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Linking negative affect, personality and social conditions to structural brain development during the transition from late adolescent to young adulthood

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ABSTRACT

Background: The transition from late adolescence to early adulthood is a period that experiences a surge of life changes and brain reorganization caused by internal and external factors, including negative affect, personality, and social conditions.

Methods: Non-imaging phenotype and structural brain variables were available on 497 healthy participants (279 females and 218 males) between 17 and 22 years old. We used sparse canonical correlation analysis (sCCA) on the high-dimensional and longitudinal data to extract modes with maximum covariation between structural brain changes and negative affect, personality, and social conditions.

Results: Separate sCCAs for cortical volume, cortical thickness, cortical surface area and subcortical volume confirmed that each imaging phenotype was correlated with non-imaging features (sCCA $|r|$ range: 0.21–0.38, all $p_{FDR} < 0.01$). Bilateral superior frontal, left caudal anterior cingulate and bilateral caudate had the highest canonical cross-loadings ($|\rho| = 0.15$–0.32). In longitudinal data analysis, scan-interval, negative affect, and enthusiasm had the highest association with structural brain changes ($|\rho| = 0.07$–0.38); at baseline, intellect and politeness were associated with individual variability in the structural brain ($|\rho| = 0.10$–0.25).

Limitations: The present study used non-imaging variables only at baseline, making it impossible to explore the relationship between changing behavior and structural brain development.

Conclusions: Individual structural brain changes are associated with multiple factors. In addition to time-dependent variables, we find that negative affect, enthusiasm and social support play a numerically weak but significant role in structural brain development during the transition from late adolescence to young adulthood.

1. Introduction

The transition from late adolescence to early adulthood is marked by a host of significant life changes (Arnett, 2000) and morphometric changes in the brain (Spear, 2000). This is a critical period of life when the student population is leaving home for college, entering the workforce, or starting a family. In Wood's view, the separation of individuals' transition from late adolescence to early adulthood as a key stage in their lives has proven to be a key factor in explaining the social, cognitive, and psychological development occurring during this period (The Oxford Handbook of Emerging Adulthood, 2015). Adolescence is not the end of brain development and changes in the structural brain continue well into the third decade of life (Spear, 2000; Taber-Thomas and Perez-Edgar, 2015). In previous cross-sectional studies, it has been reported that there is a link between inter-individual differences in the structural brain and physiological, behavioral, and environmental factors among adolescents and young adults (e.g., Spear, 2000). The phenomenon of individual variation in structural brain development has been particularly prominent in the transition from adolescence to early adulthood (Mills et al., 2021). Meanwhile, this period of life is characterized by the high prevalence of internalizing and externalizing disorders (Kessler et al., 2005), as well as unique patterns of vulnerability to psychological dysfunction. As a result, it is particularly pertinent to psychopathology to gain a deeper understanding of the influence of social environment, personality, and affective state on structural brain development during the transition from late adolescence to young adulthood.

Young people's lives undergo drastic changes during the transition from late adolescence to young adulthood, including leaving their

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parental homes and entering university. It has been observed that young people have improved their emotional stability, developed a strong sense of identity, and have even been in important relationships with others during this period (Williams et al., 2006); however, they are likely to encounter increasingly stressful situations as a result of exposure to a wide range of new social contexts at the same time. There is a possibility that negative affect will increase suddenly in the first year of college, but dynamic and static social conditions and personality traits will also play an influential role in the changing lives of college students, which are key factors associated with structural brain development. However, the brain development trajectory varies according to different structural components and Tamnes et al. have found that there is a strong positive correlation between cortical volume change and thickness change, but not between area change in most brain regions (Tamnes et al., 2017). Considering that this variation may be derived from external or internal factors, it is necessary to examine the relationship between multiple behavioral variables and developmental changes in distinct structural brain measures at the same time.

A number of cross-sectional and longitudinal studies have examined the changes in brain structure associated with aging across a wide age range (from children to young adults). The cortical volume and thickness of higher-order association cortical regions decrease rapidly throughout adolescence, leveling off by young adulthood, and cortical surface area increases steadily during early adolescence and gradually declines in mid-adolescence to young adulthood in higher-order association cortical regions (Ducharme et al., 2015; Wierenga et al., 2014). Additionally, it has been observed that structural brain development varies significantly from individual to individual during the transition from adolescence to early adulthood (Mills et al., 2021). A dynamic interplay between biological and social factors has influenced the development of structural brains. Links between genetics and biological sex and structural brain development have been reported in several studies (Brouwer et al., 2021; Gilbert et al., 2005; Modabbernia et al., 2021a). It has previously been found that negative emotions are associated with more cortical changes in the brain (Jensen et al., 2015). Researchers have demonstrated that parent socioeconomic status and social support from loved ones can significantly alleviate psychological stress in individuals. From a neurobiological perspective, parental socioeconomic status and social support are positively associated with increased gray matter volume (Hostinar and Gunnar, 2015; Kanai et al., 2012; Luby et al., 2013; Noble et al., 2015). The Big Five personality traits were found to correlate with brain volume in adults (18–40 years old) and the correlation between personality traits and brain structure was found during adolescence and into late adulthood (Delaparte et al., 2019; DeYoung et al., 2010; Kaasinen et al., 2005; Schilling et al., 2013). Throughout an individual's lifetime, this long process of structural brain development can facilitate effective adaptation to environmental changes.

