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Distinct Effects of Data Occupational Complexity On Cognitive Aging: Evidence for Dual Brain–Cognitive Reserve Pathways

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Abstract

Introduction: Occupational complexity is a major source of long-term cognitive stimulation across adulthood, yet its multidimensional effects on cognitive aging and their neural mechanisms remain unclear. This study examined how three dimensions of occupational complexity—data, people, and things—shape late-life cognitive performance, and whether brain reserve(BR) and cognitive reserve(CR) mediate these associations.

Methods: A total of 3,754 retirees meeting sex-specific age eligibility criteria were recruited from the Beijing Aging Brain Rejuvenation Initiative completed a battery of multidomain neuropsychological assessments and standardized occupational history assessments coded using O*NET-based ratings.. A subsample of 851 participants also underwent structural MRI. Linear models, structural equation modeling, and voxel-/surface-based morphometry were used to test (1) dimension-specific associations with cognitive domains, (2) links to global and regional brain structure, and (3) dual-reserve mediation pathways.

Results: Data complexity emerged as the primary protective dimension, independently predicting higher reasoning (β = 0.058), attention (β = 0.041), and reduced mild cognitive impairment(MCI) risk (− 5.7% after adjustment for education, $p < 0.05$; −14.3% unadjusted, $p < 0.001$). After accounting for data complexity, higher people complexity was associated with poorer working memory and language performance.. Things complexity, referring to demands related to tools and physical objects, showed no direct associations but demonstrated compensation via late-life leisure activities.

Neuroimaging showed that data complexity was uniquely associated with larger gray matter volume in frontotemporal–limbic regions and higher CR. Mediation models revealed that data complexity protected cognition via both BR and CR, with mediation effects observed across multiple cognitive domains..

Conclusions: Occupational complexity, particularly data complexity, is associated with enhanced cognitive aging outcomes, including improved reasoning, attention, and reduced mild cognitive impairment (MCI) risk. Neuroimaging revealed that data complexity predicts greater frontotemporal–limbic gray matter volume and higher cognitive reserve. Mediation analyses suggested dual reserve pathways, with cognitive reserve mediating multiple cognitive domains, while brain reserve influenced hippocampal and temporal regions. These findings underscore the role of occupational environments in promoting cognitive health and mitigating late-life MCI risk.

1 Introduction

The continuously accelerated aging of global population has made healthy cognitive aging a major public health challenge. Cognitive impairment is one of the most devastating health problems associated with aging and poses a particularly severe burden in China, where the absolute number of individuals living with dementia is the highest worldwide, exceeding 15 million and accounting for nearly one quarter of the global dementia population[1]. It becomes a crucial topic in healthy aging research to

identify modifiable protective factors for cognitive aging. In recent years, occupation has attracted a growing attention as a potential protective factor, on its own or as a result of education, for healthy cognitive aging[2, 3]. Because work takes a large proportion of time across lifespan, particularly in adulthood, occupational complexity may play a predominant role in cognitive functions, including cognitive trajectories well after retirement.

Theoretically, the “use it or lose it” hypothesis emphasized the promoting effect of continuous cognitive engagement on neuroplasticity[4]. Similarly, the theory of environmental complexity highlighted the cumulative effects of cognitive reserve (CR) as assessed by the characteristics of professional tasks (such as decision variations, conflicting information resolution)[5]. Most researchers use metrics of occupational complexity to examine the impact of occupations on cognitive abilities in older adults. Occupational complexity (OC), as a multi-dimensional concept to quantify cognitive stimulation, has advantages in two aspects: (1) it quantifies the complexity through objective characteristics of tasks; (2) it systematically covers a three-dimension concept of “data-people-things”[6], thus enabling the analysis of the effects of each dimension independently and their interactions on cognition. Briefly, data complexity refers to cognitive demands related to information processing, reasoning, and decision-making; people complexity captures the extent of interpersonal interaction, communication, and coordination at work; whereas things complexity reflects demands associated with handling tools, machines, or physical objects.

Most longitudinal studies have shown that high people complexity (e.g., management or education) is associated with a lower risk of dementia and better cognitive function, and the protective effect remains significant after controlling for education[7, 8]. The role of data complexity remains controversial: Some studies show that it can enhance processing speed and memory[9], while others suggest that prolonged high-intensity work may actually increase the risk of Alzheimer's disease due to chronic stress[10]. The influence of things complexity is generally weak and unstable, which may depend on the task novelty rather than the complexity itself[11]. Furthermore, the cognitive effect of occupational complexity on cognitive function is moderated by the retirement transition and leisure activities in old age, suggesting that the effect is context-dependency[12, 13]. Overall, high occupational complexity is generally associated with better cognitive ability in old age, with significant heterogeneity across dimensions.

Neuroimaging studies provide crucial evidence supporting the mechanisms of brain reserve (BR) and CR in relation to occupational complexity. BR (i.e., a neuroanatomic resource reflecting structural properties that afford surplus capacity to tolerate neuropathology) and CR (i.e., the acquired skills and flexible processing strategies that allow more efficient use of remaining neural resources) together can explain why individuals with similar brain pathology often show different clinical outcomes[14]. Research on BR and CR clarifies interindividual variability in cognitive aging trajectory, informs prevention strategies for dementia, and guides interventions to promote resilient cognitive aging[15, 16]. Experimental and observational studies further indicate that life-course activities — including mentally stimulating work —

modulate both reserves via neuroplastic mechanisms[17]. Furthermore, the relative contributions of BR and CR may differ across pathologies and cognitive domains[18].

Consistent with with reserve-based theories of cognitive aging rooted in environmental complexity, evidence suggests that occupational complexity contributes to brain reserve accumulation across the life course. Longitudinal and cross-sectional studies in older adults demonstrate that supervisory and managerial experience in midlife is associated with larger hippocampal and medial temporal gray matter volumes and substantially slower rates of late-life hippocampal atrophy, independent of demographic, genetic, and late-life lifestyle factors[19]. Extending these findings to earlier stages of adulthood, occupational cognitive complexity during early to midadulthood has also been linked to higher white matter integrity and superior executive functioning in midlife, indicating that work-related cognitive demands may shape neural substrates of reserve decades before old age[20]. These findings suggest that complex professional experiences promote BR accumulation, in light of the "brain maintenance" theory[21]. Furthermore, even when experiencing brain atrophy, individuals with high occupational complexity can maintain relatively preserved cognitive function[22], through CR by which the brain responds to aging and pathological changes by more efficient and flexible resource utilization. Moreover, different occupational complexity dimensions showed distinct effects on different brain regions. For example, high physical demands correlate with cortical thickness in pre- and postcentral gyri[23], whereas high-pressure working environment may be associated with the degeneration of the prefrontal cortex and the limbic structures[24, 25].

However, there remained several key issues understudied. First, it is unclear about the specific mechanisms through which different dimensions of occupational complexity affect cognitive function. In particular, the relative contributions of retirement timing and post-retirement lifestyle require further clarifications. Second, it remains unclear whether the effects might be mediated by BR, CR, or both. Finally, further research is needed to elucidate how occupational complexity contributes to post-retirement cognitive engagement and brain structural maintenance, and whether late-life activities reinforce or compensate for the reserve mechanisms established during one’s occupational years. Therefore, this study used a multi-modal data analysis approach to systematically examine the differential effects of different occupational complexity dimensions on cognitive function in old age. We aim to (1) analyze the heterogeneous effects of data, people, and things complexity on specific cognitive domains; (2) reveal the association patterns between different dimensions of occupational complexity and brain structural changes; and (3) construct a mediation model of “occupational complexity–BR/CR–cognitive function” to elucidate the associated cognitive protection mechanism. This study will provide a theoretical and empirical basis for developing cognitive intervention strategies based on occupational characteristics

2. Methods

2.1 Participants

A total of 3,754 community-dwelling retirees aged 50 years and older participated in the Beijing Aging Brain Rejuvenation Initiative (BABRI), an ongoing community-based prospective cohort study in China focusing on higher-order cognitive aging and its neural mechanisms (Fig. 1).The study protocol was approved by the Institutional Review Boards of the Beijing Normal University Imaging Center for Brain Research and Beijing Tiantan Hospital and was conducted in accordance with the Declaration of Helsinki. All participants provided informed consent in written format.

