certain personality traits have a protective function. A protective function implies that certain personality traits can modify the effects of age- and disease-related brain pathology on cognition. Alternatively, in the absence of a modifying effect, whether personality traits have an effect on cognition that cannot be explained by brain status.

Colombo et al. (2020) investigated in 100 healthy participants aged 50–90 years the relationship between personality and CR and found that higher openness as well as some personality subfacets were related to higher CR. In this study, brain status was not considered as CR was assessed using the CoRe-T measurement, which consists of a self-report section on educational level, leisure activities, and occupation history, and two tasks assessing fluidity of thoughts.

In an autopsy study, Terracciano et al. (2013) investigated whether individuals with AD pathology who were asymptomatic during their lifetime differed from individuals diagnosed with AD in terms of personality. Personality was measured 1–30 years before death (mean (SD)=15 (7) years). They found that the asymptomatic individuals had higher conscientiousness scores and lower neuroticism scores than the individuals diagnosed with AD (Terracciano et al., 2013). This finding suggests that high conscientiousness and low neuroticism are related to high CR. Compared to the study by Colombo et al. (2020), this study has the advantage that they tested directly whether personality moderates the association between AD pathology and clinical diagnosis. However, in this study the outcome was a diagnosis of AD versus no diagnosis, which is a dichotomous rather than a continuous outcome. Using a dichotomous variable rather than a continuous outcome to classify how successfully someone has aged cognitively is an oversimplification, as individuals without a diagnosis of AD can vary widely in their cognitive performance and some individuals may also fall in the other category depending on the diagnostic criteria used.

Tautvydaitė et al. (2017) also focused on AD pathology and examined whether premorbid personality moderates the relationship between cerebrospinal fluid (CSF) markers of AD (amyloid beta1–42, phosphorylated tau, and total-tau) and global cognition or explains additional variance in cognition after correcting for these CSF AD markers. They found that premorbid conscientiousness, agreeableness, and neuroticism moderated the relationship between CSF biomarkers and cognition. Here, CSF biomarkers were almost unrelated to cognitive performance if the score for conscientiousness was high, the agreeableness score was low, or the neuroticism score was medium. Further, higher premorbid openness predicted better cognitive performance after correcting for CSF biomarkers. However, in addition to healthy controls (N=44), their study sample consisted of individuals with mild cognitive impairment (MCI) (N=57) and patients with mild AD (N=9). That is why participants' proxies were asked to retrospectively rate participants' personality traits at the time five years prior to onset of symptoms, which might be subject to memory bias.

Graham et al. (2021) also treated CR as a continuous variable by regressing cognitive performance onto various measures of brain pathology and then extracting the residual as a measure of CR. Like Terracciano et al. (2013), they found in their autopsy study that low neuroticism was cross-sectionally associated with higher CR and that high conscientiousness was longitudinally associated with higher CR. However, the study sample had a high mean age as participants were recruited either from retirement communities and senior housing facilities (Rush Memory and Aging Project) or from church (older nuns, priests, and brothers; Religious Orders Study). Personality is considered to be rather stable but changes in personality still occur across the adult lifespan (Wrzus and Roberts, 2017). Thus, it is unclear whether personality can also underly CR in younger age. Further, in this study a global cognition score was used, leaving the question open whether personality can account for the discrepancy between brain pathology and performance in all or only certain cognitive domains.

This project therefore uses both cross-sectional and longitudinal data to investigate whether personality represents a factor underlying CR in individuals aged 19–80 years who had at the time of recruitment no medical or psychiatric conditions (including MCI) that might affect cognitive performance. The inclusion of participants from a wide age range provides new insights into the question of whether personality is a factor underlying CR even at a young age. Further, screening for conditions that may affect cognition should prevent bias in personality assessment. In addition, we used a very rigorous, state-of-the-art methodology to assess whether personality traits underlie CR. To apply the CR-test proposed by the "Reserve and Resilience" collaboratory rigorously, we created brain status variables that explain the maximum amount of variance in cognitive performance. As outcome variables, we used four cognitive domain scores that have been measured on a continuous scale rather than a global dichotomous outcome. The use of four cognitive domain scores rather than a global cognition score has the added advantage of providing insight into whether personality traits can account for the discrepancy between brain pathology and performance in all or only certain cognitive domains.

Overall, this study contributes to a better understanding of which personality traits are favorable and associated with higher CR across the adult lifespan, which may also help to identify individuals at higher risk of developing dementia. Based on the findings from previous studies, we hypothesize that high openness (Colombo et al., 2020; Tautvydaitė et al., 2017), high conscientiousness (Graham et al., 2021; Tautvydaitė et al., 2017; Terracciano et al., 2013), and low neuroticism (Graham et al., 2021; Terracciano et al., 2013) underlie CR and are therefore associated with better cognitive performance and lower cognitive decline after accounting for brain status and/or moderate the brain status-cognition relationship.