There are numerous factors contributing to the development of the structural brain, which is why univariate statistical approaches may only account for a small proportion of the variance. In this case, the multivariate method can be helpful in quantifying the development of brain structure and its relationship to phenotype. It is possible that the same brain regions are associated with different environmental variables and behavioral characteristics, and that different brain regions are associated with similar psychological characteristics. The use of multivariate analysis can take into account potential joint effects or covariates within both brain variables and behavioral variables (Genon et al., 2022). Canonical Correlation Analysis (CCA) is used to identify the sources of common variation in two sets of high-dimensional variables (Wang et al., 2020). It should be noted, however, that traditional CCA models are prone to overfitting and are not well suited to dealing with intercorrelated variables. By penalizing some variables by setting their contributions to the overall model to zero, sparse canonical correlation analysis (sCCA) controls overfitting and penalizes the complexity of a learning model (Modabbernia et al., 2021b).

In the present study, we employed a longitudinal dataset gathered at a single site to investigate the relationship between the development of cortical volume, cortical thickness, and cortical surface area and negative affect, personality, and social conditions during the transition from late adolescence to young adulthood. There have been numerous studies conducted using the massive univariate general linear model to examine relationships between structural brain and behavioral variables in small samples of healthy individuals. The reliability of these results of brain-wide association studies has been challenged (Marek et al., 2022). Furthermore, the relationship between behavioral variables and the structural brain is likely to be multivariate in nature. Therefore, by sCCA (Witten et al., 2009), the current study explored primarily the relationship between the structural brains of participants who were transitioning into adulthood and many non-imaging factors, including their negative affect, personality, and social conditions, and explored how these variables affect their subsequent structural brain development using data from Southwest University Longitudinal Imaging Multimodal (SLIM) (SLIM) (Liu et al., 2017).

2. Material and methods

2.1. Participants

We used the Southwest University Longitudinal Imaging Multimodal dataset (here after referred to as SLIM; Liu et al., 2017), comprising of a total of 580 healthy individuals at Southwest University in China scanned between the ages of 17 and 27 (Detailed age distribution of participants is shown in Supplementary Fig. S1). As shown in Supplementary Figs. S1 and S2, most participants were initially scanned in the first year after entering university. This study has been approved by the IRB at Southwest University. We obtained appropriate ethics committee approval for the research reported, and all subjects gave written informed consent to our study. This neuroimaging data has been shared through the International Data-sharing Initiative (INDI; http://fcon_1000.projects.nitrc.org/). First, we selected participants ($n = 522$) with both imaging and behavioral data, and then removed 6 subjects whose imaging phenotype exceeded 3 standard deviations and 19 subjects whose ages were over 22 years old at baseline (baseline sample: $n = 497$, 279 females and 218 males), as well as both baseline and follow-up assessments (developmental change sample: $n = 503$, 267 females and 236 males). For details about participants see Liu et al., 2017.

2.2. Non-imaging variables

We evaluated variables related to participants' demographic characteristics (age, scan interval, and sex), negative affect, personality, and social conditions (socioeconomic status and social support). Detailed variables and measurement tools are presented in Table S1.

Missing values for non-imaging features were imputed using MetImp online (http://metabolomics.cc.hawaii.edu./software/MetImp). We set the imputing threshold to 0.6 because up to 38 % of the total participants did not complete a specific assessment.

2.3. Imaging acquisition and processing

All participants underwent structural (T1w) scanning. The T1w images were preprocessed on surface-based space using a longitudinal stream in FreeSurfer software (v 6.0.0) (http://surfer.nmr.mgh.harvard.edu/). Briefly, the entire process includes skull stripping, segmentation of brain tissue, separation of hemispheres and subcortical structures, and construction of the gray/white interfaces and the pial surfaces. Later the cortical surfaces were divided into 68 regions in the Desikan-Killiany atlas (Detailed ROIs of Desikan-Killiany atlas considered in the study are shown in Table S2). Participants were excluded before statistical analysis if they had images with poor scan quality.

For each region, we estimated regional mean cortical thickness, surface area, cortical volume, and subcortical volume by using the command *mri_surf2surf* which maps the fsaverage standard space template into individual space, and then we used the command *mris_anatomical_stats* to calculate regional mean values in individual space.

2.4. Statistical analysis

Sparse canonical correlation analyses (sCCA, Witten et al., 2009) were used to identify covariations between structural brain development and non-imaging variables. CCA aims to find linear combinations of variables that are maximally correlated with each other from two multivariate sets of variables. By using a sparsity parameter, sCCA implements regularization by penalizing some variables by setting their contribution to the overall model to 0, thus reducing the overfitting that is a disadvantage of CCA. sCCA generates pairs of variates (i.e. the linear combinations of variables from each dataset), weights (i.e. magnitude of the contribution of the variable to the variate from the same dataset), and canonical cross-loading (i.e. coefficient of the correlation of the variable with the variate of the opposite dataset) (Modabbernia et al., 2021b).