Participants were screened with the following inclusion criteria: (1) retired individuals (≥ 50 years for women, ≥ 55 years for men); (2) native Chinese speakers; (3) right-handed; and (4) with normal or corrected-to-normal vision and hearing, as well as the following exclusion criteria: (1) a history of major neurological disorders (e.g., stroke, intracranial lesions); (2) a current clinical diagnosis or a history of neuropsychiatric conditions (e.g., depression, schizophrenia, or epilepsy); and (3) a history of substance abuse (e.g., alcohol dependence or sedative abuse).

Among these participants, a sub-sample of 851 MRI eligible participants voluntarily underwent MRI scanning. All participants met the MRI safety requirements, with no metallic implants (e.g., dental prostheses, cardiac stents, orthopedic plates or screws), and had no history of claustrophobia, Ménière's disease, or other ear-related disorders that might interfere with MRI procedures. All participants provided written informed consent prior to scanning. No participant withdrew during image acquisition, and all scans were successfully completed with high image quality and minimal head motion artifacts. Participants completed T1-weighted structural MRI and an extensive cognitive battery within a month.

Mild cognitive impairment (MCI) was diagnosed according to Petersen's criteria[26]. Specifically, participants were classified as having MCI if they met the following conditions: (1) the presence of subjective cognitive complaints reported by the participant and/or an informant; (2) preserved general cognitive functioning, defined as a Mini-Mental State Examination (MMSE) score greater than 23; (3) intact activities of daily living, indicated by a score of 0 (no functional impairment) on both the Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL) scales; and (4) objective cognitive impairment in at least one cognitive domain, operationalized as performance 1.5 standard deviations below the normative mean on at least one neuropsychological test[27]. Participants who did not meet the diagnostic criteria for MCI were classified as cognitively normal, with neuropsychological test scores within 1.5 standard deviations.

2.2 Measures

2.2.1 Occupational Complexity

Occupational complexity was evaluated based on the matrix of U.S. occupations developed for the 1970 U.S. Census[28, 29] and standardized using the O*NET database to ensure cross-cultural comparability. Each participant's primary occupation—defined as the occupation held for at least five years—was rated along three dimensions: people complexity(0–8), data complexity(0–6), and things complexity(0–7). In

the original coding scheme, higher scores indicated lower occupational demands. For ease of interpretation, we reversed the scores so that higher values reflected greater occupational demands. The three dimensions were then summed to yield a total occupational complexity score ranging from 0 to 21, with higher scores indicating greater overall complexity[30].

2.2.2 Retirement Duration and Leisure Activities after Retirement

As the original dataset did not directly record the retirement duration, it was operationalized through retrospective calculation:

Retirement Duration = Baseline Survey Year − Official Retirement Year.

Leisure activities after retirement were assessed using a personal information questionnaire consisting of 23 items covering cognitive, social, and physical leisure activities. Participants were asked to recall their engagement in leisure activities during the past year, including reading, writing, attending senior university courses, playing chess, poker, or mahjong, and engaging in handcrafts. The frequency of each activity was defined as either “frequent” if being engaged several times per week or “rare” if being engaged for less than once per week. A weighted composite score across all 23 items was calculated, with higher scores indicating greater engagement in leisure activities in later life[31].

2.2.3 Neuropsychological Test and Personal Information Questionnaire

All participants completed a comprehensive neuropsychological battery to assess eight cognitive domains, including: (1) general cognition, assessed by the Mini-Mental State Examination (MMSE) total score; (2) episodic memory, assessed by the Auditory Verbal Learning Test (AVLT)—covering immediate recall (N1–N3), short-delay recall (N4), long-delay recall (N5), and total recall (N1–N5), and the Rey–Osterrieth Complex Figure Test (ROCF) delayed recall; (3) working memory, measured by the Digit Span Test (DST)—backward; (4) reasoning, assessed by the Similarities Test (SIM); (5) visuospatial processing, assessed by ROCF copy and the Clock Drawing Test (CDT); (6) language, evaluated by the Category Verbal Fluency Test (CVFT)—animal, vegetable, and fruit categories, and the Boston Naming Test (BNT); (7) attention, assessed by the Symbol Digit Modalities Test (SDMT) and the Trail Making Test A (TMT-A); and (8) executive function, assessed by the Trail Making Test B (TMT-B) and the Stroop Color-Word Test C (SCWT-C).

Demographic and health information were collected using a standardized personal information questionnaire, including age, sex, and years of education as demographic variables, and chronic conditions such as hypertension, hyperlipidemia, diabetes, coronary heart disease, and cerebral small vessel disease. The number of cardiometabolic conditions, together with age and sex, were used as covariates in subsequent statistical analyses.

2.3 Statistic Analysis

Analyses were conducted for both behavioral and neuroimaging data. All statistical analyses were performed using SPSS version 22.0 and R version 4.0. MRI morphological analyses were implemented using the Computational Anatomy Toolbox (CAT12; http://www.neuro.uni-jena.de/cat/) within the Statistical Parametric Mapping software (SPM12; https://www.fil.ion.ucl.ac.uk/spm/) running in the MATLAB (R2020a) environment. To improve interpretability of effect estimates, key continuous predictors were Z-standardized prior to analysis. Statistical significance was set at two-tailed $p < 0.05$, and corrections for multiple comparisons were applied using either the False Discovery Rate (FDR) or Family-Wise Error (FWE) method, as appropriate.

2.3.1 Behavioral Data

Outliers ($|Z| > 3$) were removed, and missing values were imputed using a linear regression method with 20 iterative estimations to ensure data completeness and robustness. Cognitive performance was evaluated across eight domains (general cognition, episodic memory, working memory, reasoning, visuospatial processing, language, attention, and executive function). Domain scores were Z-standardized and averaged to obtain composite indices; reverse-coded measures (e.g., TMT-A) were reciprocally transformed prior to standardization.

Descriptive statistics were used to summarize demographic and cognitive characteristics. Group differences across levels of occupational complexity (people, data, and things) were examined using independent-sample t tests and chi-square tests. To assess the independent effects of occupational complexity on cognitive domains, multivariable linear regression models were constructed, in which people, data, and things complexity were entered simultaneously, with sex, age, education years, retirement duration, and cardiometabolic conditions entered hierarchically as covariates.

Further, within a path analysis framework, the PROCESS macro (Model 1 and Model 4) was applied to examine the mediating role of late-life leisure activities and the moderating effect of retirement duration. Indirect effects were estimated using bias-corrected bootstrap procedures (5,000 resamples), and significance regions were determined via the Johnson–Neyman technique, distinguishing between “enhancement” and “compensation” patterns of association.

2.3.2 Neuroimaging

To investigate the neural correlates of occupational complexity and to test hypothesized brain reserve pathways, primary neuroimaging analyses focused on whole-brain morphometric measures using voxel-based morphometry (VBM) and surface-based morphometry (SBM).

VBM analyses involved whole-brain voxel-wise regression models and two-sample t tests to examine associations between occupational complexity dimensions and local gray matter volume, controlling for sex, age, retirement duration, cardiometabolic conditions, and total intracranial volume (TIV). SBM analyses were conducted using cortical thickness measures derived from the Desikan–Killiany atlas, with regression and group comparison models assessing associations between occupational

complexity dimensions and regional cortical thickness. Covariates in SBM analyses were identical to those used in the VBM models, excluding TIV.