2. Material and methods

2.1. Participants

We used baseline and follow-up data from the Reference Ability

Neural Network (RANN) and the Cognitive Reserve (CR) studies (Habeck et al., 2016; Stern, 2009; Stern et al., 2014). Both studies are ongoing at Columbia University Irving Medical Center and acquire the same basic subject information, neuropsychological examinations, and brain measures. Participants were carefully screened for psychiatric or medical conditions that could affect cognition (including MCI), as the presence of these conditions represented an exclusion criterion for both studies. Out of 591 participants, 449 (76%) participants had data in all personality dimensions available. For 441 (98.2%) of those participants, at least one cognitive domain score could be calculated. Cortical thickness and subcortical gray matter data were available for all but 42 (9.5%) of those 441 individuals, yielding a sample size of 399 individuals for the cross-sectional analyses. Longitudinal analyses were calculated in a smaller subset of this sample (N=273) as not all individuals have completed their first follow-up visit yet. The average follow-up period was 5 years (SD = 0.7 years).

2.2. Personality

Participants filled out the 50-item Big Five scale from the International Personality Item Pool (IPIP), which measures the five personality dimensions openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (reversed emotional stability, so higher values indicate higher neuroticism and lower emotional stability) (Goldberg, 1999). In this inventory, participants are asked to indicate on a 5-point scale ranging from "strongly agree" to "strongly disagree" the extent to which each statement applies to them.

2.3. Cognition

Performance was assessed in four cognitive domains: perceptual speed, episodic memory, fluid reasoning, and vocabulary. During both the baseline and the follow-up visit, the neuropsychological examination included three cognitive tasks per domain. Participants in the RANN study additionally performed three computerized tasks per cognitive domain during the MRI examination (Stern et al., 2014). The assessment of perceptual speed encompassed the WAIS-III Digit-symbol task, the Stroop Color and Word Test (Golden, 1975), and the trail-making test A. In the MRI scanner, participants performed the perceptual speed tasks Digit Symbol, Letter Comparison, and Pattern Comparison (Salthouse and Babcock, 1991). Episodic memory was measured out of scanner with three measures from the Selective Reminding Test (SRT): long-term storage, continuous long-term retrieval, and number of words remembered in the last retrieval (Buschke and Fuld, 1974). In the scanner, episodic memory was assessed with the Logical Memory, Word Order Recognition, and Paired Associates tasks. Fluid reasoning was measured with the Matrix Reasoning and the Letter-number Sequencing task of the Wechsler Adult Intelligence Scale III (WAIS-III) as well as the Block Design test in the neuropsychological examination. In addition, the three in-scanner tasks Paper Folding, Matrix Reasoning and Letter Sets (Ekstrom et al., 1976) were administered to assess fluid reasoning. Vocabulary was assessed outside the MRI scanner with the WAIS-III Vocabular test, the Wechsler Test of Adult Reading (Wechsler, 2001), and the American National Adult Reading Test (Grober and Sliwinski, 1991), and within the scanner with the Synonyms (Salthouse, 1993), Antonyms (Salthouse, 1993), and Picture Naming tasks (Salthouse, 1998).

Previously the cognitive tasks had been assigned to the four cognitive domains using factor analysis and we decided to keep the same factor structure. We then used the lavaan package in R (Rosseel, 2012) to apply confirmatory factory analysis to extract combined domain scores. We restricted the factor loadings to be the same for both baseline and follow-up assessment to ensure measurement invariance. Domain scores were only created if participants had at least two cognitive test scores per domain available. To handle missing values, we used full information maximum likelihood. When we evaluated how well confirmatory factor analysis performed, we found that the chi-square test as an absolute measure of model fit was significant (chi-square = 835.8; degrees of freedom = 246; $p < 0.001$), indicating that the confirmatory model does not optimally fit to the data (Alavi et al., 2020). However, the chi-square index is strongly affected by sample size and by the number of variables in the model (Alavi et al., 2020). Thus, we also checked model performance using two incremental fit indices and one residuals-based fit index. Overall, these indices indicated a fair but improvable model fit. "Bollen's incremental fit index" was 0.90 and the "Tucker-Lewis index" was 0.88, and the lenient recommended cut-off for both indices is >0.90, whereas the strict recommended cut-off is >0.95 (Hu and Bentler, 1999). The residual-based fit index "root mean square error of approximation" was 0.07 (95% confidence interval (CI): 0.07–0.08), with lower values indicating a better model fit and 0.08 being classified as "fair model fit" according to Marcoulides and Yuan (2017). When we subsequently checked the factor structure, we observed small factor loadings for the Logical Memory (estimate = 0.29), the Paired Associates (estimate = 0.42), and the Word Order Recognition tasks (estimate = 0.46) on the episodic memory score. The other 21 factor loadings ranged between 0.54 and 0.98. One reason for these small loadings on the episodic memory score may be that the three other memory outcomes are from the same task, the Selective Reminding task, and are highly correlated with each other (Pearson's product-moment correlations between 0.78 and 0.89). Subsequent exploratory factor analysis confirmed that the three memory tasks loaded slightly higher on the fluid reasoning domain score than on the episodic memory domain score (Logical memory task: 0.27 versus 0.15, Paired Associates task: 0.52 versus 0.25, Worder Order Recognition task: 0.51 versus 0.27). However, from a theoretical perspective these tasks represent memory task even if fluid intelligence may also influence overall task performance (Spaan, 2016). In addition, we wanted to keep all three highly correlated memory outcomes for the episodic memory domain score and be consistent with our previous work. Thus, we decided not to optimize the factor structure.

