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RESEARCH

The effect of age on the architecture of psychological and cognitive dimensions: a network perspective

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Abstract

Ageing involves changes across the life span in cognitive abilities, mental health, and personality traits. Although these domains are often studied separately, recent findings highlight their interdependence and dynamic interplay. To examine these relationships, we analysed data from the Human Connectome Project (HCP-Young and HCP-Aging datasets) divided into three age groups: Young (22–39; $n=230$), Middle-aged (40–59; $n=242$), and Older adults (60–79; $n=209$). The interrelationships among 19 cognitive, psychological, and personality variables were investigated using a psychometric network approach, estimating one network per age group and examining how variables clustered into communities (exploratory graph analysis) and comparing the emerging networks using the network comparison test (NCT). We observed substantial differences across age groups. In younger adults, cognitive variables were split into two communities, separating lower from higher cognitive functions, whereas middle-aged and older adults did not present this separation. Two variables—delay discounting and emotion recognition —associated with cognition in younger populations clustered with personality traits and psychological factors in the Older Adults' network, suggesting an increased relevance of their affective significance. The NCT confirmed that the architectures of the Young Adults and the two older groups' networks were significantly different. Compared to the Young Adults, the Older Adults network also showed reduced overall association strength. Altogether, these findings support the view that ageing is associated with structural transformations in the relationships among cognitive, psychological, and personality domains, following a dedifferentiation trajectory across cognitive variables and a general reorganization of psychometric factors.

Keywords Human Connectome Project · Network · Ageing · Exploratory graph analysis · Network comparison test

Introduction

The concept of ageing encompasses a set of complex and multifaceted processes involving physiological, cognitive, and psychosocial changes that occur throughout the life span and impact an individual's health, independence, and overall well-being (Pathy et al. 2006). Historically, ageing has often been associated with a negative connotation, framed as a gradual and irreversible decline in physical and mental capacities (Diehl et al. 2020). Contemporary research, however, increasingly challenges this perspective, suggesting that ageing involves a dynamic reorganization of cognitive and psychological resources (Park and McDonough 2013), marked not only by decline but also by compensatory adaptations, preserved abilities, and new forms of resilience (Carstensen and DeLiema 2018; Salthouse 2019).

Cognitive functions, for instance, have traditionally been viewed as undergoing a generalized decline with age. However, research shows a more nuanced picture: While certain abilities—such as executive functioning and mathematical reasoning—tend to decline across the life span (Salthouse 2004), others, including implicit and semantic memory, remain stable or even improve (Fleischman et al. 2004; Nyberg et al. 2012). According to the dedifferentiation hypothesis (Anstey et al. 2003; Balinsky 1941), ageing is also characterized by a functional reorganization of cognitive resources, whereby abilities become less distinct and

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increasingly intercorrelated. This reorganization may serve as a compensatory, adaptive mechanism, allowing different cognitive domains to interact and support one another in the face of age-related losses and everyday challenges.

The concept of ageing as an interplay between losses and compensation extends beyond cognition. The socioemotional selectivity theory (SST; Carstensen 1992; Carstensen et al. 2003) offers a framework emphasizing how individuals adapt to age-related changes by actively selecting emotionally meaningful goals and prioritizing close social relationships. This motivational reorientation helps explain why older adults often report greater emotional well-being, better emotional regulation (Doerwald et al. 2016; Gross et al. 1997), and lower levels of negative emotions than younger adults (Carstensen et al. 2000; Charles and Carstensen 2010). For instance, depression and anxiety were found to decrease in later adulthood, and externalizing tendencies such as antisocial and rule-breaking behaviours become less frequent (Blazer 2003; Stone et al. 2010).

Regarding personality, although core aspects have traditionally been considered relatively stable across adulthood (Debast et al. 2014; Soto et al. 2011), accumulating longitudinal evidence reveals meaningful mean-level changes across the life span, as well as individual differences in these changes (Graham et al. 2020; Roberts and Mroczek 2008). For example, Neuroticism—reflecting emotional instability and negative emotions—typically declines with age, fostering greater emotional stability and resilience (Roberts et al. 2006; Terracciano et al. 2005). Longitudinal studies of older adults, however, identified a shift in this trend after the age of 70, possibly due to the increasing occurrence of negative experiences and self-efficacy declines (Kandler et al. 2015; Wagner et al. 2016). In contrast, Agreeableness, encompassing traits like kindness, cooperation, and empathy, has been observed to increase steadily with age, likely as older adults prioritize nurturing relationships and enhancing others' well-being (Costa and McCrae 1997, 1999; Soto et al. 2011). Openness to experience—creativity, curiosity, willingness to engage in new ideas and experiences—has been found to either increase or remain stable depending on life circumstances and personal interests, reflecting enduring intellectual curiosity and engagement with new ideas (McCrae and Costa 2004).