As supporting analyses, associations between occupational complexity dimensions and global brain structural indices were examined, and exploratory region-of-interest (ROI) analyses based on the Automated Anatomical Labeling (AAL) atlas were performed to provide complementary regional validation of whole-brain findings.

All whole-brain analyses were corrected for multiple comparisons using the Family-Wise Error (FWE) or FDR method, as appropriate.

2.3.3 CR Quantification and Mediation Modeling

CR was quantified using the residual-based approach, which operationalizes cognitive reserve as the portion of cognitive performance not explained by structural brain integrity, an approach that has been well established in prior work[32–34]. Conceptually, this framework defines CR as better-than-expected cognitive functioning given measurable brain structure and relevant covariates.

First, overall cognitive performance (observed value, Y_{cog})was treated as the dependent variable, and total gray matter volume (X_{GMV})as the independent variable. GMV was selected because it represents a global macrostructural marker of brain integrity that has been explicitly incorporated into residual-based neuroimaging models of cognitive reserve, particularly in aging and neurodegenerative contexts[35].A multiple linear regression model was constructed, controlling for sex(X_{sex}), age(X_{age}), retirement duration(X_{retire}), cardiometabolic conditions($X_{disease}$), and total intracranial volume (X_{TIV}):

$$Y_{cog} = \beta_0 + \beta_1 X_{GMV} + \beta_2 X_{sex} + \beta_3 X_{age} + \beta_4 X_{retire} + \beta_5 X_{disease} + \beta_6 X_{TIV} + \epsilon$$

The predicted cognitive score was then computed as:

$$hat: Y_{cog} = \hat{\beta}_0 + \hat{\beta}_1 X_{GMV} + \hat{\beta}_2 X_{sex} + \hat{\beta}_3 X_{age} + \hat{\beta}_4 X_{retire} + \hat{\beta}_5 X_{disease} + \hat{\beta}_6 X_{TIV}$$

CR was defined as the residual difference between the observed and predicted cognitive scores:

$$CR = Y_{cog} \hat{-} Y_{cog}$$

Higher CR values indicate better-than-expected cognitive performance given an individual's level of brain structure. Differences in CR between occupational complexity groups were examined using t tests, and associations between continuous measures of occupational complexity and CR were assessed using partial correlations and multivariable regression models controlling for the same covariates.

To evaluate whether CR functioned as a pathway linking occupational complexity to cognitive performance, mediation models were constructed using the PROCESS macro with 5,000 bootstrap resamples. These models estimated the indirect effect of occupational complexity on cognition through

CR while adjusting for demographic and health variables. Similar mediation analyses were then conducted to examine BR as an alternative pathway, employing the same modeling strategy and covariates.

2.3.4 Model Robustness and Validation

All regression models were evaluated for residual normality and multicollinearity among predictors, including the three occupational complexity dimensions and covariates, with variance inflation factors (VIFs) below 5, indicating acceptable model fit. The findings remained consistent across different sampling strategies and covariate adjustments, supporting the robustness of the results.

3. Results

3.1 Demographic and Cognitive Characteristics

In the total sample (N = 3,754), participants in the high occupational complexity group were older, more often male, and had more years of education. They also engaged more frequently in cognitive, social, and physical activities, and exhibited lower levels of depressive symptoms, body mass index, and a lower prevalence of cardiometabolic conditions (all $p < .05$).

3.2 Associations Between Occupational Complexity Dimensions and Cognitive Function

Across multiple cognitive domains, data complexity demonstrated a robust and consistent positive association with cognitive performance. Before controlling for education, data complexity predicted performance across all domains except for executive function (standardized β = 0.057–0.109, all $p < .001$) and was associated with a 14.3% reduction in MCI risk ($p < .001$). After controlling for education, associations with global cognition, episodic memory, working memory, reasoning, visuospatial processing, and attention remained significant (β = 0.016–0.058, all $p < .05$), corresponding to a 5.7% reduction in MCI risk ($p < .05$). The people complexity was only associated with reasoning (β = 0.034, $p < .001$) and attention (β = 0.018, $p < .05$), whereas the things complexity showed no significant effects.

Moderation analyses indicated that retirement duration significantly moderated the association between occupational complexity and cognitive performance. Specifically, the positive effect of the data complexity on visuospatial processing was stronger with increasing retirement duration. (interaction β = 0.002, $p = .029$) and enhanced the predictive effect of the people complexity on visuospatial processing (interaction β = 0.003, $p = .001$), suggesting that the benefits of occupational complexity may accumulate over time.The moderating effects of retirement duration on the associations between occupational complexity dimensions and visuospatial processing are visually depicted in Fig. 2.

Mediation analyses further suggested that late-life activities constituted key behavioral pathways linking occupational complexity to cognitive performance. Specifically, data complexity was indirectly associated with attention through engagement in intelligent activities. This indirect pathway showed

conditional effects ranging from 0.0071 to 0.0080 across low, medium, and high retirement-duration strata and was consistently stronger than the corresponding pathways through social activities (0.0028–0.0036) and physical activities (0.0019–0.0024), indicating that intelligent activity represented the strongest and most stable behavioral mediator linking data complexity to attention..In contrast, people complexity demonstrated a weaker but significant indirect association with visuospatial processing through social activities, with effects varying across retirement duration (0.0001–0.0018) .

Moderated mediation models further revealed compensatory effects among individuals with low things complexity. Specifically, these participants showed greater cognitive gains in multiple domains, including episodic memory and attention, through more frequent intelligent (β = 0.19–0.24, $p < .01$) and social activities (β = 0.15–0.18, $p < .05$). Enhancing effects were observed only for reasoning (β = 0.12, $p < .05$) and executive function (β = 0.09, $p < .05$).The moderated mediation models illustrating the pathways from occupational complexity to cognitive outcomes through intelligent activity are presented in Fig. 3.

3.3 BR as a Pathway Linking Occupational Complexity to Cognition

To establish the structural basis for mediation analyses, we first examined the associations between occupational complexity and brain morphology in the MRI subsample. After adjusting for demographic and health covariates, regression analyses on global brain measures indicated that data complexity significantly predicted larger intracranial volume (β = 4.93, $p < .05$), whereas its associations with total gray matter and white matter volumes were not statistically significant. Region-specific analyses revealed robust structural correlates. After FDR correction, several associations remained significant (Fig. 4), including greater cortical thickness in the right inferior temporal gyrus for data complexity ($p = .011$), and significant associations of things complexity with the right ventrolateral thalamic nucleus and the left middle frontal gyrus (both FDR-corrected $p < .05$). People complexity showed negative associations with cortical thickness in both the left anterior cingulate cortex (FDR-corrected $p < .05$) and the left inferior orbital frontal gyrus (FDR-corrected $p = .015$). These findings indicate that data-related occupational demands provide the strongest and most spatially extensive neural correlates relevant for subsequent brain-reserve analyses.

Building on these structural associations, we then tested whether occupational complexity influenced cognitive outcomes via BR, indexed by hippocampal gray matter and regional cortical thickness. Hippocampal volume was selected as it reflects episodic memory and global cognition, and larger volume has been linked to experiences that increase brain reserve[36–38]. Cortical thickness was included as it captures local neuronal integrity, with greater thickness associated with higher reserve and better tolerance to cortical loss[15, 39, 40]. As shown in Fig. 5, mediation models revealed that data complexity exerted significant indirect effects on multiple cognitive domains through structural markers of BR. Specifically, higher data complexity predicted greater left hippocampal gray matter volume and increased cortical thickness in the right inferior temporal gyrus, which in turn mediated performance in general cognition (β = 0.005–0.006, $p < .05$), episodic memory (β = 0.004, $p < .05$), language (β = 0.004, p

< .05), and attention (β = 0.004, *p* < .05). A small negative indirect effect was observed for executive function (β = − 0.005, *p* < .05), suggesting domain-specific differences. While data complexity–related structural adaptations generally benefited memory, language, and attention, their influence on executive function was limited, consistent with prior findings that cognitive and brain reserve often show weaker effects on executive domains compared to memory or attention[18, 41, 42].