2.4. Imaging data

The 12 in-scanner cognitive tasks in the RANN study were acquired during a two-hour magnetic resonance imaging (MRI) session in Tesla Philips Achieva Magnet scanners with a standard quadrature head coil. T1-weighted magnetization-prepared rapid gradient echo (MPRAGE) scans were acquired for each subject using the following parameters: TE/TR of 3/6.5 ms, flip angle of 8°, in-plane resolution of 256×256, field of view of 25.4×25.4 cm, and 165–180 slices in axial direction with slice-thickness/gap of 1/0 mm. Each subject's structural T1 scan was reconstructed, and the cortex was parceled into 68 regions of interest

Table 1
Brain status-cognition associations.

Cognitive outcome	β (95-% CI) for cognitive domain-specific brain status variable	R^2 (%)
Perceptual speed	0.635 (0.427, 0.843)	43.1
Episodic memory	0.727 (0.407, 1.047)	26.5
Fluid reasoning	0.977 (0.772, 1.183)	32.9
Vocabulary	1.491 (1.184, 1.798)	24.4

Multivariable regression analyses were performed to assess how well the created cognitive domain-specific brain status variables capture interindividual differences in cognitive performance. Regression model: cognitive domain score ~ b_0 + cognitive domain-specific brain status variable*b_1 + age*b_2 + sex*b_3 + residual error. Regression coefficients for cognitive domain-specific brain status variables indicate the change in the corresponding cognitive domain score per one standard deviation increase in the brain status variable. All p values <0.001. R^2 refers to the variance explained in the cognitive domain scores by the corresponding brain status variable.

Table 2
Sample characteristics for the cross-sectional analyses.

Characteristic	Participants	Missing values [%]
Sex, N_{female} (%)	220 (55.1)	0
Age, median [IQR] in years	59.0 [39.0, 65.5]	0
Race, N (%)		0
White	254 (63.7)	
Asian	15 (3.8)	
Black/African American	97 (24.3)	
Native Hawaiian or other Pacific Islander	5 (1.3)	
Black/African American + White	1 (0.3)	
Asian + White	1 (0.3)	
Other	26 (6.5)	
Education, M (SD) in years	15.9 (2.3)	0.3
Openness, M (SD), scale from 1 to 5	3.8 (0.6)	0
Conscientiousness, M (SD), scale from 1 to 5	4.0 (0.6)	0
Extraversion, M (SD), scale from 1 to 5	3.3 (0.7)	0
Agreeableness, median [IQR], scale from 1 to 5	4.2 [3.8, 4.6]	0
Neuroticism, median [IQR], scale from 1 to 5	2.4 [1.8, 2.9]	0
Mean cortical thickness, M (SD) in mm	2.5 (0.1)	0
Perceptual speed		
WAIS-III Digit-symbol task [n correctly assigned symbols to digits in 90 s, max=93 symbols], M (SD)	53.5 (14.2)	0.8
Stroop Color and Word Test [number of colors correctly said in 45 s], M (SD)	72.1 (13.8)	1.5
Trail-making test A [completion time in s], median [IQR]	25.0 [20.7, 33.0]	1.0
Digit Symbol [median RT in s across correct trials], M (SD)	1.5 (0.2)	28.8
Letter Comparison [median RT in s across correct trials], M (SD)	1.6 (0.2)	28.8
Pattern Comparison [median RT in s across correct trials], M (SD	1.5 (0.3)	28.3
Episodic memory		
Selective Reminding Test (SRT): long-term storage [n words, max= 72], M (SD)	45.1 (15.0)	1.3
SRT: continuous long-term retrieval [n words, max= 72], M (SD)	34.9 (17.4)	1.3
SRT: last retrieval [n words recalled, max=12], median [IQR]	10.0 [9.0, 12.0]	1.3
Logical Memory [% on time correct], median [IQR]	77.1 [68.4, 85.0]	25.3
Word Order Recognition [% on time correct], M (SD)	49.3 (22.4)	25.1
Paired Associates tasks [% on time correct], median [IQR]	70.0 [50.0, 90.9]	25.8
Fluid reasoning		
WAIS-III Matrix Reasoning [% on time correct], M (SD)	65.2 (19.7)	1.5
WAIS-III Letter-number Sequencing task [% on time correct], M (SD)	55.1 (15.2)	1.3
Block Design test [% on time correct], M (SD)	59.2 (19.5)	2.3
Paper Folding [% on time correct], median [IQR]	52.9 [31.2, 75.0]	24.8
Matrix Reasoning [% on time correct], median [IQR]	45.8 [22.2, 66.7]	24.3
Letter Sets [% on time correct], median [IQR]	76.9 [58.3, 87.5]	25.1
Vocabulary		
WAIS-III Vocabular test [% correct], median [IQR]	58.0 [50.0, 63.0]	4.5
Wechsler Test of Adult Reading [% correct], median [IQR]	42.0 [34.0, 47.0]	2.0
American National Adult Reading Test [% errors], median [IQR]	10.0 [5.0, 18.0]	1.3
Synonyms [% correct], M (SD)	64.2 (22.1)	29.6
Antonyms [% correct], M (SD)	58.4 (21.3)	28.6
Picture Naming task [% correct], M (SD)	54.2 (17.7)	30.3