Altogether, these findings indicate that psychological and cognitive factors follow multiple, distinct trajectories throughout the life span. Crucially, emerging evidence suggests that their interrelationships may play a pivotal role in shaping these developmental pathways, highlighting the necessity for integrated and cross-domain approaches to investigate their evolution across the life span. For instance, higher levels of Openness to experience have been linked to better-preserved cognitive abilities (Bastelica et al. 2023; Curtis et al. 2015), while chronic stress is associated with accelerated cognitive decline and poorer health outcomes (Lupien et al. 2009). Nonetheless, existing cross-domain studies often limit their focus to specific dyadic associations (e.g. depression and working memory), rarely capturing the broader, reciprocal influences among multiple psychological and cognitive variables (Soubelet and Salthouse 2011; Wolf and Ackerman 2005). These limitations also depend on the challenge of collecting large datasets including cognitive, psychological, and behavioural measures, as well as on the choice of the statistical methodology selected to analyse them.

A more comprehensive understanding of ageing may emerge from multivariate approaches to examine how cognitive, personality, and psychological factors interact as a system. Psychometric network analysis is one such method, enabling the concurrent examination of multiple variables and their interrelations. In this framework, variables (nodes) are embedded within a broader structure (network), with edges representing associations and the overall architecture reflecting systemic properties (Epskamp et al. 2012). This approach allows for the analysis of both local features (e.g. strength of specific edges) and global features (e.g. community structures), and can be extended to comparisons between groups or conditions (Chandrasekaran et al. 2010; Golino and Demetriou 2017). Originally employed in neuroscience and psychopathology, network analysis is now more broadly applied to psychological and cognitive domains, offering new insights into the complex interdependencies that characterize ageing (Borsboom et al. 2021; Costantini et al. 2019; Siew et al. 2019).

The present study

This project extends the investigation conducted by Granziol and Cona in a previous study (2024), which applied network analysis to data from the Human Connectome Project-Young Adults dataset (HCP-YA) to investigate the architecture of relationships among cognitive, personality, and psychological variables in young adults (22–35 years). In the present study, we applied the same methodology to investigate these relationships across different age groups, hypothesizing that ageing may lead to modifications in the network structure and in the associations among variables. Specifically, data from the HCP-YA and from the Human Connectome Project-Aging dataset (HCP-A), a repository of data from participants spanning between 36 and 100 years of age, were considered. Data were divided into three age groups: Young Adults (22–39), Middle-aged Adults (40–59), and Older Adults (60–79). A subset of psychological, personality, and cognitive variables was selected and analysed through the exploratory graph analysis (EGA) approach to investigate the properties of the emerging networks, including their architectures and the communities in which variables clustered in each age group. Subsequently, networks were compared using the network comparison test (NCT) approach to identify structural changes associated with ageing.

A first aim of this study was to replicate the findings of Granziol and Cona (2024) in the Young Adults group. Specifically, we expected cognitive variables to separate into two communities (higher vs. lower cognitive functions), personality and psychological measures to cluster together, and externalizing behaviours to form a distinct cluster.

The second goal was to examine differences in network structure across age groups. In line with the dedifferentiation hypothesis (Anstey et al. 2003; Balinsky 1941), we expected cognitive variables in the Older Adults group to merge into a single community, reflecting greater integration/dedifferentiation of cognitive functions (Baltes et al. 1980). Concerning personality and psychological factors, we hypothesized a reorganization of factors and communities. Specifically, links between personality traits and externalizing behaviours were expected to weaken with age, given the reduced prevalence of such symptoms in later life (Petersen et al. 2015; Sampson & Laub. 2017) and consistent with the socioemotional selectivity theory (Carstensen 1992; 2021), which posits that ageing strengthens prosocial motivations and fosters the active pursuit of emotionally meaningful goals and harmonious social interactions. Together, these differences in cognitive and motivational functioning were expected to manifest in distinct configurations of networks and communities between younger and older age groups. Ultimately, this exploratory study aimed to elucidate how the interplay among cognitive, personality, and psychological variables changes with age, proposing psychometric network analysis as a valuable tool to understand structural changes in behavioural functioning across the life span.