3.4 CR as a Pathway Linking Occupational Complexity to Cognition

CR was quantified using a residual-based modeling approach (see Methods) and examined as a potential mediator between occupational complexity and cognitive function. After adjusting for sex, age, years of education, and cardiometabolic conditions, data complexity remained an independent predictor (β = 0.19, *p* = .018).

Mediation analyses demonstrated that CR played a central role in linking data complexity to cognitive performance. The detailed mediation effects of data complexity on cognitive domains through CR are summarized in Fig. 5. CR significantly mediated the associations between data complexity and global cognition, reasoning, episodic memory, visuospatial processing, language, and executive function, with indirect effects ranging from β = 0.01 to 0.03 for most domains, and all 95% bootstrap confidence intervals excluding zero. A negative indirect effect was observed for executive function. Partial mediation effects were observed for working memory and attention. The largest total effect was observed for attention (β = 0.068, *p* < .001).

Exploratory, uncorrected analyses further suggested potential contributions of the right inferior temporal gyrus and left hippocampus; however, these effects did not survive FDR correction. Together, these findings indicate that CR serves as a key mechanism through which data complexity supports cognitive performance in later life.

(b) Forest plot displaying the standardized indirect effects (β) of occupational data complexity on eight cognitive domains. Estimates and 95% confidence intervals are shown for three specific pathways, distinguished by color and shape: Light blue circles: Indirect effects via the CR pathway (residual-based score), representing functional reserve. Royal blue squares: Indirect effects via the BR pathway mediated specifically by the left hippocampus. Navy blue triangles: Indirect effects via the BR pathway mediated specifically by the right inferior temporal gyrus. Error bars indicate 95% bias-corrected bootstrap confidence intervals. Intervals that do not cross the vertical dashed line (*x* = 0) are statistically significant (*p* < 0.05). The right-hand column lists the precise standardized point estimates and [95% CI] for each path. Note that while CR mediates effects across most domains, structural BR mediation is domain-specific, and a negative indirect effect is observed for executive function.

4 Discussion

In the present sample, occupational complexity demonstrated clear dimension-specific associations with later-life cognition and brain structure. Data complexity showed the most robust and generalized benefits, predicting higher global cognition, reasoning, and attention after adjustment for education, demographic covariates, and cardiometabolic conditions. It was also associated with a lower risk of MCI and exhibited the broadest indirect pathways through CR and structural markers. In contrast, people complexity showed selective associations with reasoning and attention but was negatively related to cortical thickness in the left anterior cingulate cortex (ACC-L), whereas things complexity displayed only modest effects largely restricted to sensorimotor regions. Late-life cognitive and social engagement partially mediated several of these associations, and retirement duration amplified specific pathways.

The cognitive and neural protective effects of occupational complexity exhibited marked dimensional heterogeneity. Data complexity emerged as the most robust protective factor in this study. Even after controlling for education, it independently contributed to global cognition, reasoning, and attention, and lower risk of MCI, consistent with previous findings that occupations with high cognitive demands delay cognitive decline[7, 9]. Mechanistically, data complexity was associated with larger gray matter volumes and greater cortical thickness in frontotemporal–limbic regions, including the hippocampus and inferior temporal gyrus, and was the only dimension showing a significant positive correlation with CR quantified via the residual-based approach.

One plausible explanation for these advantages lies in the core cognitive features of data-intensive occupations, which emphasize relational processing, abstract reasoning, and the integration of multiple information streams. Tasks characterized by high data complexity require individuals to simultaneously coordinate multiple variables and rules, a form of relational complexity that has been shown to recruit large-scale cognitive control networks involving frontoparietal and cingulo-opercular systems, with the dorsolateral prefrontal cortex supporting flexible, trial-by-trial control and integration of task sets[43].

In addition, data-intensive work is associated with information-rich yet efficient neural processing. Neuroimaging evidence suggests that higher-order cognitive engagement is supported by brain activity patterns that are both highly informative and highly compressible, reflecting optimized representational efficiency rather than increased neural redundancy[44]. Such information-rich yet compressible neural activity patterns may reflect an efficient and flexible mode of processing during high-level cognitive engagement. This characterization is conceptually aligned with descriptions of neural efficiency in the cognitive reserve framework.

Finally, the sustained and cumulative nature of data-related cognitive demands may facilitate long-term neuroplastic adaptation. Continuous engagement in abstract problem solving and decision-making has been linked to synaptic plasticity mechanisms that support adaptive reorganization of neural systems across multiple temporal scales[45]. Consistent with a life-course perspective, higher occupational cognitive complexity earlier in adulthood has been associated with better white matter integrity and executive function in midlife, capturing a potential pathway through which prolonged exposure to data complexity contributes to reserve accumulation over time[20].

These results indicate that data-intensive occupations can simultaneously enhance brain and CRs, optimizing both brain structure and neural efficiency, thereby providing broad protection across multiple cognitive domains[19, 21, 22].

We observed that people complexity did not uniformly confer cognitive benefits: although it modestly predicted better reasoning, it was also associated with poorer working memory and language performance, as well as reduced cortical thickness in the left anterior cingulate cortex (ACC-L). This pattern contrasts with several studies reporting protective effects of “people-oriented” work. For example, higher lifetime people complexity has been linked to better executive and episodic memory performance in the KHANDLE cohort[46], and to lower risks of MCI/dementia and greater MRI-based BR in the SNAD study[47]. Yet other community-based or cross-cultural studies have failed to detect consistent cognitive benefits of people complexity after accounting for education, socioeconomic gradients, or heterogeneity in work environments[48], suggesting that the effects of this dimension are not universally positive.

Three sources of heterogeneity may help reconcile the discrepancies between our findings and prior reports suggesting protective effects of people complexity. One important source lies in cultural and occupational-context differences. Studies reporting strong benefits of people complexity typically draw samples with higher education, stable professional careers, and limited involvement in manual or informal labor[9, 47, 49]. In these contexts, interpersonal demands often reflect cognitively stimulating managerial or supervisory responsibilities. In contrast, our community-based cohort likely includes a broader range of people-oriented occupations—particularly service and caregiving roles characterized by low autonomy and high emotional demands. Such roles may transform “social engagement” into chronic stress rather than cognitive stimulation, echoing recent concerns regarding occupational generalizability[50, 51].

Beyond contextual variation, methodological heterogeneity in the operationalization of people complexity constitutes a further source of inconsistency across studies. The present study employs the Dictionary of Occupational Titles (DOT), which quantifies interpersonal complexity based on the frequency and intensity of interactions with others. Other studies have also used later occupational coding frameworks such as O*NET; however, both systems share a key limitation: they collapse qualitatively distinct forms of interpersonal demands into a single composite dimension. Methodological reviews have noted that such frameworks often fail to differentiate cognitively stimulating social tasks from emotionally taxing or low-autonomy interactional roles[52, 53]. This conflation reduces the ability of occupational complexity measures to capture the critical distinction between cognitively stimulating and emotionally draining forms of interpersonal work, potentially contributing to the mixed pattern of cognitive gains and structural costs observed for the interpersonal dimension in our cohort.