Note. N=399 participants. All cognitive measures refer to the baseline performance. We indicated the mean and interquartile range for skewed variables and the mean and SD for almost normally distributed variables. N = number, IQR = interquartile range, M = mean, SD = standard deviation, RT = reaction time, WAIS-III = Wechsler Adult Intelligence Scale III.

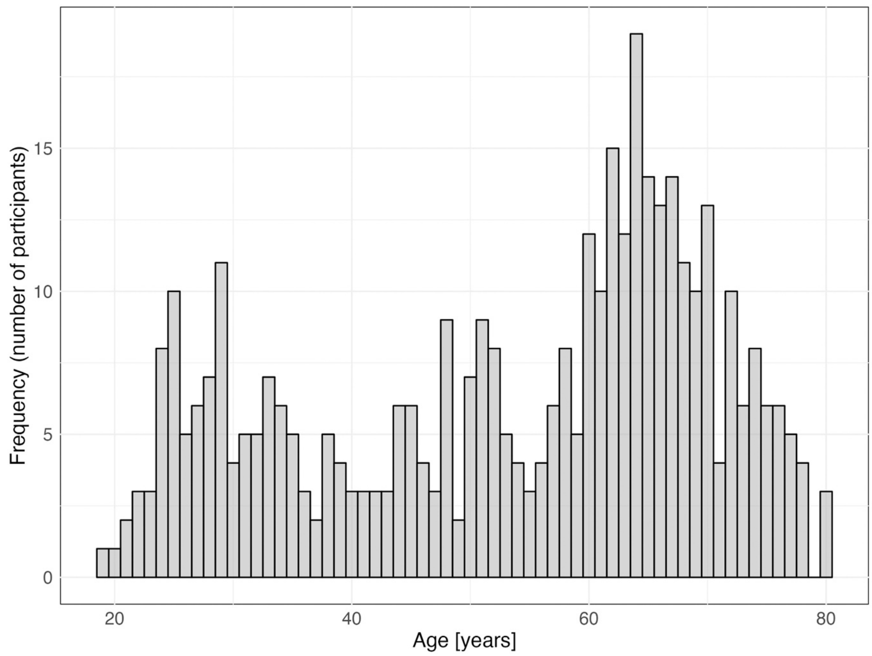

Fig. 1. Age Distribution. This histogram shows the age distribution in the sample. Each bin represents 1 year of age.

(ROIs), that are specified in the Desikan-Killiany cortical atlas, using the FreeSurfer 5.1 analysis package. We visually inspected how well FreeSurfer had performed the cortical parcellation by inspecting slice by slice each subject's white and gray matter boundaries and the gray matter and cerebral spinal fluid (CSF) boundaries. Manual control points were added in case of any visible discrepancy and the reconstruction was repeated until the results were satisfactory. We then calculated cortical thickness as the distance between the gray/white matter surface and the gray/CSF surface at each point across the cortical mesh and obtained one mean cortical thickness value for each of the 68 ROIs. Each subject's scans were reviewed by a neuroradiologist. Significant findings were conveyed to the subject's primary care physician and led to the removal of the scans from the sample.