The present study used the sgcca.wrapper function from the mixOmics package to implement sCCA in R. All variables were standardized to a mean of 0 and a standard deviation of 1 before being entered into the sCCA models (Witten et al., 2009). We then followed standard procedures to identify the optimal sparsity parameters for each sCCA model as previous study (Modabbernia et al., 2021b). For each analysis, we computed the sparse parameters by running the sCCA with a range of candidate values (from $1/\sqrt{p}$ to 1, at 10 increments, where p is the number of features in that view of the data) for each imaging and non-imaging dataset, and then fitted the resulting models. We selected the optimal sparse criteria combination based on the parameters that corresponded to the values of the model that maximized the sCCA correlation value. We then computed the optimal sCCA model and determined its significance based on exact *P* values calculated from 1000 random permutations. The P value was defined as the number of permutations that resulted in an equal or higher correlation than the original data divided by the total number of permutations. Because we implemented multiple sCCA models throughout the manuscript, the significance of each mode was further adjusted using false discovery correction (FDR). In addition, statistically significant modes were tested for reliability and reproducibility (described below) and only models that survived these analyses are reported. For significant sCCA mode, we reported weight and loading of the contributing variables if these are at least of small effect ($>|0.1|$) according to current standards.

2.5. Reliability, reproducibility, and supplemental analyses

We undertook the following analyses to determine the robustness of our results following the previous study (Modabbernia et al., 2021b): (i) each sCCA was evaluated for its stability with regard to the sample size and composition. In order to achieve this, we repeated each sCCA in 100 randomly generated subsets containing 10–150 % of the original data in 10 % increments (1500 subsamples in total); (ii) following the previous study (Moser et al., 2018), we calculated redundancy reliability (RR) scores for each sCCA; to achieve this we repeated each sCCA in 500 randomly generated subsets and quantified the reliability of canonical cross-loading; (iii) we randomly sampled 50 % of the data 500 times (training set), calculated sCCA on each training set and then used the weights from the sCCA on the training set on the remaining 50 % of the data (test set) to calculate the canonical correlations in the test set. We reported only those modes that met the following robustness criteria: (i) statistically significant at an FDR-corrected P value <0.001; (ii) had a median RR-score > 0.70, and (iii) average canonical correlation on the resampled test sets was at least 70 % of that of the training sets. We performed additional sCCAs to evaluate the effect of including sex on the results.

2.6. Datasets

The neuroimaging and non-imaging datasets and their constituent variables have been described above. Cortical volume, cortical thickness, cortical surface area, and subcortical volume were examined separately because these phenotypes are genetically independent and follow different developmental trajectories (Wierenga et al., 2014). As a result of focusing on the predictive effect of behavioral variables on their developmental changes of structural brains, we only used non-imaging data at baseline. Each participant's developmental changes in imaging variables were calculated as (follow-up value – baseline value), which was then residualized by the baseline value. Age was retained in the main model as it exerts a continuous influence on brain structural development during the transition from late adolescence to early adulthood.

3. Result

The correlations of non-imaging variables are shown in Tables S3 and S4. The imaging characteristics of the developmental change are shown in Table S5 and are shown in Fig. S3.

3.1. Cortical volume

3.1.1. Baseline

The sCCA testing the association between cortical thickness measures and non-imaging variables was significant ($r = -0.37$, $P_{FDR} < 0.001$, mean (SD) permuted $r = 0.18(0.03)$) (Fig. 1A) and accounted for 13.78 % of the covariance. The canonical weights and loading for the imaging and non-imaging variables are shown in Supplementary Tables S5–S8. Intellect, expressive suppression, negative emotion, suicidal attitude, age, and assertiveness had the highest positive canonical cross-loading on the imaging variate while politeness, support utilization, perceived social support, family income, withdrawal, cognitive reappraisal, and enthusiasm had the highest negative canonical cross-loading (Fig. 1B). Canonical cross-loading of $\rho > 0.10$ were noted for nearly all cortical regions and were highest for rostral middle frontal (Fig. 1C).

3.1.2. Developmental change

The sCCA testing the association between developmental changes in cortical thickness measures and non-imaging variables at baseline was significant ($r = 0.38$, $P_{FDR} < 0.001$, mean (SD) permuted $r = 0.16(0.02)$) (Fig. 1E) and accounted for 14.75 % of the covariance. The canonical weights and cross-loading for the imaging and non-imaging variables are shown in Supplementary Tables S9–S12. Age, negative emotion, nervous, withdrawal, out of control, and objective support had the highest positive canonical cross-loading while scan interval, enthusiasm, suicidal attitude, orderliness, politeness, and industriousness had the highest negative canonical cross-loading (Fig. 1F). Developmental changes in cortical thickness with canonical cross-loading of $\rho > 0.1$ were noted in most cortical regions; the highest loadings were superior frontal and right posterior cingulate (Fig. 1G).

3.2. Cortical thickness

3.2.1. Baseline

The sCCA testing the association between cortical thickness measures and non-imaging variables was not significant ($r = -0.17$, $P_{FDR} > 0.05$, mean (SD) permuted $r = 0.21(0.03)$) (Fig. 2A) and accounted for 3.04 % of the covariance. The canonical weights and cross-loading for the imaging and non-imaging variables are shown in Supplementary Tables S13–S15. Volatility, trait anxiety, negative emotion, out of control, depression, and mother's socioeconomic status had the highest