Finally, differences in the motivational and regulatory demands of interpersonal work offer a plausible mechanistic account for the observed trade-offs. High-autonomy interpersonal roles typically support goal-directed cognitive engagement and recruit prefrontal systems associated with reserve accrual,

including the frontal pole and dorsolateral prefrontal cortex[54, 55]. In contrast, service- and caregiving-oriented roles impose sustained emotional labor, requiring continuous emotion regulation, conflict management, and behavioral compliance, which is associated with elevated allostatic load, reduced cognitive flexibility, and executive-resource competition[56, 57]. The magnitude of these trade-offs may further be shaped by cultural norms regarding social roles and relational expectations. In collectivistic contexts that emphasize interdependence and social harmony, interpersonal occupations often carry stricter demands for emotional regulation, role compliance, and collaboration, potentially intensifying cognitive and physiological costs[58–60]. By contrast, in individualistic contexts valuing autonomy and self-expression, similar interpersonal demands may be experienced as less taxing, allowing more open communication and active engagement[58, 61]. Collectively, these mechanisms are consistent with the "resource competition" hypothesis aligns with the profile observed in our cohort, wherein modest improvements in reasoning coexisted with deficits in working memory and language.

The protective effects of things complexity were the most limited, being associated only with gray matter volume in motor-related regions and failing to contribute to CR, which may be because occupations high in things complexity predominantly involve repetitive, routine tasks with limited innovation or problem-solving, providing minimal stimulation to neural circuits critical for higher-order cognitive processes[62, 63], reflecting the constraints of mechanized tasks in driving higher-order neuroplasticity[64]. However, individuals with low things complexity could achieve cross-domain cognitive compensation through engagement in late-life cognitive and social activities, highlighting the value of alternative environmental stimulation[13].

Furthermore, distinguishing between BR and CR enabled a more precise delineation of the neural pathways through which occupational complexity contributes to cognitive aging. Data complexity was the only dimension simultaneously associated with preserved structural markers and higher CR quantified using the residual-based approach (Methods). Together, these patterns support a dual-pathway model, in which structural preservation provides an anatomical buffer (BR), whereas the residual cognitive advantage reflects more efficient or flexible neural processing (CR). Importantly, the CR index captures variance in cognitive performance unexplained by contemporaneous brain structure, allowing it to be empirically separable from BR. Whereas brain reserve captures the absolute capacity of neural resources, including their structural quantity and integrity, cognitive reserve reflects the efficiency and adaptability of the neural processes that support performance despite age-related structural decline. This methodological distinction permits the dissociation of structural preservation from processing-level compensation, which is essential for isolating the unique contribution of occupational experiences.

At the regional level, the hippocampus—central to episodic encoding, retrieval, and attentional allocation—has been consistently associated with superior cognitive performance in aging cohorts and frequently identified as a structural substrate of occupational or lifestyle reserve proxies[65, 66]. The inferior temporal gyrus (ITG), which supports high-level visual–semantic representation and object/word recognition, may further contribute to cross-domain transfer effects involving language, reasoning, and visuospatial

processing. Recent evidence indicates that occupation-related reserve proxies correspond to increased ITG volume and to CR-related moderation of pathology–performance associations[67].

By contrast, people- and things-related complexity showed more restricted and domain-specific neural correlates. People complexity was linked to a localized reduction in cortical thickness within the left anterior cingulate cortex (ACC-L) and did not coincide with higher residual cognitive reserve. Considering the ACC's well-established involvement in conflict monitoring, emotion regulation, and effort allocation—as well as its documented susceptibility to prolonged emotional and social demands—this focal reduction in thickness is more plausibly interpreted as reflecting chronic functional load on this region[68]. This neural profile is consistent with the selective pattern of cognitive effects observed in the current study, in which slight gains in reasoning ability coexisted with lower performance in working memory and language. In contrast, things complexity was primarily associated with structural variation in sensorimotor cortices, which support motor and perceptual functions, suggesting that object- or skill-focused occupations may enhance localized BR without generating cross-domain CR benefits[23, 69]. Together, these dissociable patterns highlight the complementary roles of BR and CR in the context of the present study, in which BR was operationalized through region-specific structural markers, including left hippocampal volume and right inferior temporal gyrus cortical thickness, and CR was quantified using a residual-based modeling approach capturing cognitive performance beyond what could be predicted from brain structure. This methodological distinction likely contributes to the observed dissociation: BR reflects structural reinforcement shaped by data-related occupational demands, whereas CR captures broader, task-independent processing advantages, allowing individuals to maintain cognitive performance despite age-related or localized structural decline.

Moreover, from a life-course perspective, this study confirmed that the protective effects of occupational complexity can persist and be reinforced after retirement through engagement in late-life activities. Path analyses indicated that high occupational complexity, particularly in the data dimension, served as an important predictor of sustained participation in cognitively stimulating activities post-retirement. Notably, retirement duration positively moderated the pathway from "occupational complexity → cognitive activity → cognitive function." This suggests that cognitive and BR accumulated during the occupational period provide a solid foundation for cognitive health in later life, while leisure activities after retirement play a role in activating and maintaining these reserves. As retirement duration increases, the protective effects, grounded in occupational experience and driven by late-life engagement, become increasingly pronounced, forming a synergistic effect across the lifespan[70]. Importantly, the observation that these protective effects become more evident with longer retirement duration may reflect an adaptive process during the post-retirement transition. The initial phase after retirement can involve a sudden loss of structured mental demands, which may temporarily attenuate cognitive benefits, as suggested by longitudinal findings showing accelerated decline in some cognitive domains immediately post-retirement[71]. Over time, however, individuals with higher occupational complexity are likely better equipped to navigate this transition, gradually re-establishing cognitively stimulating routines and engaging in leisure activities that reinforce previously accumulated cognitive

and brain reserves[72]. These findings emphasize the long-term value of cognitive stimulation during the occupational period and integrate it with lifestyle factors in retirement to form a coherent model of healthy cognitive aging.

The present study makes several key contributions to the literature on occupational complexity and cognitive aging. By disentangling the heterogeneous effects of the three occupational complexity dimensions, our findings refine and extend the theoretical framework of environmental complexity. Building on this distinction, we further propose and empirically validate a dual-pathway model linking occupational complexity to both brain structure and cognitive reserve, thereby elucidating their synergistic yet dissociable mechanisms. Importantly, by situating these pathways within a life-course perspective, the study highlights the dynamic interplay between midlife occupational experience and late-life engagement, offering an integrative account of cognitive aging trajectories.Taken together, these findings not only consolidate previously fragmented evidence but also yield actionable implications for the development of targeted cognitive interventions and policy strategies aimed at promoting healthy aging.

Nonetheless, certain limitations should be noted. The cross-sectional and short-term follow-up design restricts causal inference. Although the O*NET indicators offer objective quantification, they cannot fully capture within-occupation heterogeneity. In addition, the cognitive reserve index derived in the present study reflects a model-dependent construct that is contingent on the specific cognitive and neuroanatomical variables included in the estimation procedure. Because CR was inferred from individual differences in cognitive performance relative to structural brain measures, its magnitude may vary with the choice of cognitive domains assessed and the extent to which the selected brain markers capture relevant neurobiological variation. As a result, the residual-based CR measure may incorporate sources of variance that are not uniquely attributable to reserve-related processes, and its comparability across studies employing different variable sets may be limited. Finally, potential biases in self-reported late-life activities warrant caution. Future studies should adopt longitudinal designs with harmonized cognitive and neural assessments to further refine reserve quantification and to validate the dynamic effects of occupational complexity on cognitive aging, while exploring occupation-specific intervention strategies tailored to diverse occupational trajectories.

5 Conclusion

This study provides large-scale behavioral and neuroimaging evidence that occupational complexity constitutes an important life-course determinant of late-life cognitive health. Data complexity stands out as the primary driver, conferring broad cognitive benefits through coordinated enhancement of BR and CR. In contrast, people and things complexity exert narrower or context-dependent effects, suggesting substantial heterogeneity in how occupational environments shape cognitive aging. By delineating these domain-specific pathways and identifying reserve-based mechanisms, our findings highlight occupational complexity as a modifiable and quantifiable target for dementia prevention strategies.