Methods

Participants

Data for this study were obtained from two Human Connectome Project (HCP) databases (http://www.humanconnectomeproject.org/): the HCP-Young Adult (HCP-YA) and the HCP-Aging (HCP-A) datasets. The HCP-YA comprises data from 1206 participants aged 22–35 years (Van Essen et al. 2012) collected roughly between 2012 and 2015. Data were collected from healthy participants without neurological, psychiatric, or systemic medical conditions at the Washington University in St. Louis and at the University of Minnesota (US). The HCP-Aging included data from 726 healthy adults aged 36–100 years. Recruitment occurred between 2016 and 2020 and involved the two abovementioned institutions: the University of California Los Angeles and the Massachusetts General Hospital. Since the target was to collect data associated with healthy ageing, participants with neurological diseases, major psychiatric disorders, severe sensory impairments, or cognitive scores below threshold on the MoCA (Montreal Cognitive Assessment; cutoff = 19 for ages 36–59 and 60–79) and the TICS-M (Modified Telephone Interview for Cognitive Status; administered only to participants aged 60 years and older, cutoff = 29) were excluded (Bookheimer et al. 2019).

To better examine age-related differences, the HCP-Aging dataset was divided into two subgroups: Middle-aged Adults (40–59 years) and Older Adults (60–79 years). Participants aged 80 and above were excluded from the Older Adults network to reduce heterogeneity. Moreover, their small sample size ($n = 61$) and uneven age distribution (concentrated in the ranges 80–85 and 95–100) precluded treating them as a separate group and prevented a reliable network estimation. The selected age thresholds were guided by both methodological and practical considerations. First, we aimed to create subgroups with adequate sample sizes (approximately 230 participants each), as network psychometrics typically recommend at least 200–250 participants to estimate networks formed from up to 20 nodes (Constantin 2018; Constantin et al. 2023). Second, some of the measures used in this study (e.g. the Achenbach Adult Self-Report Scale) provide different versions based on age, with 60 years serving as the threshold. Exclusion criteria included having missing data on more than two of the selected variables (see "Measures" section) and the presence of a twin/sibling within the dataset, in which case only one individual per pair was retained (randomly selected). Finally, 20 participants were excluded from the Middle-aged Adults group (the largest subgroup) to match demographic criteria (sex distribution) of the Older Adults group and to reduce their difference in sample size (Epskamp and Fried 2018). These criteria yielded a final sample of 451 participants: 242 in the Middle-aged Adults group and 209 in the Older Adults group. To allow for comparability, the same exclusion criteria were applied when defining the third group, which was drawn from the HCP-YA dataset and the subset of HCP-A participants aged 39 or younger. From this combined pool, 230 participants were pseudo-randomly selected to form the Young Adults group, matched to the two older groups in both size and gender distribution. Sample size, age, and gender of each group are reported in Table 1.

Measures

The HCP datasets include a wide range of behavioural and demographic data, including participant information, a comprehensive battery of cognitive tests, and various personality and psychological questionnaires. The full list of measures included in the HCP datasets, together with

Table 1 Sample size, age, and percentage of female participants (F) across the three age groups

Population	Sample size	Age	Sex
Young adults	230	29.94 ± 4.86	56% F
Middle-aged adults	242	49.64 ± 5.72	57% F
Older adults	209	69.24 ± 5.69	56% F

a brief description of their functions, can be found in Van Essen et al. (2013; HCP-Young Adult) and Bookheimer et al. (2019; HCP-Aging).

In this project, measures were selected to investigate the relationships across personality, cognition, and psychological factors such as mental health and emotion recognition. Hence, the three datasets were composed of information on the five personality traits collected through the NEO Five Factor Inventory (McCrae and Costa 2004); responses to the cognitive assessment battery administered by HCP experts; measures of mental and behavioural disorders collected through the Achenbach Adult Self-Report (ASR) and its version for older adults (OASR; Achenbach et al. 2004; Achenbach 2009); and a measure of emotion recognition collected through the Penn Emotion Recognition Task (Gur et al. 2010). The full list of the measures included in our analysis is provided in Table 2. Details on the mean and standard deviations for each variable in each group are reported in the Supplementary Information (Tables S1, S2, and S3).

Network analysis

The network analysis employed in this study consisted of two separate procedures. First, each age group was analysed using the exploratory graph analysis (EGA) approach (Golino and Epskamp 2017; Hudson and Alexander 2024). EGA is a methodological approach that examines a large set of variables from a network perspective, considering the relationships between each measure and estimating the best way to categorize them into separate clusters (or communities). Considered an innovative approach to investigate multivariate data, EGA has been found to perform as well as several traditional factor analytic techniques (Golino et al. 2020). EGA involves multiple steps: First, a Gaussian graphical model is computed to calculate the network structure that better represents the relationships among the variables. In the network computation, each variable represents a node and each association between two nodes constitutes an edge. The edges are estimated as partial correlation coefficients between each pair of nodes, controlling for all other variables. Given the large number of nodes (and edges), the network was regularized using the LASSO (least absolute