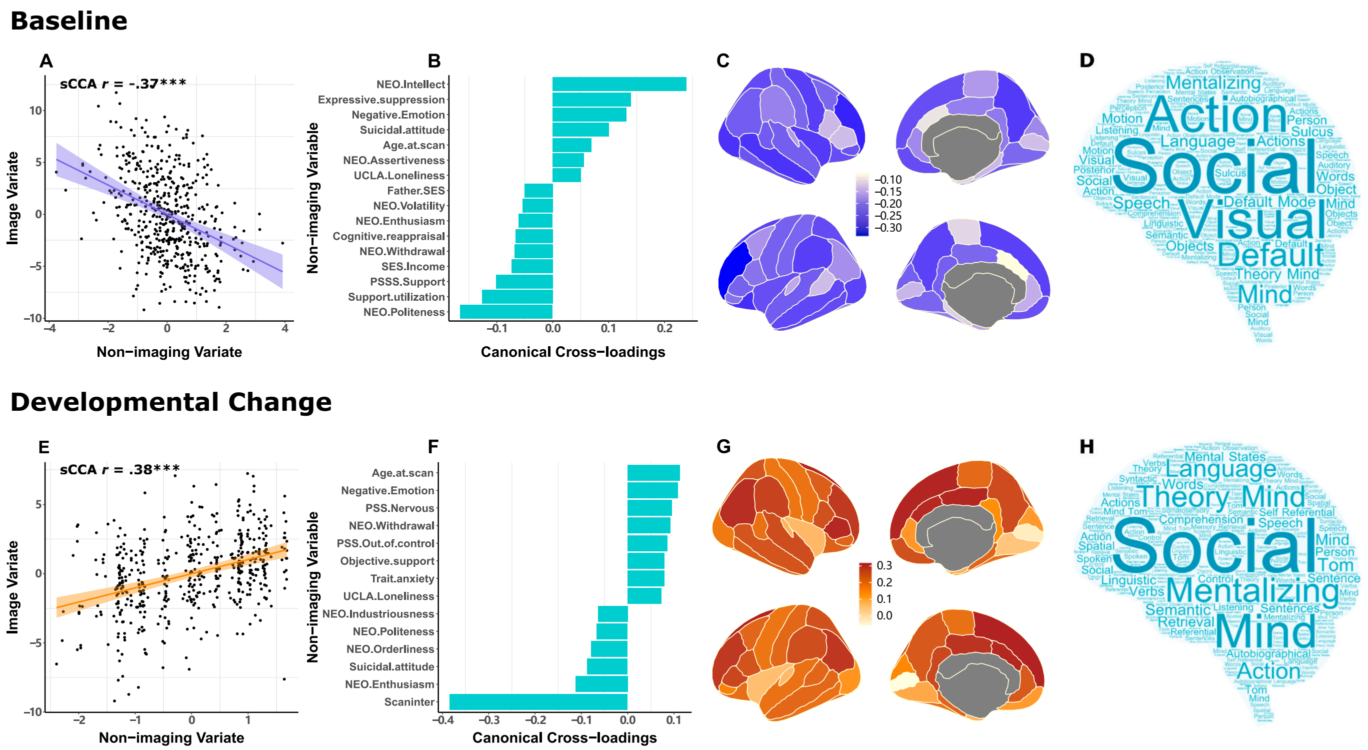

Fig. 1. sCCA for baseline and developmental change in cortical volume. Upper panel: Baseline: A. First canonical correlation coefficient. B. Canonical cross-loading for non-imaging variables. C. Canonical cross-loading for imaging variables. D. Decoding result on Neurosynth. Lower panel: Developmental change: E. First canonical correlation coefficient. F. Canonical cross-loading for non-imaging variables. G. Canonical cross-loading for imaging variables. H. Decoding result on Neurosynth.