Interventions that enrich cognitive stimulation during working life or reinforce reserve accumulation after retirement may yield long-term benefits for maintaining cognitive resilience in aging populations.

Abbreviations

BR
Brain Reserve
CR
Cognitive Reserve
MCI
Mild Cognitive Impairment
MRI
Magnetic Resonance Imaging
BABRI
Beijing Aging Brain Rejuvenation Initiative
ADL
Activities of Daily Living
IADL
Instrumental Activities of Daily Living
MMSE
Mini-Mental State Examination
AVLT
Auditory Verbal Learning Test
ROCF
Rey–Osterrieth Complex Figure Test
DST
Digit Span Test
SIM
Similarities Test
CDT
Clock Drawing Test
CVFT
Category Verbal Fluency Test
BNT
Boston Naming Test
SDMT
Symbol Digit Modalities Test
TMT
Trail Making Test
SCWT-C

Stroop Color-Word Test C
FDR
False Discovery Rate
FWE
Family-Wise Error
VBM
Voxel-Based Morphometry
SBM
Surface-Based Morphometry
ROI
Region of Interest
AAL
Automated Anatomical Labeling
GMV
Gray Matter Volume
TIV
Total Intracranial Volume
VIFs
Variance Inflation Factors
SD
Standard Deviation
ITG
Inferior Temporal Gyrus
ACC
Anterior Cingulate Cortex

Declarations

Ethics approval and consent to participate

The study was conducted in accordance with the Declaration of Helsinki and was approved by the institutional review board (IRB) at the State Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University (protocol code was ICBIR_A_0041_002_02). All participants provided written informed consent for our protocol.

Consent for publication

Not applicable

Competing interests

The authors declare no competing interests.

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Author Contribution

LRNX, JW, XL, and ZJZ contributed to the conception and design of the study; LY, JWL, and TL contributed to the acquisition and analysis of data; LRNX, and LY contributed to drafting the original manuscript and preparing the figures; LXY, KWC, XL, and ZJZ contributed to the reviewing and editing the manuscript. All authors approved the final manuscript.