Table 2 List of the variables included in the study

Category	Scale	HCP measure	Variable name
Personality	Five Factor Inventory (NEO-FFI)	NEOFAC_A	AGREEABLENESS
		NEOFAC_C	CONSCIENTIOUSNESS
		NEOFAC_E	EXTRAVERSION
		NEOFAC_N	NEUROTICISM
		NEOFAC_O	OPENNESS
Emotion/affect	Penn Emotion Recognition Task	Emotion Recognition (ER40)	EMOTION_REC
	Delay Discounting Task	Delay Discounting (200 $)	DD_200
Cognition	Picture Sequence Memory Test	Picture Sequence Memory	PIC_SEQ
	Dimensional Change Card Sorting task	Dimensional Change Card Sorting	CARD_SORT
	Pattern Comparison Processing Speed task	Pattern Comparison Processing Speed	PROC_SPEED
	List Sorting Working Memory Task	List Sorting Working Memory Task	LIST_SORT
	Flanker Task	Flanker Task	FLANKER
	Oral Reading Recognition Task	Oral Reading Recognition Task	ORAL_READ
Psychological symptoms	Achenbach Adult Self-Report (ASR)	WithDrawal	WITHDRAWAL
		Anxiety_Problems	ANXIETY
		Depression	DEPRESSION
		Antisocial_Behaviours	ANTISOCIAL
		Externalizing_Behaviours	EXTERNALIZING
		Rule_Breaking	RULE_BREAK

The column *Category* refers to the broad construct domain, as defined in the HCP documentation. *Scale* indicates the original questionnaire or task from which each measure was obtained. *HCP Measure* corresponds to the labels used within the HCP datasets for each specific score or subscale. *Variable Name* refers to the name adopted in our analyses, tables, and network figures shrinkage and selection operator) method (Epskamp et al. 2018), which prevents overfitting. After regularization, a walktrap community detection algorithm is applied to identify the clusters in which variables can be grouped to better explain their relationships (Christensen and Golino 2019; 2021). Finally, the reliability and replicability of the identified networks and communities are tested using a nonparametric bootstrap approach with 5,000 replications to assess the robustness of the results.

The second procedure involved the direct comparison between the so-obtained networks through the network comparison test (NCT; van Borkulo et al. 2022) approach. This method evaluates the networks for their level of invariance (the similarity between the structures of the two networks) and compares their global strength (the absolute sum of network edge weights). The networks from the three age groups were compared in pairs (Young vs. Middle-aged: Middle-aged vs. Older; Young vs. Older). Post hoc analyses were conducted to identify specific edges with significant differences in strength between each pair of networks. For each comparison, the permutation seed was set to 123, and 1,000 permutations were performed. Given the large number of nodes and edges, the results were corrected for multiple comparisons using the false discovery rate (FDR) method (Benjamini and Hochberg 1995).

Results

EGA network: Young adults

In the Young Adults group, the EGA identified four distinct clusters, each reflecting a unique community of variables. The four-community solution was the most stable (replicated 45.4% of the time, compared to the 26.4% of the three-community solution and the 19.6% of the five-community solution). Cognitive measures clustered into two main communities: the first comprising basic executive functions, including processing speed, inhibition, and set shifting (*Low_Cognition*), and the second encompassing higher-order cognitive abilities, such as oral reading, working memory, and socioemotional processing (*High_Cognition*). Notably, this second community also included performance on the emotion recognition and delay discounting tasks—both classified within the Emotion/Affect domain in the HCP manuals—as well as the Openness personality trait. A third community brought together internalizing mental health factors (depression, anxiety, withdrawal) along with all personality traits except Openness (*Mental_Health*), whereas the fourth was formed by all the externalizing mental health factors (*Externalizing*). A complete overview of edge weights and zeroth-order correlations among all variables is provided in the Supplementary Information (Table S1) (Fig. 1).

EGA network: Middle-aged Adults

In the Middle-aged group, the EGA revealed a structure composed of three communities. The *Externalizing* and