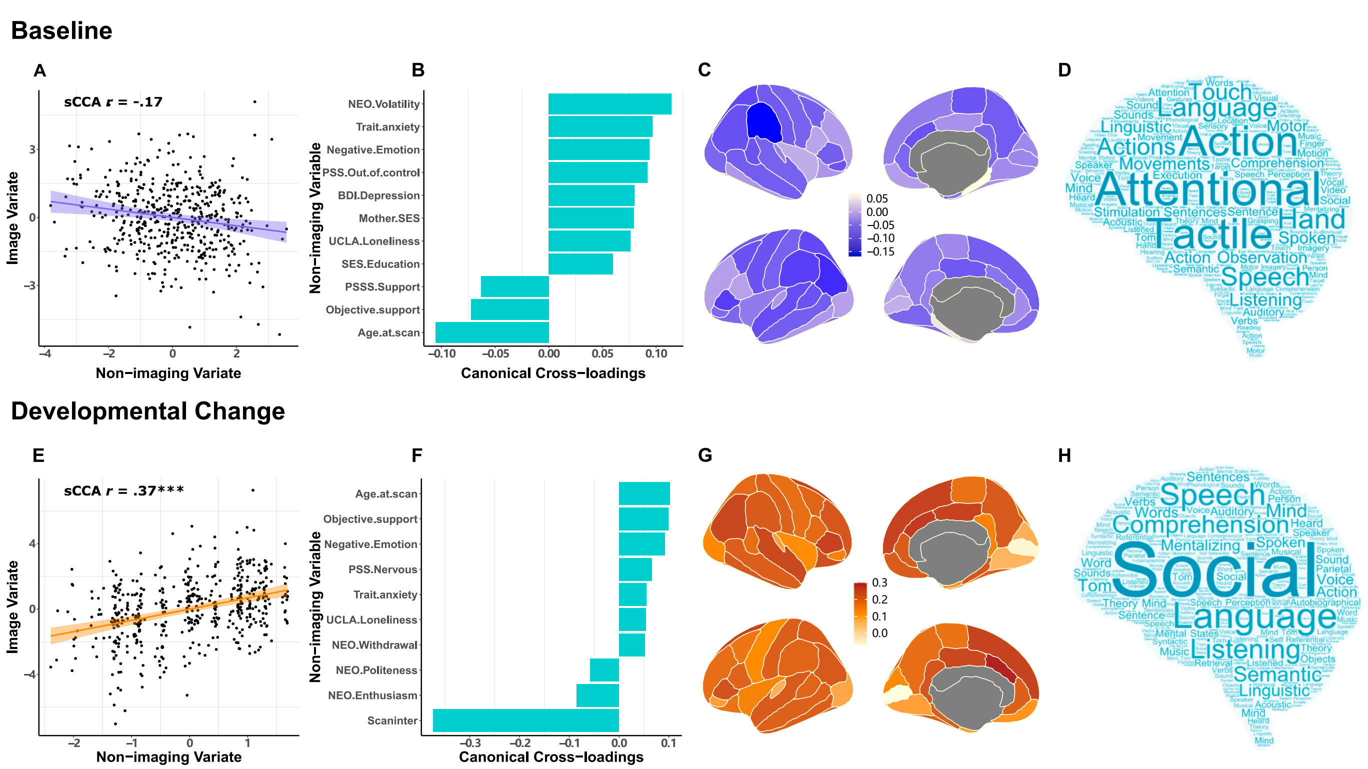

Fig. 2. sCCA for baseline and developmental change in cortical thickness. Upper panel: Baseline: A. First canonical correlation coefficient. B. Canonical cross-loading for non-imaging variables. C. Canonical cross-loading for imaging variables. D. Decoding result on Neurosynth. Lower panel: Developmental change: E. First canonical correlation coefficient. F. Canonical cross-loading for non-imaging variables. G. Canonical cross-loading for imaging variables. H. Decoding result on Neurosynth.

positive canonical cross-loading on the imaging variate while age, objective support, and perceived social support had the highest negative canonical cross-loading (Fig. 2B). Canonical cross-loading of $\rho > 0.10$ were noted in most cortical regions; the highest loading was right superior parietal, left inferior parietal, left pars triangularis and left supramarginal (Fig. 2C).

3.2.2. Developmental change

The sCCA testing the association between developmental changes in cortical thickness measures and non-imaging variables at baseline was significant ($r = 0.37$, $P_{FDR} < 0.001$, mean (SD) permuted $r = 0.17(0.02)$) (Fig. 2E) and accounted for 13.95 % of the covariance. The canonical weights and cross-loading for the imaging and non-imaging variables are shown in Supplementary Tables S16–S20. Age, objective support, negative emotion, and nervous had the highest positive canonical cross-loading while scan interval, enthusiasm, and politeness had the highest negative canonical cross-loading (Fig. 2F). Developmental changes in cortical thickness with canonical cross-loading of $\rho > 0.1$ were noted for nearly all cortical regions and were highest for caudal anterior cingulate (Fig. 2G).

3.3. Cortical surface area

3.3.1. Baseline

The sCCA testing the association between cortical surface area measures and non-imaging variables was significant ($r = -0.37$, $P_{FDR} < 0.001$, mean (SD) permuted $r = 0.18(0.03)$) (Fig. 3A) and accounted for 13.64 % of the covariance. The canonical weights and cross-loading for the imaging and non-imaging variables are shown in Supplementary Tables S21–S24. Politeness, support utilization, withdrawal, volatility, perceived social support and cognitive reappraisal had the highest positive canonical cross-loading on the imaging variate while intellect, expressive suppression, negative affect, age, and suicidal attitude had the highest negative canonical cross-loading (Fig. 3B). Canonical cross-loading of $\rho > 0.10$ were noted for nearly all cortical regions and were highest for rostral middle frontal and right lateral occipital (Fig. 3C).

3.3.2. Developmental change

The sCCA testing the association between developmental changes in cortical surface area measures and non-imaging variables at baseline was significant ($r = 0.37$, $P_{FDR} < 0.001$, mean (SD) permuted $r = 0.19$ (0.02)) (Fig. 3E) and accounted for 13.39 % of the covariance. The canonical weights and cross-loading for the imaging and non-imaging variables are shown in Supplementary Tables S25–S28. Trait anxiety, age, out of control, negative emotion, withdrawal, nervous and volatility had the highest positive canonical cross-loading while scan interval, suicidal attitude, compassion, politeness, enthusiasm, openness, orderliness, family income, and industriousness had the highest negative canonical cross-loading (Fig. 3F) Developmental changes in cortical thickness with canonical cross-loading of $\rho > 0.1$ were noted for most cortical regions; the top 5 highest loadings were right superior frontal, bilateral rostral middle frontal, left precuneus and left superior frontal (Fig. 3G).