To obtain the segmentation for the subcortical gray matter structures brain stem, hippocampus, amygdala, nucleus accumbens, nucleus caudatus, thalamus, putamen, and pallidum, we used the automatically segmented brain volume atlas (ASEG) (Fischl, 2012). To check the subcortical parcellations, we overlaid the subcortical structure borders on the T1 image using Freeview visualization tools and manually corrected any discrepancies. Afterwards we divided each subcortical structure by the estimated total intracranial volume to correct for the effect of head size (Buckner et al., 2004).

We then used the mean cortical thickness values for each of the 68 ROIs, all aforementioned subcortical gray matter measures, and the ventricle sizes and regressed them all together on each of our four cognitive domain scores separately using generalized linear models with elastic net regularization (glmnet package in R; (Friedman et al., 2010)). Elastic net regularization is a linear regression technique that was developed for variable selection (Zou and Hastie, 2005). It combines the advantages of ridge and lasso regularization. Its main advantage is that it deals well with highly correlated predictor variables, as correlated variables can be selected together, rather than arbitrarily selecting one of these correlated variables. At the same time, variables that have no predictive value for the outcome of interest are removed. This approach leads to a parsimonious, stable, and easily interpretable solution (Zou and Hastie, 2005). We applied elastic net regularization to select those brain variables that best predict cognition and chose for each cognitive domain score the model with the lowest mean cross-validated error (20 folds). Next, we used the selected model and forward predicted cognitive performance and extracted the predicted values as cognitive domain-specific measures of brain status. To test how well the construction of our cognitive domain-specific brain status variables worked, we associated them separately with the corresponding domain score using linear regression models with the brain status variable as predictor, the cognitive domain score as outcome variable, and age and sex as covariates. The regression results can be found in Table 1. We also tested with a likelihood ratio test whether the brain status-cognition relationships significantly varied with age and found that they did not and therefore did not create age group-specific brain status variables.

2.5. Statistical analyses

We performed all statistical analyses in R Studio (version 2022.12.0, R-base version 4.2.2) (RStudio, 2019). We carefully subjected the five personality factors to the rigorous CR-test established by the "Reserve and Resilience" collaboratory (Stern et al., 2020). We therefore tested whether personality traits explain variance in cognitive performance after controlling for brain status and whether personality traits moderate brain-cognition relationships.

For testing for cross-sectional associations, we separately performed a multiple regression model for each cognitive domain score and personality trait pair with the cognitive score as a dependent variable, one personality trait as a predictor, and the cognitive domain-specific brain status variable either as an additive covariate or by adding a personality trait*brain status interaction term to the model. In each of the 20 models, we included age and sex as additional covariates. We did not include education as a covariate in our main models because education represents a CR proxy (Opdebeeck et al., 2016), but we calculated a sensitivity analysis in which education was included as a covariate in all models.

Further, we assessed whether the cross-sectional associations varied with age or sex by including either an age*personality trait or sex*personality trait interaction term in each model and testing with a likelihood ratio test whether the model including the interaction terms was superior to the model without interaction term.

For testing for longitudinal associations, we used the lmerTest package in R (Kuznetsova et al., 2017) and performed a linear mixed model per cognitive domain score and personality trait. In each model,