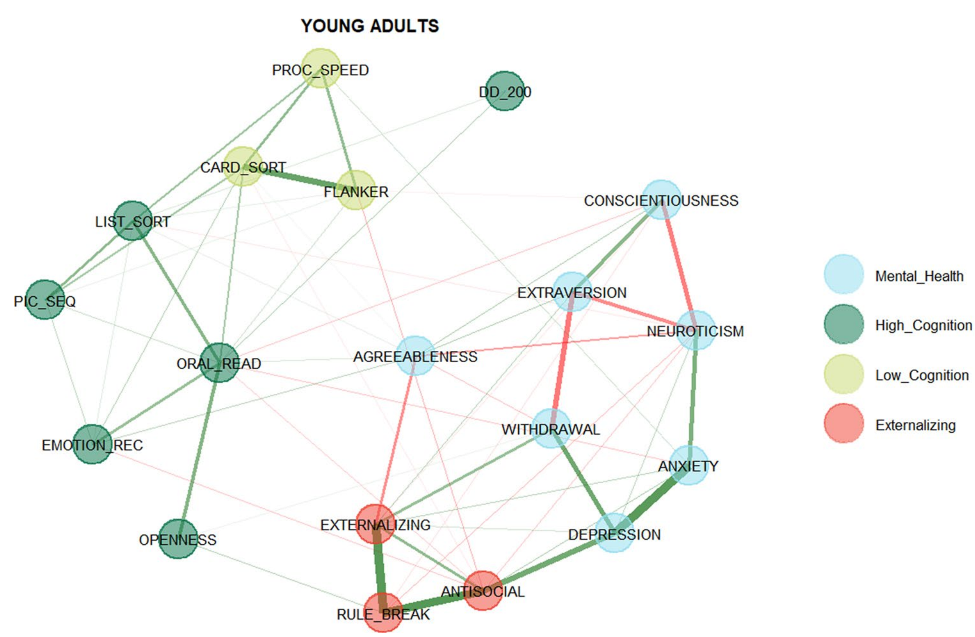

Fig. 1 Network estimated from the data of the Young Adults population. Node colours represent the communities identified by the EGA, and the legend (right) indicates the labels adopted for each community

Mental_Health communities retained a composition similar to that observed in the Young Adults network, whereas cognitive variables merged into a single community (*Cognition*) that encompassed both lower- and higher-level cognitive functions. Notably, also in this age group this cluster included the personality trait Openness to experience and the two measures of emotion/impulsivity (emotion recognition and delay discounting). The three-community solution presented a strong stability (replicated 92.2% of the time). Detailed edge weights and zeroth-order correlations are reported in the Supplementary Information (Table S2) (Fig. 2).

EGA network: Older adults

The network structure in the Older Adults group revealed three communities (replicated 70.4% of the time, compared to 26% for the alternative four-community solution). In general, these clusters paralleled those described in the Middle-aged group: *Cognition, Externalizing,* and *Mental_Health*. However, subtle yet meaningful shifts in variable organization were observed. Specifically, performance on the emotion recognition and the delay discounting tasks, which clustered with cognitive variables in the other age groups, merged in this age group within the *Mental_Health* community, showing stronger associations (either positive or negative) with factors such as Extraversion, Neuroticism, and Withdrawal. Openness, on the other hand, continued to cluster within the *Cognition* community. Edge weights and correlations are detailed in Supplementary Information (Table S3) (Fig. 3).

Network comparison test

The NCT revealed significant differences in network architecture across the three age groups. The Young Adults network differed structurally from both the Middle-aged ($M = 0.509$, $p < 0.001$) and the Older Adults ($M = 0.493$, $p < 0.001$) networks. Regarding global strength (i.e. the absolute sum of all edge weights), the Older Adults network showed a significantly lower value (5.206) compared to the Young Adults network (8.273; $GS = 3.068$, $p = 0.016$). The Middle-aged network displayed an intermediate global strength (7.507), which did not differ significantly from the other two groups. Post hoc tests further identified edge-specific differences in connection strength across networks. The comparison between the Young and Older Adults networks revealed 15 edges with significantly different weights, mostly associations within *Mental_Health* nodes and between them and variables belonging to the *Externalizing* and *Cognition* communities. In contrast, the Middle-aged network differed from both Young and Older Adults on 5 edges, in both cases primarily involving associations within the *Externalizing* community and between *Externalizing* and *Mental_Health* nodes. A graphical overview of the edges showing significantly different strengths across age groups is presented in Fig. 4, while the complete list of significantly different edges between each couple of networks is reported in the Supplementary Information (Table S4, S5, and S6).