3.4. Subcortical volumes

3.4.1. Baseline

The sCCA testing for the association between subcortical volumes and non-imaging variables was significant ($r = -0.20$, $P_{FDR} < 0.001$, mean (SD) permuted $r = 0.12(0.02)$) (Fig. 4A) and accounted for 3.38 % of the covariance. The canonical weights and loading for the imaging and non-imaging variables are shown in Supplementary Tables S29–S32. Politeness, support utilization, perceived social support, withdrawal, family income, volatility, father's socioeconomic status, and parents' education showed the highest positive canonical cross-loading while intellect, age, suicidal attitude, negative emotion,

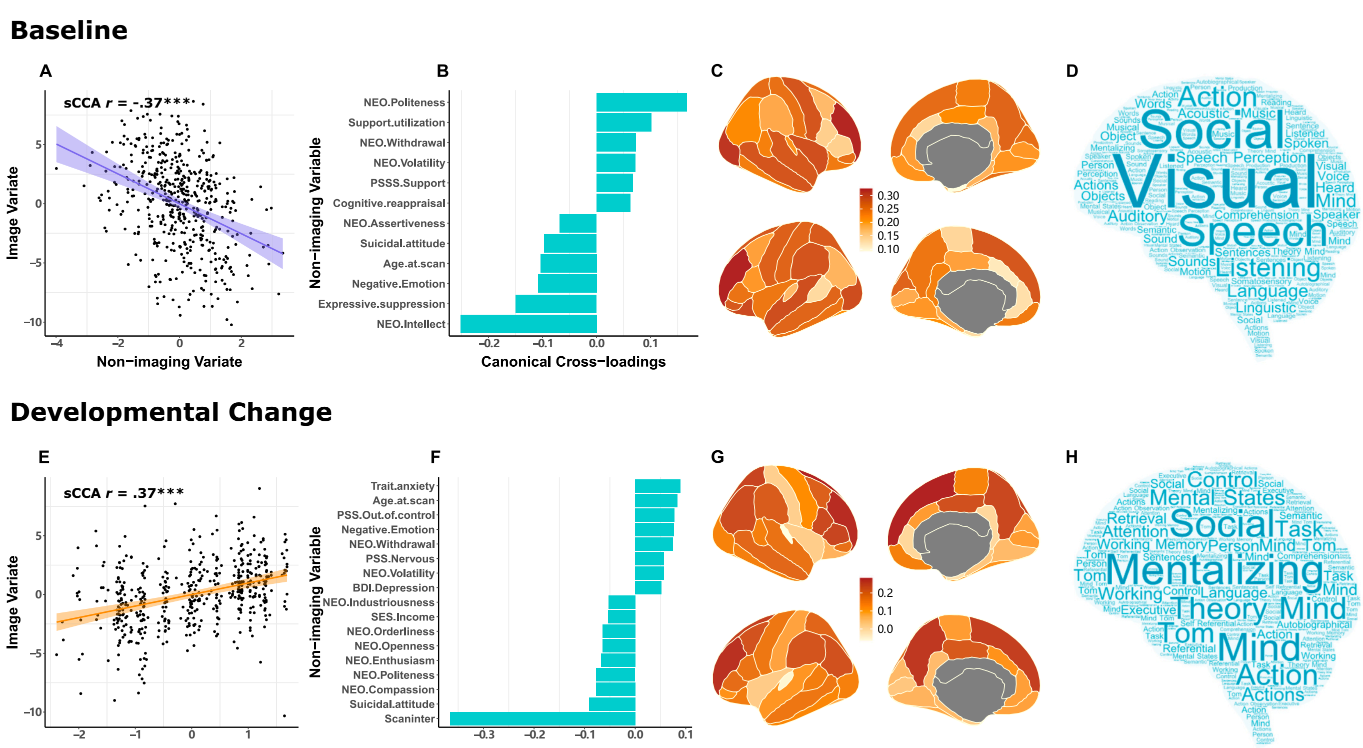

Fig. 3. sCCA for baseline and developmental change in cortical surface area. Upper panel: Baseline: A. First canonical correlation coefficient. B. Canonical cross-loading for non-imaging variables. C. Canonical cross-loading for imaging variables. D. Decoding result on Neurosynth. Lower panel: Developmental change: E. First canonical correlation coefficient. F. Canonical cross-loading for non-imaging variables. G. Canonical cross-loading for imaging variables. H. Decoding result on Neurosynth.