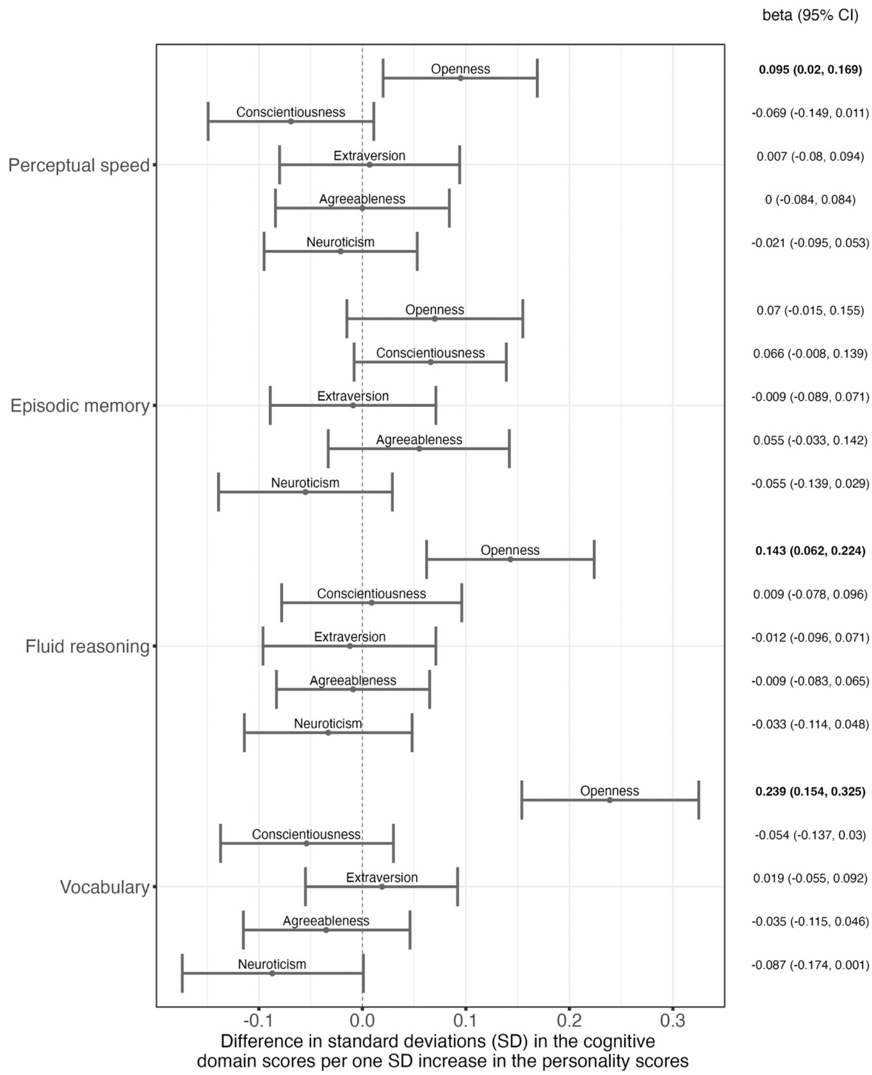

Fig. 2. Personality and Cognitive Domain Scores. This forest plot shows how much performance in different cognitive domains (see y-axis) differs per one SD increase in each of the BIG 5 personality dimensions. Associations were adjusted for the cognitive domain-specific brain status variable, age, and sex. Each dot represents the standardized estimate for the association, while the lines around it show the 95%-confidence interval belonging to this estimate. The corresponding values are shown in the column on the right side with significant associations printed in bold. Notably, all dots on the right side of the dotted vertical line indicate that higher values in the respective personality dimension are associated with better cognitive performance in the specific domain, while all dots on the left side indicate that higher values in the respective personality dimension were associated with lower cognitive performance.

the cognitive domain score represented the dependent variable, while the personality trait represented the predictor and was included as both individual term and personality*time (years between baseline and follow-up) interaction term. We adjusted each model for age at baseline, time, age at baseline*time interactions, sex, brain status, and brain status*time interactions. In all longitudinal models, we additionally included a random intercept to account for within-subject correlations due to the repeated measurement of cognitive performance. Significant personality*time effects would indicate that personality is associated with cognitive changes after accounting for brain structure, age at baseline, and sex. We then used the models described before but additionally added a three-way interaction term for personality*time*brain status to test whether personality moderates the relationship between brain status and cognitive change.

To exclude the possibility that our longitudinal results are influenced by those individuals who may have developed MCI or AD at follow-up assessment, we calculated a sensitivity analysis controlling for cognitive status (cognitively normal versus potentially cognitively impaired). To identify cognitively impaired individuals due to MCI or AD, we selected those individuals whose normative scores in the neuropsychological tests at follow-up assessment were 1.5–2 SD below the mean. Their cognitive test scores, informant information, and medical information were then reviewed by a neuropsychologist and a neurologist, and a research diagnosis was made. Our criteria resulted in the identification of 5 individuals with MCI and 3 individuals with probable AD.

We corrected all our analyses for multiple testing of the 20 hypotheses that we had separately for cross-sectional and for longitudinal associations between personality and CR (4 cognitive outcomes times 5 personality predictors) applying the false discovery rate (FDR) correction. Multiple-testing corrected p-values below 0.05 were considered statistically significant. We corrected for multiple testing because we were not only interested in whether certain personality traits are beneficial in counteracting the negative effects of age-related brain pathology on performance in specific cognitive domains, but also wanted to generalize from single cognitive domains to cognition in general. So, we were both interested in individual testing and in disjunction testing (Rubin, 2021).