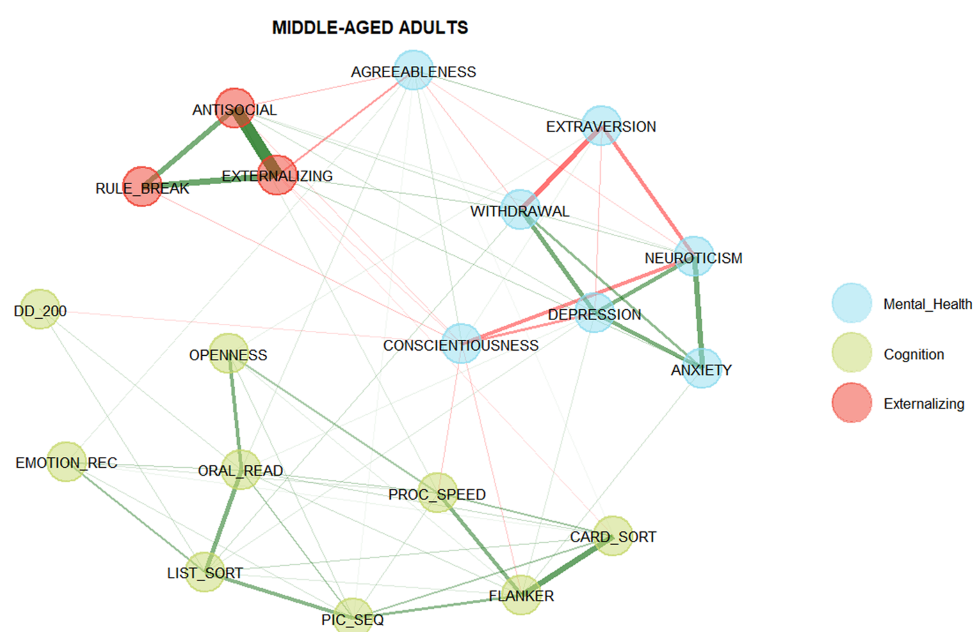

Fig. 2 Network estimated from the data of the Middle-aged Adults population. Node colours represent the communities identified by the EGA, and the legend (right) indicates the labels adopted for each community

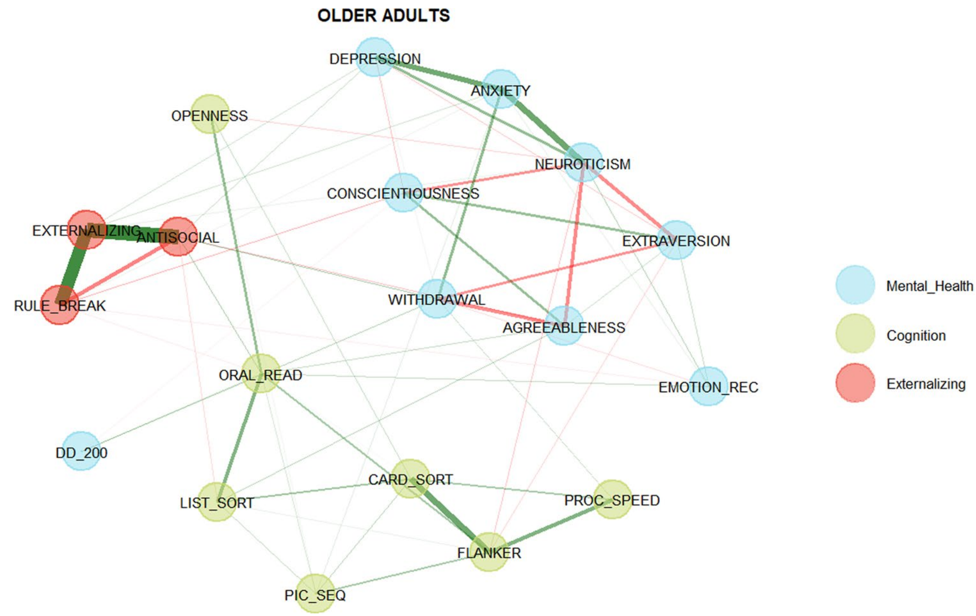

Fig. 3 Network estimated from the data of the Older Adults population. Node colours represent the communities identified by the EGA, and the legend (right) indicates the labels adopted for each community

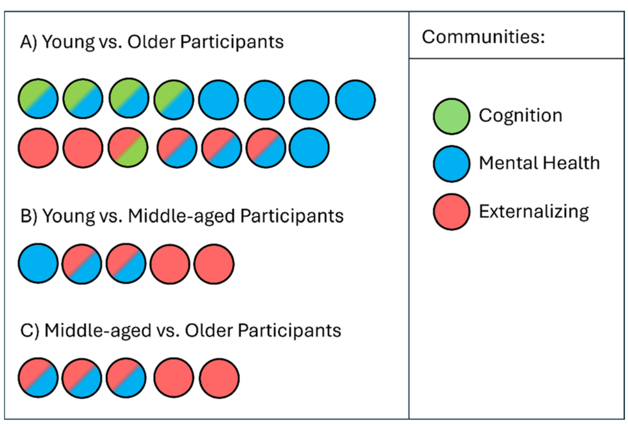

Fig. 4 Graphical representation of edges showing significant strength differences across age groups. Each circle represents a specific edge in the network and is coloured according to the clusters of the two connected nodes. To reduce complexity, nodes belonging to the *Low_Cognition* and *High_Cognition* communities in the Young Adults are both displayed in light green. **A** Young versus Older adults. **B** Young versus Middle-aged adults. **C** Middle-aged versus Older adults

Discussion

This study investigated how the structure and interrelations among personality, psychological, and cognitive variables change across the adult life span. Using network analysis, we compared these patterns across three age groups: Young adults (22–39 years), Middle-aged adults (40–59 years), and Older adults (60–79 years). Our findings revealed marked age-related differences in the organization of these domains, highlighting both structural and functional transformations across the adulthood.