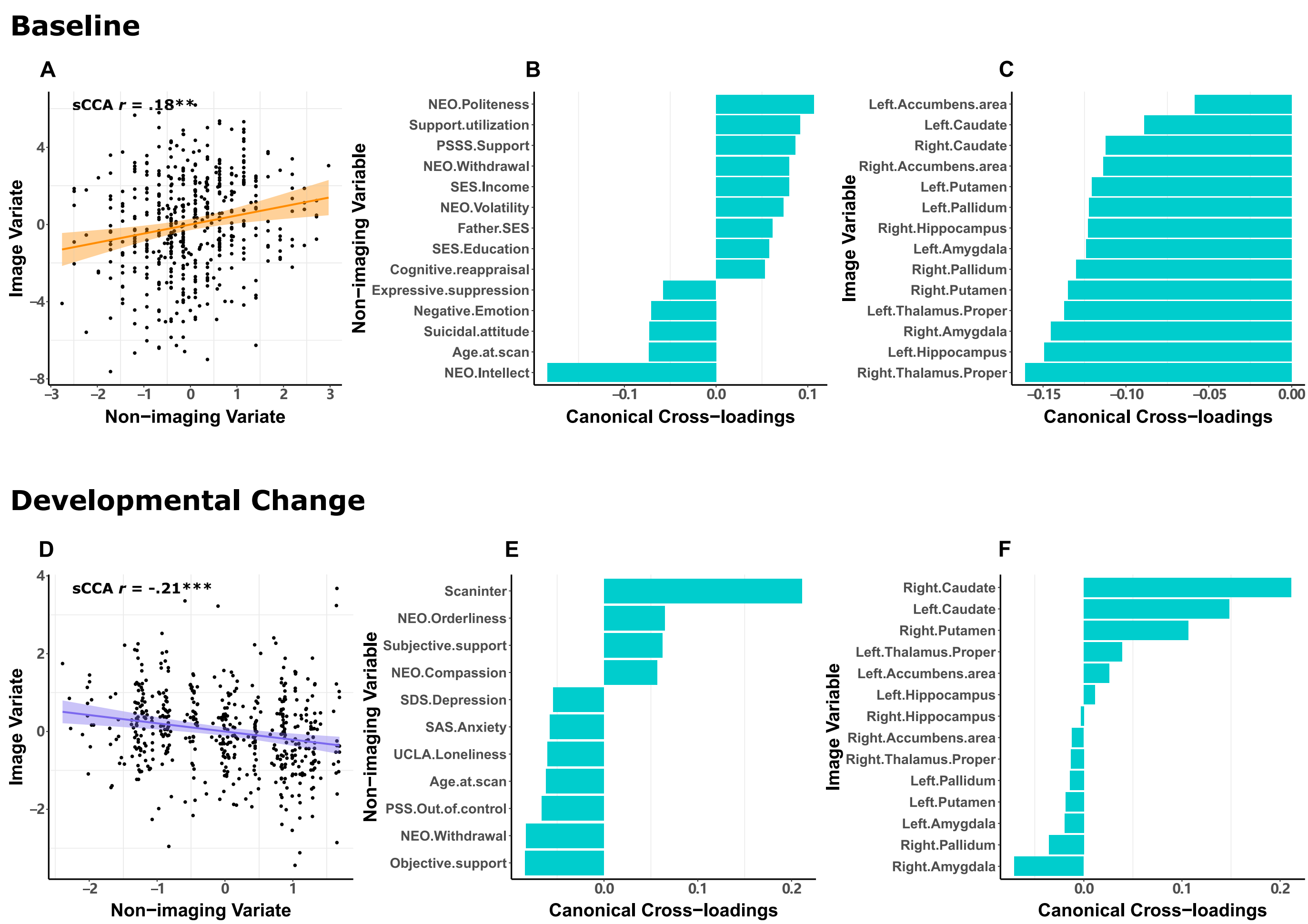

Fig. 4. sCCA for baseline and developmental change in subcortical volume. Upper panel: Baseline: A. First canonical correlation coefficient. B. Canonical cross-loading for non-imaging variables. C. Canonical cross-loading for imaging variables. Lower panel: Developmental change: D. First canonical correlation coefficient. E. Canonical cross-loading for non-imaging variables. F. Canonical cross-loading for imaging variables.

and expressive suppression showed the highest negative canonical cross-loading (Fig. 4B). Canonical cross-loading with the non-imaging variate with ρ values ranging from −0.05 to −0.16 were noted for all subcortical regions with the top five being the right thalamus proper, left hippocampus, right amygdala, left thalamus and right putamen (Fig. 4C).

3.4.2. *Developmental change*

The sCCA testing the association between developmental changes in regional subcortical volumes and non-imaging variables was significant (r = 0.-24, PFDR <0.001, mean (SD) permuted r = 0.12(0.02)) (Fig. 4D) and accounted for 4.46 % of the covariance. The canonical weights and cross-loading for the imaging and non-imaging variables are shown in Supplementary Tables S33–S36. Scan interval, orderliness, subjective support, and compassion showed the highest positive canonical cross-loading while objective support, withdrawal, out-of-control, age, loneliness, anxiety, and depression showed the highest negative canonical cross-loading (Fig. 4E). Developmental changes in regional subcortical volumes with showed canonical cross-loading with ρ values from −0.01 to 0.21, with right caudate having the biggest positive canonical cross-loading and right amygdala having biggest negative canonical cross-loading (Fig. 4F).

4. Discussion

Based on longitudinal data from SLIM, we examined patterns of covariation between structural brain characteristics and negative affect, personality traits, and social conditions during the transition from late adolescence into young adulthood. Through multivariate analysis, we determined that the structural brain development during the transition from late adolescence to young adulthood showed the highest correlations with scan intervals, negative affect, enthusiasm, and politeness, whereas social conditions have a weaker association with structural brain development. Besides, we found that the development of subcortical volume was strongly correlated with scan intervals and social support. Furthermore, we conducted a cross-sectional analysis and highlighted the effect of intellect and politeness traits on the structural brain at baseline.

Our findings demonstrate that scan intervals or age are the most significant factors explaining changes in cortical volume, cortical thickness, cortical surface area, and subcortical volume when compared with personality traits, social conditions, and negative affect. The findings of this study are consistent with previously published research that suggests factors associated with time-dependent development remain the primary factors driving brain development when other physiological-psychological-social factors are taken into consideration (Modabbernia et al., 2020), and we extend it by including a sample of young adult. Moreover, a more pronounced decrement in structural morphology was observed in higher-order association cortical regions, such as the superior frontal and caudal anterior cingulate. The spatiotemporal patterning of cortical maturation thus proceeds hierarchically during the transition from late adolescence to young adult, conforming to an evolutionarily rooted sensorimotor-to-association axis of a cortical organization (Burt et al., 2018; Xu et al., 2020).