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Data Availability

The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

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Figures

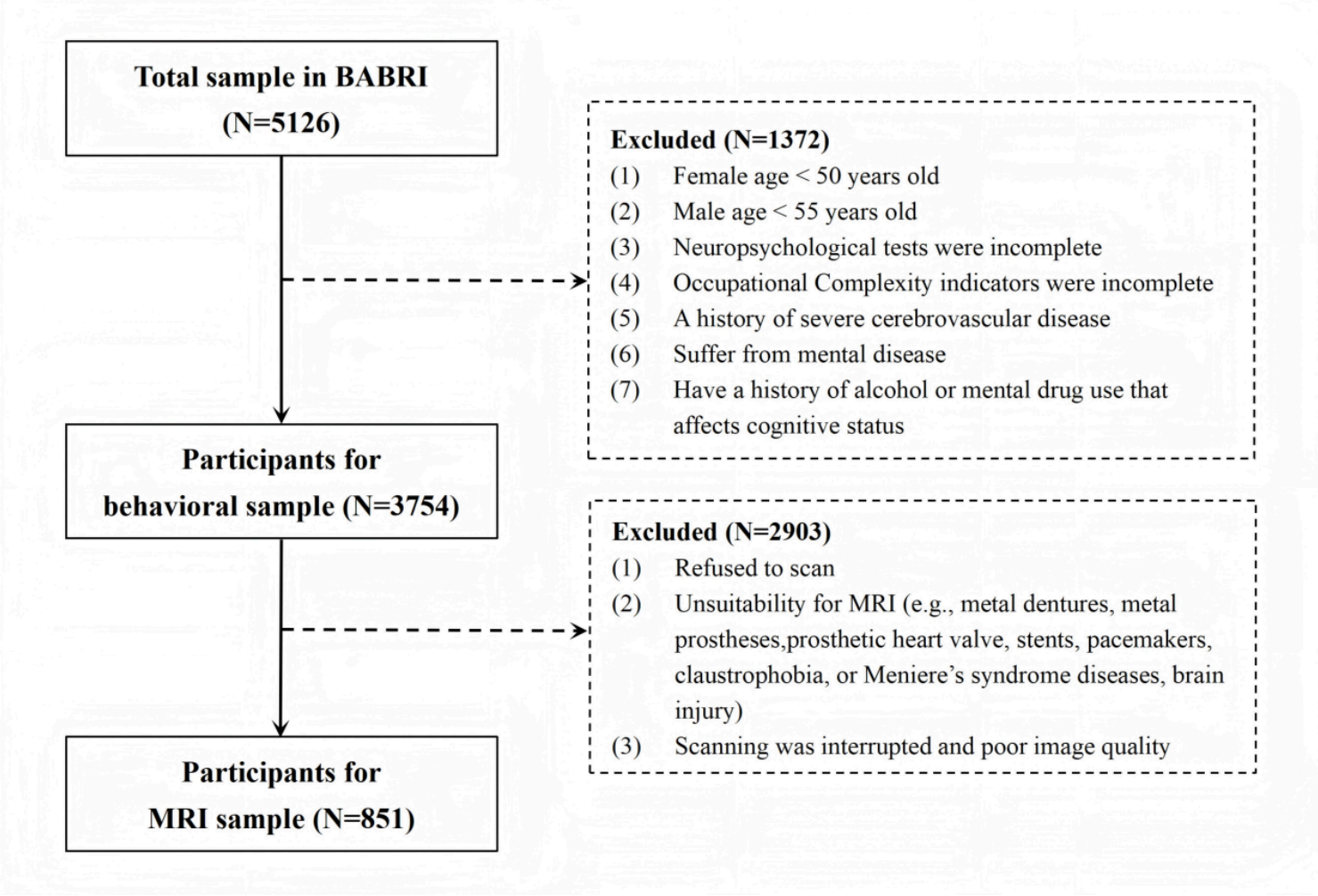


Figure 1

Participant flow chart. BABRI: Beijing Aging Brain Rejuvenation Initiative

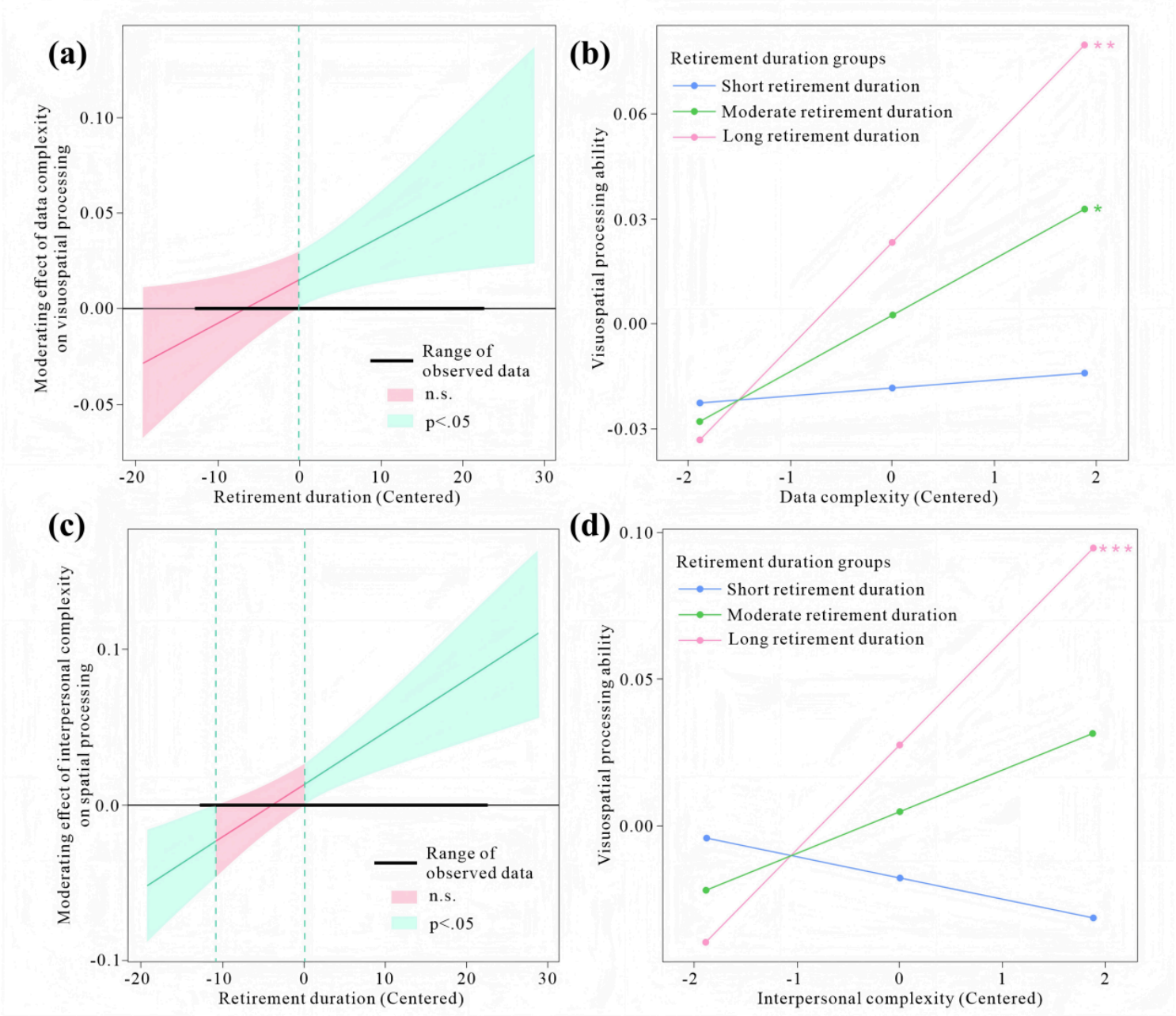


Figure 2

Moderating effects of retirement duration on the associations between occupational complexity dimensions and visuospatial processing

Note. (a) Johnson–Neyman analysis shows the conditional effect of data complexity across the full range of retirement duration. The y-axis represents the regression coefficient (β) for data complexity. (b) Simple slopes depict the effect of data complexity at low (−1 SD), medium (mean), and high (+1 SD) levels of centered retirement duration. (c) Johnson–Neyman analysis shows the conditional effect of people complexity across the full range of retirement duration. The y-axis represents the regression coefficient (β) for people complexity. (d) Simple slopes depict the effect of people complexity at low (−1 SD), medium (mean), and high (+1 SD) levels of centered retirement duration. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

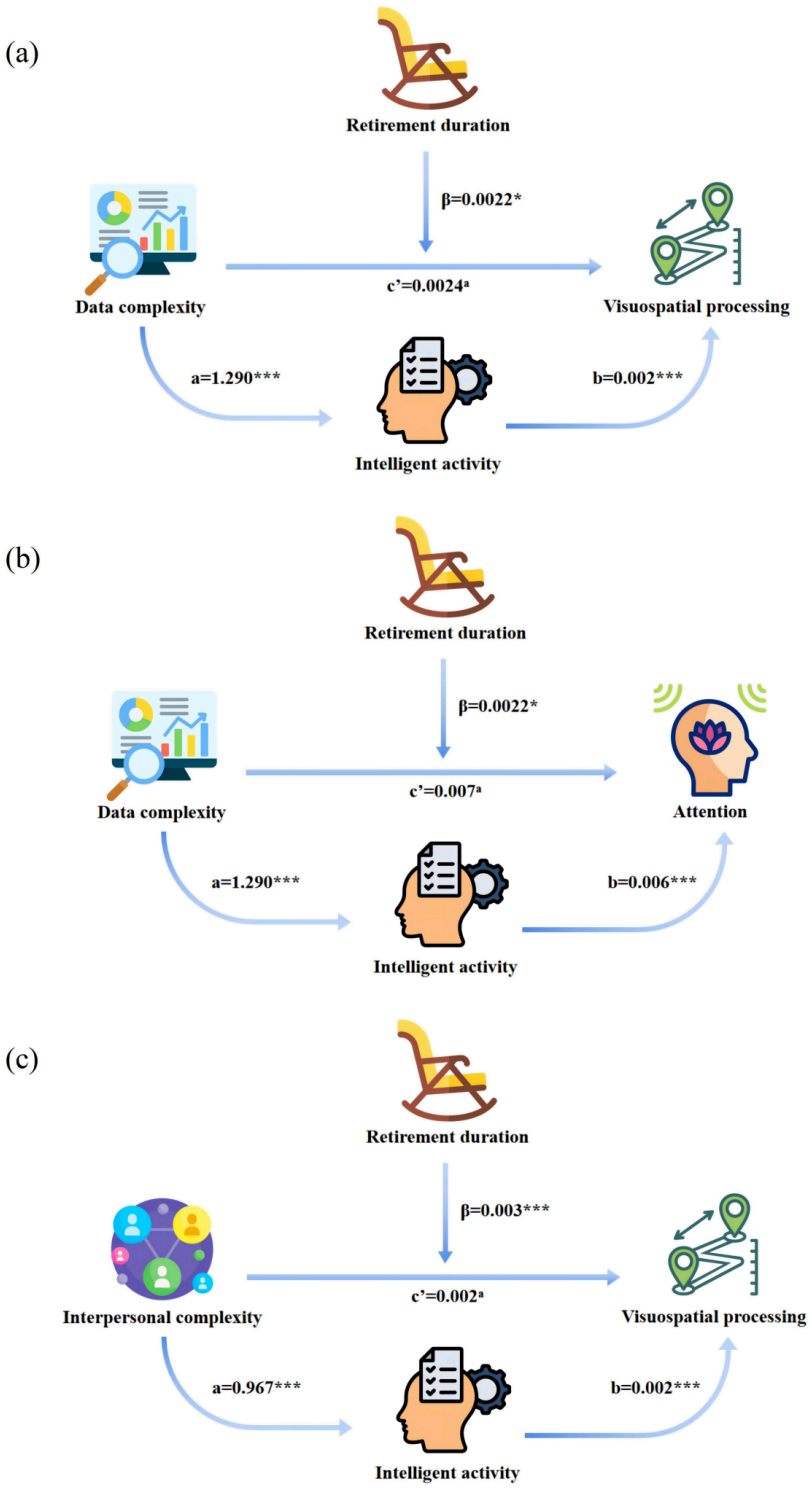


Figure 3

Moderated Mediation Models of Occupational Complexity on Cognitive Outcomes

Note. Path coefficients are unstandardized. These models tested whether intelligent activity mediated the effects of occupational complexity on cognitive performance, and whether this mediation was moderated by retirement duration. Subplots show different complexity–outcome pairs: (a) data

complexity → visuospatial processing, (b) data complexity → attention, and (c) people complexity → visuospatial processing. All models were adjusted for sex, age, education, and cardiometabolic conditions. *p< 0.05; ***p< 0.001.