First, we used exploratory graph analysis (EGA: Golino and Epskamp 2017) to examine how variables clustered into communities within each age group. In the Young Adults group, four distinct communities emerged: two encompassing cognitive measures (*Low_Cognition* and *High_Cognition*), one grouping externalizing behaviours (*Externalizing*), and the last combining internalizing symptoms with personality traits (*Mental_Health*). Although the four-community solution was replicated in only approximately 50% of the iterations, this configuration still occurred twice as often as the alternative three- or five-community solutions. Additionally, these results closely mirror the findings of Granziol and Cona (2024), who, despite analysing a larger sample and a broader set of variables (38 vs. 19), also reported a similar division between low- and high-level cognitive functions. More generally, each variable of interest in the present study clustered within the same communities identified by those authors.

The analysis performed on the Middle-aged and the Older Adults groups revealed the emergence of networks characterized by a lower number of communities (three), suggesting decreased segregation among variables. Specifically, cognitive variables (split into lower and higher cognitive functions in young adults) were merged into a single community (*Cognition*). In line with the dedifferentiation hypothesis (Anstey et al. 2003; Balinsky 1941), this pattern suggests a progressive dedifferentiation of cognitive domains in later adulthood, reflecting reduced functional specialization and increased integration across abilities, which may serve as a compensatory mechanism to maintain cognitive functioning.

Overall, the community structure remained largely robust across late adulthood (a comprehensive overview of the variables and their community assignments across the three age groups is provided in the Supplementary Information, Table S7). However, some nodes clustered differently between the Middle-aged and the Older Adults networks. Namely, two variables—emotion recognition and delay discounting—which clustered within cognitive domains in both the Young Adult (*High_Cognition*) and Middle-aged (*Cognition*) networks, were instead grouped within the *Mental_Health* community in the Older Adult network. These two measures, belonging to the Emotion/Affect category in the HCP manuals (Bookheimer et al. 2019; Van Essen et al. 2013), consist of measures that are cognitive in nature but also reflect affective and motivational processes. In detail, the emotion recognition task assesses the ability to infer affective states from facial expressions, while the delay discounting task measures preferences between smaller immediate versus larger delayed rewards. According to the socioemotional selectivity theory (SST; Carstensen 1992; Carstensen et al. 2003), as time horizons shorten, older adults actively prioritize emotionally meaningful goals and social harmony over novelty and long-term rewards. In this context, emotion recognition and delay discounting may become less reflective of abstract cognitive control and more indicative of motivational and affective orientations in the oldest age group. Together with the decreased segregation across cognitive functions, the increased integration of these processes with personality and psychological factors in later life highlights the increased interplay across cognition, personality, and mental health, blurring the traditional boundaries between these domains (Payne and Lohani 2020).

Openness to experience, on the other hand, clustered consistently within the *Cognition* community, from early to later adulthood. This pattern aligns with prior evidence linking Openness to cognitive functioning and its trajectory across the life span (Curtis et al. 2015; Nishita et al. 2019; Soubelet and Salthouse 2011) and suggests that intellectual curiosity, flexibility, and engagement remain closely intertwined with cognitive abilities from early to late adulthood. Nevertheless, this result warrants caution: The construct of Openness is known to vary across cultural contexts and, in Western samples in particular, tends to overlap more strongly with measures of intelligence (Church 2016).