As well as scan interval and age, there appears to be an antagonistic relationship between personality traits (enthusiasm and politeness) associated with positive emotion or well-being and negative affect, such as negative emotion or perceived stress. Personality and negative affect showed significant negative and positive cross-loading with the development of the structural brain separately. These findings were consistent with recent studies, which have found that the pattern of covariation of brain structural changes (Modabbernia et al., 2021b), brain connectivity (Smith et al., 2015), and behavioral phenotypes was predominantly spread along a single "positive-negative" axis. Enthusiasm is the sub-dimension of extroversion co-variated with the volume of brain regions involved in mentalizing (DeYoung et al., 2010) and politeness is a sub-dimension of agreeableness that indicates adherence to social norms and refraining from belligerence and exploitation of others (Allen et al., 2017). In addition, our meta-analysis confirms that the multivariate pattern of brain-behavior associations is located in brain areas involving the social, mentalizing, and theory of mind. This may imply that brain maturation plays a significant role in mastering social skills and complying with social norms for emerging adulthood (The Oxford Handbook of Emerging Adulthood, 2015) and thus helps individuals to integrate from school life into society during the transition from late adolescence to young adulthood.

It is inevitable for students to experience negative emotions and stress during their transition from late adolescence to young adulthood due to dramatic changes in their living and learning conditions. Our imaging results also showed that superior frontal, posterior cingulate, and caudal anterior cingulate are most closely related to these variables. Prior research had shown that these regions are relevant to emotional cognition and adaptive coping skills, as well as symptoms or characteristics of first-episode schizophrenia, autism spectrum disorder, and Alzheimer's disease. (Asmal et al., 2018; Brosch et al., 2021; Laidi et al., 2019; Lehmann et al., 2010). In short, this may indicate that the abnormal developmental changes of the structural brain involved in adaptive and maladaptive performance account for many mental health diseases, particularly during a period of vulnerability to negative affect, such as the transition from late adolescence to young adulthood.

Beyond the scan intervals, we observed that social support including both objective and subjective support was most associated with a decelerated decrease in subcortical volumes, which was primarily observed in the bilateral caudate. Previous cross-section studies declared smaller volume of bilateral caudate was related to negative outcomes such as depression (Kim et al., 2008), early life stress (Cohen et al., 2006), and suicidal ideation (Ho et al., 2021). The negative relationship between social support and the reduction of volume of these regions found in our research seems to indicate that the existence of social support can protect individuals during the transition from late adolescence to young adulthood when maladaptive behavior is easy to occur due to internal and external factors.

At baseline, we found that measures of cortical volume, cortical thickness, surface area, and subcortical volumes all showed unitary correlation patterns with phenotype, which are intellect and politeness traits but they had opposite cross-loading with these measures. The intellect trait reflects cognitive exploration and sensitivity to the reward value of information while the politeness indicates adherence to social norms as well as a willingness to refrain from exploiting others (Allen and DeYoung, 2016). This result indicates that politeness is likely to be associated with cognitive regulation and social mentalizing. In contrast, the intellect aspect of openness is likely to be associated with motivation and action. These functions are vital to obtaining social and academic success for individuals during the transition from late adolescence to young adulthood (Veroude et al., 2013; Wu et al., 2020). In longitudinal data analysis, the association between intellect and structural brain changes is weak. In some cases, this may be due to the dynamic relationship between certain personalities and the structure of the brain during the first thirty years of life. There should be a focus on the relationship between inter- and intra-individual differences in personality traits and the structural brain across a broad age range in future studies.

5. Summary and limitation

The present study has some limitations. Firstly, in terms of the scan interval between baseline and follow-up, it ranged from 4 months to 3 years, but brain development at these ages is still critical evolving. Following prior work, developmental changes in imaging variables were calculated as (follow-up value - baseline value), which was then residualized by the baseline value (Modabbernia et al., 2021b), but this indicator is susceptible to scan interval and has limitations in describing the trajectory of brain development. Secondly, the non-imaging variables in the present study are only at baseline, making it impossible to examine the relationship between changing behavior and structural brain development. But our research also has some advantages. First of all, most longitudinal studies of brain development have focused on Caucasian populations while Asian populations have been studied less, and we have collected structural brain data from Asian individuals using the same scan parameters at the same site. Additionally, multivariate statistical techniques were used to examine the complex correlation between negative affect, personality, as well as social condition and the structural brain development of individuals during the transition from late adolescence to early adulthood.

By using multivariate methods, we found the structural brain is still changing during the transition from late adolescence to young adulthood, showing a decrease in cortical volume, thickness, surface area, and subcortical regions, especially bilateral superior frontal, left caudal anterior cingulate, and bilateral caudate. During this period, a time-dependent manner (scan interval) had a critical effect on brain development. Nevertheless, our results also provide evidence for statistically robust associations between structural brain changes and negative affect, enthusiasm, politeness and social support. These factors may be associated with a person's mental health, as well as their future academic and social success.

CRediT authorship contribution statement

Jiahui Liu: Conceptualization, Formal analysis, Data curation, Writing – original draft. **Yi Zhang:** Formal analysis, Data curation. **Jiang Qiu:** Data curation, Project administration, Supervision. **Dongtao Wei:** Conceptualization, Data curation, Project administration, Supervision, Writing – review & editing.

Conflict of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2023.01.015.

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