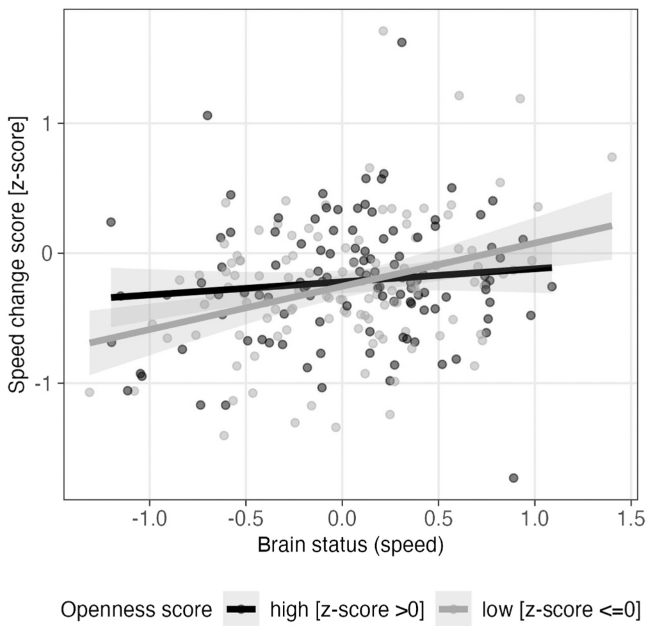

Fig. 3. Personality x Brain Structure Interaction on Cognitive Change. The scatterplot depicts on the x-axis the brain status variable that has been derived specifically for perceptual speed. The y-axis depicts change in perceptual speed from baseline to follow-up assessment, which was calculated by subtracting the perceptual speed score at baseline assessment from the perceptual speed score at follow-up assessment. Thus, negative values indicate a decline in performance and positive values indicate an increase in performance from baseline to follow-up. Each data point represents one participant. The black dots represent participants with a high openness (z-standardized score above 0) and the light-gray dots represent participants with low openness (z-standardized score below or equal to 0). For both groups of participants (high versus low expression of openness), there exists one superimposed function for the relationship between the brain status and cognitive change. The gray area around the group-specific regression lines indicates the 95% confidence interval in each case.

3. Results

3.1. Study sample

Our cross-sectional sample consisted of 399 individuals aged 19–80 years, of whom 55.1% were female, according to the sex designated at birth (Table 2). The average educational level was 15.9 years (SD=2.3 years) (Table 2). This table also provides descriptive characteristics of cognitive performance in the 24 cognitive tasks at baseline. Fig. 1 shows the age distribution in our sample.

3.2. Cross-sectional associations between personality and CR

Cross-sectionally, higher openness was associated with higher fluid reasoning (standardized regression coefficient (ß)=0.143; 95% CI: 0.062–0.224; p=0.001; p_{FDR}=0.010) and better vocabulary (ß=0.239; 95% CI: 0.154–0.325; p<0.001; p_{FDR}<0.001) after controlling for brain status (Fig. 2). Including education as an additional covariate in the models reduced the association between openness and fluid reasoning (ß=0.083; 95% CI: 0.004–0.162; p=0.040; p_{FDR}=0.245) and the association between openness and vocabulary (ß=0.158; 95% CI: 0.078–0.239; p<0.001; p_{FDR}<0.001), with the former being no longer significant after correction for multiple testing. Higher openness was also associated with higher perceptual speed (ß=0.095; 95% CI: 0.020–0.169; p=0.013; p_{FDR}=0.087) before correcting for multiple testing and before controlling for education. None of the other personality traits were associated with any cognitive outcome after correcting for brain structure (Fig. 2). When we assessed whether the BIG5 personality traits moderate the brain structure cognition relationship, we found no moderation effects.

The results from the likelihood ratio tests indicated that the models with age*personality trait or sex*personality trait interaction terms were not superior to the basic models (all p_{FDR} > 0.330). This finding indicates that the associations between personality and cognition did not significantly vary with age or sex.

3.3. Longitudinal associations between personality and CR

Before FDR-correction, we found that higher conscientiousness was associated with faster cognitive decline in perceptual speed (ß for conscientiousness*time=−0.012; 95% CI: −0.023 to −0.001; p=0.038; p_{FDR}=0.760) after controlling for brain status. When we included personality trait*brain status interaction terms, openness moderated the relationship between brain status and decline in processing speed (ß for openness*time*brain status=−0.033; 95% CI: −0.053 to −0.013; p=0.001; p_{FDR}=0.020). Here, in those individuals with high openness, brain status was almost unrelated to decline in perceptual speed (Fig. 3). However, in individuals with low openness, the relationship between brain status and change in perceptual speed was steeper, with individuals with low brain status showing a stronger decline in perceptual speed (Fig. 3). The longitudinal results were unchanged when education was added to the models as covariate. Excluding those individuals who developed MCI or AD at follow-up also did not substantially affect the results.

4. Discussion

The relationship between personality and cognition has been studied extensively (Stanek and Ones, 2023), but the extent to which personality traits underlie CR requires further investigation. Our aim was to investigate whether the BIG5 personality traits underlie CR across the adult lifespan and are accordingly associated with better cognitive performance and less cognitive decline in the presence of age-related brain changes. To do so, we applied a rigorous CR test that included four cognitive domain-specific brain status variables and cognitive domain scores. We were able to confirm the finding of previous studies that high openness benefits CR (Colombo et al., 2020; Tautvydaitė et al., 2017), but not previous reports that high conscientiousness (Graham et al., 2021; Tautvydaitė et al., 2017; Terracciano et al., 2013) and low neuroticism (Graham et al., 2021; Terracciano et al., 2013) are associated with high CR.