The network comparison test (NCT) confirmed significant structural differences across age groups. Pairwise comparisons revealed that the Young Adults network differed substantially from both Middle-aged and Older Adults, whereas no significant differences were found between the two older groups. Arguably, this may suggest that the most pronounced reorganization of associations among personality, psychological, and cognitive variables occurs between early and mid-adulthood, followed by a relative stabilization from midlife to later life (Löckenhoff and Carstensen 2004). In terms of global strength—the overall level of connectivity within the network—the Older Adults network showed significantly weaker associations compared to the ones of the Young Adults network. The Middle-aged group displayed an intermediate value, not significantly different from the other groups. This pattern may suggest a progressive reduction in overall associations' strength with age, unfolding gradually rather than abruptly. Edge-specific analyses further clarified the nature of these changes. The largest differences were observed between Young and Older Adults, with 15 edges showing significant differences, most of which linked *Mental_Health* nodes within themselves or with *Externalizing* and *Cognition* variables. In contrast, the Middle-aged network differed from both Young and Older Adults on only 5 edges, primarily involving associations within the *Externalizing* community and between *Externalizing* and *Mental_Health* nodes. The only edges showing significant strength differences across all age groups were those connected to the Externalizing community. Specifically, associations between antisocial tendencies, rule-breaking, and depression progressively weakened with age, approaching zero in the oldest group. Likewise, the negative association between Externalizing behaviours and Agreeableness diminished and was nearly absent in older adults. By contrast, the positive link between antisocial tendencies and externalizing behaviours strengthened across the life span. Taken together, these findings indicate that the most pronounced and progressive age-related differences in edge strength involve the interplay between externalizing behaviours, personality traits, and internalizing symptoms. This finding, together with the decreasing global strength across age groups and the migration of sociocognitive variables towards the Mental_Health community in the Older Adults network may reflect a gradual reduction in the segregation of psychological functioning across the life span. Consistent with SST (Carstensen 1992; Carstensen et al. 2003), this convergence may reflect a shift towards emotionally and socially meaningful regulation goals in later adulthood.

Limitations

This study has several limitations that should be acknowledged. First, the delineation of age groups was constrained by the structure of the available datasets (HCP-YA: 22–36; HCP-A: 36–100), the use of different questionnaire versions across age ranges (ASR for younger participants versus OASR for those over 60), the presence of a small sample of participants aged 80 and above (that had therefore to be excluded from the analyses), and the need to maintain roughly balanced sample sizes (200–250 participants per group). Second, the relatively small sample size of the Older Adults group (209 participants) may have introduced survivor bias, limiting variability across individuals and capturing patterns that reflect only a partial ageing trajectory. The limited numerosity also reduced the number of variables that could be included in the analysis, which, following recommendations by Constantin and DeLiema (2018) and Constantin et al. (2023), had to be kept below 20. This restriction prevented the integration of social, physical, and sensory measures, which would have offered a more comprehensive view of ageing as a multidimensional process. Future releases of the HCP-Aging dataset are expected to provide broader coverage and may support such integration. Third, the cross-sectional design precludes strong causal inferences and limits conclusions about within-person developmental trajectories. Differences in network structure across groups could reflect cohort effects or unmeasured confounds rather than genuine age-related change. Longitudinal data will be essential to clarify the dynamic processes through which psychological and cognitive domains reorganize across adulthood. Finally, it must be pointed out that while exploratory graph analysis (EGA) reflects the current best practice for data-driven identification of network community structure and has shown high replicability in prior work (Golino et al. 2020), it remains an exploratory approach. Future studies using confirmatory techniques and testing for measurement invariance across age groups would help validate the robustness of these findings.

Conclusion

This study provides evidence of age-related differences in the organization of cognitive, personality, and psychological constructs, as revealed by network analysis. In young adults, four distinct communities were identified, including a division between lower and higher cognitive functions. In both middle-aged and older adults, however, all cognitive variables clustered into a single community, consistent with the dedifferentiation hypothesis and suggesting reduced specialization and greater interdependence across cognitive abilities with age. Additionally, two tasks with strong socioemotional relevance—emotion recognition and delay discounting—shifted from the *Cognition* to the *Mental_Health* community in older adults, indicating that processes with both cognitive and affective components may become increasingly integrated with personality and emotional dispositions later in life.

Altogether, these findings highlight structural changes in the relationships among psychometric variables across age groups, supporting the view that ageing is accompanied by functional reorganization. As the global population continues to age, understanding how the components of individuality interact and evolve across the life span is increasingly important. Beyond their theoretical contribution, these findings may help identify potential markers of vulnerability (e.g. stronger integration of socioemotional processes with mental health in later life) as well as protective factors (e.g. the enduring connection between Openness and cognition), informing interventions aimed at strengthening personality- and cognition-based resources to promote well-being in older adulthood. Finally, this study illustrates the value of network analysis in capturing age-related differences, moving beyond traditional compartmentalized approaches and offering new insights into the complex interplay among cognitive, personality, and psychological domains in ageing.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10433-025-00903-8.

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Data availability The raw data used in this study were obtained from the Human Connectome Project (HCP) and are subject to access restrictions imposed by the National Institutes of Health (NIH). Due to licencing agreements, the authors cannot redistribute the raw data. However, all R scripts and code used for analysis and visualization are publicly available on the Open Science Framework (OSF) at https://osf.io/9q74d/

Declarations

Competing interests The authors declare that they have no competing interests.

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