Cross-sectionally, higher openness was associated with higher vocabulary, higher fluid reasoning, and better perceptual speed after controlling for brain structure, with the latter two associations being less robust to FDR-correction. Longitudinally, our study findings suggest that the relationship between brain status and change in perceptual speed differs depending on an individual’s level of openness. Specifically, for individuals with high openness, brain status did not serve as a predictor of change in perceptual speed. However, for individuals with low openness, a lower baseline brain status was associated with a more pronounced decline in perceptual speed from baseline to follow-up assessment. One potential explanation for why openness showed longitudinal associations only with perceptual speed but with no other cognitive domain might be that the mean cognitive change from baseline to follow-up was greatest in this domain (speed: −0.254 SD, memory: −0.071 SD, reasoning: −0.144 SD, vocabulary: 0.187). Thus, the statistical power to detect the interaction effect on perceptual speed was potentially larger. Taken together, our cross-sectional and longitudinal findings suggest that high openness can buffer the negative effects of brain atrophy on performance and decline in certain cognitive dimensions. Since most of the associations survived correction for multiple testing, our findings indicate that high openness helps to counteract the negative effects of age-related brain pathology on cognition in general. Thus, openness seems to be an important factor underlying CR, which is consistent with the findings from Colombo et al. (2020) and Tautvydaitė et al. (2017).

Higher conscientiousness was associated with a stronger decline in perceptual speed. However, this effect did not remain significant after correction for multiple testing, which suggests that this association was not very robust and might be a false positive finding. The studies by Terracciano et al. (2013), Tautvydaitė et al. (2017), and Graham et al. (2021) all reported that higher conscientiousness was related to higher CR. It could be that our finding goes in the opposite direction because we used perceptual speed as outcome variable rather than diagnosis of AD (Terracciano et al., 2013) or global cognition (Graham et al., 2021; Tautvydaitė et al., 2017). However, high conscientiousness also seems to be beneficial for speed task, as shown by a recent large-scale meta--analysis on personality-cognition relationships (Stanek and Ones, 2023). Thus, our correction for multiple testing was very likely not too stringent, and our result represented a false positive finding.

Extraversion, agreeableness, and neuroticism were all not associated with cognitive performance or cognitive decline after correcting for brain status and did not moderate the brain status-cognition relationships. Thus, our findings indicate that extraversion, agreeableness, and neuroticism do not underlie CR. In line with this observation, extraversion has not been found to underlie CR in previous studies (Colombo et al., 2020; Graham et al., 2021; Terracciano et al., 2013). Concerning agreeableness, it has been found that this personality trait has the weakest associations with cognitive performance (Stanek and Ones, 2023). Tautvydaitė et al. (2017), who focused specifically on AD markers in CSF and analysed data from a sample that also contained individuals with MCI and AD, found that low agreeableness relates to higher CR. However, it remains unclear how generalizable this finding is to a healthy population. Similarly, neuroticism has been found to be negatively related to CR in the cross-sectional analyses by Terracciano et al. (2013) and Graham et al. (2021), even if this finding could not be confirmed in previous longitudinal analyses (Colombo et al., 2020; Graham et al., 2021; Terracciano et al., 2013). The lack of longitudinal evidence and the fact that all three studies that found this association included either only very old individuals or individuals with an AD diagnosis and that this association was not found in a previous study that included only healthy individuals with a wider age range (Colombo et al., 2020), leaves open the possibility that this effect is driven by those individuals who are about to develop or already have AD. These individuals are not (anymore) able to withstand high brain pathology and therefore have a low CR. At the same time, they may develop high neuroticism as result of the self-perception that their own cognitive abilities are declining. These individuals would then have both low CR and high neuroticism without high neuroticism necessarily being the cause of low CR.

One limitation of our study is that we administered only the 50-item Big Five scale from the IPIP to our participants and, therefore, had too little items to study sub facets of personality. An extended personality assessment would be interesting as different personality sub facets have been found to relate differently to cognitive performance (Stanek and Ones, 2023) and CR (Colombo et al., 2020). Future studies should also consider using a brain-based measure of CR to test which personality traits are related to CR, such as a task-invariant network of CR (Stern et al., 2018), as some personality-cognition associations depend on the cognitive domain under study (Stanek and Ones, 2023).

5. Conclusions

To conclude, our findings imply that high openness benefits CR and that individuals with low openness are therefore at great risk of developing cognitive decline in the presence of brain pathologies. Interventions could therefore be targeted specifically at these individuals, and a high level of openness should be encouraged across the adult lifespan.

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CRediT authorship contribution statement

Annabell Coors: Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Seonjoo Lee:** Writing – review & editing, Methodology. **Christian Habeck:** Writing – review & editing, Validation, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Yaakov Stern:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

Declaration of Competing Interest

None.

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Verification

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