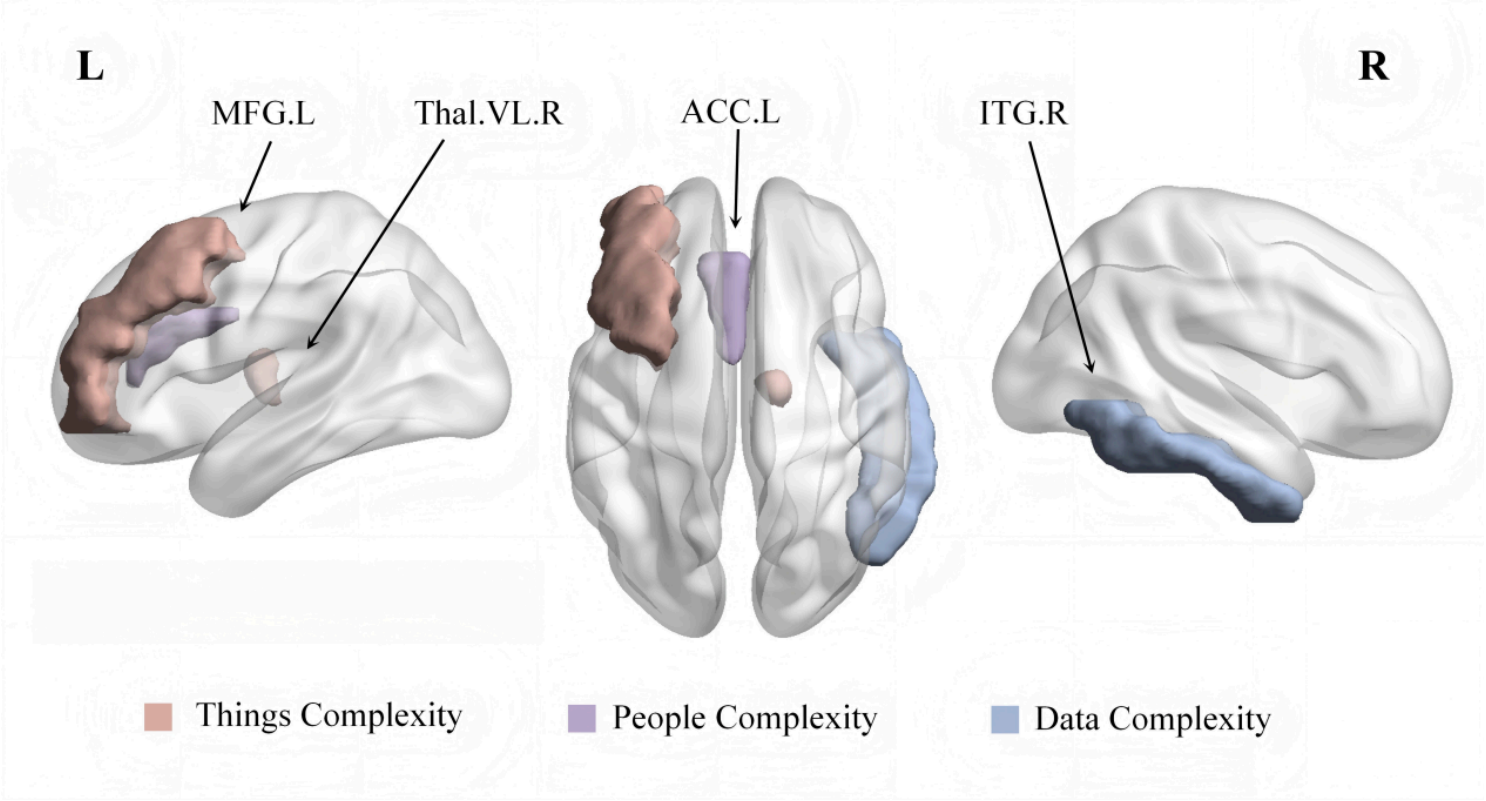


Figure 4

Structural correlates of occupational complexity across the cortex.

Note. Colors correspond to occupational complexity dimensions: green = data, yellow = things, blue = people.R-ITG, right inferior temporal gyrus; L-MFG, left middle frontal gyrus; R-VL Thal, right ventrolateral thalamic nucleus; L-ACC, left anterior cingulate cortex.

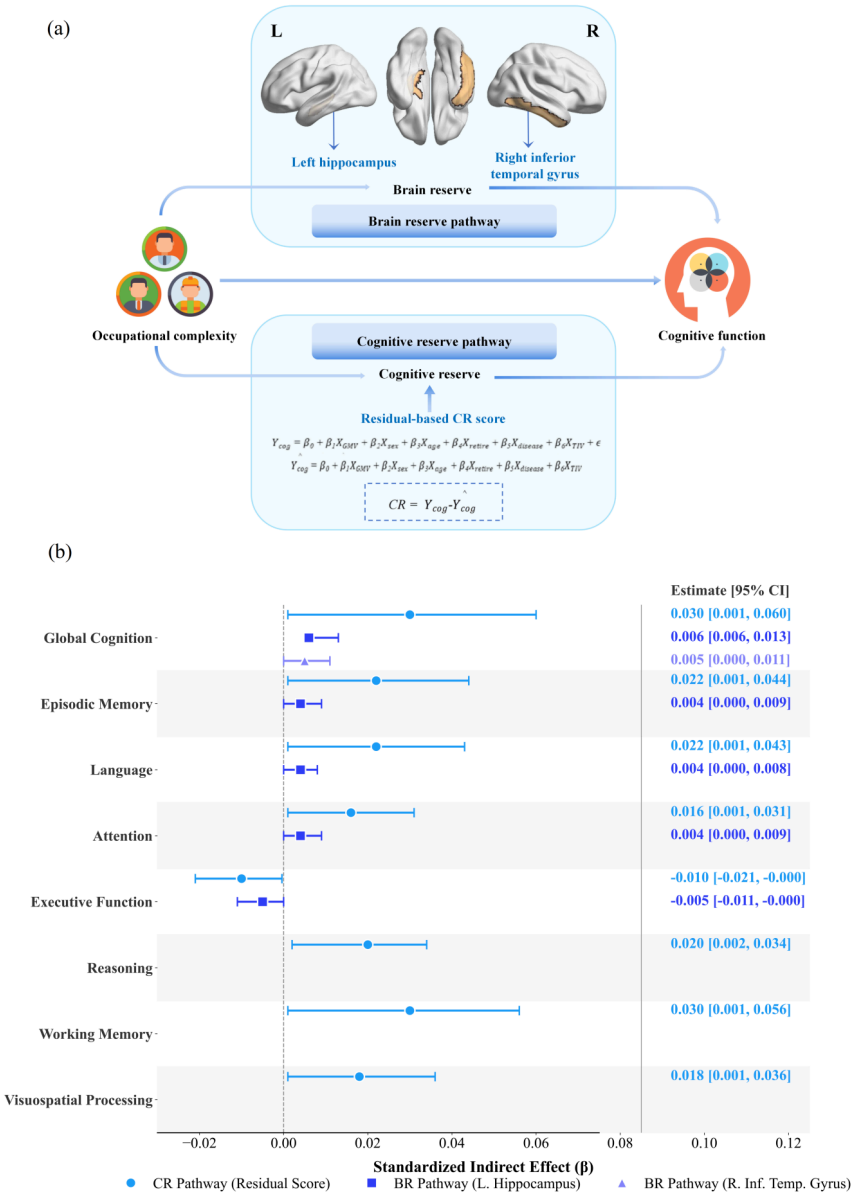


Figure 5

Distinct neurostructural and functional mediation pathways linking occupational data complexity to cognitive preservation.

Note. (a) Schematic representation of the dual-pathway mediation model. The model illustrates how occupational data complexity contributes to cognitive function through two distinct mechanisms: a

structural BR pathway (top panel) and a functional CR pathway (bottom panel). The BR pathway is indexed by the structural integrity of specific brain regions, including the left hippocampus and right inferior temporal gyrus. The CR pathway is quantified with a residual-based latent score reflecting functional adaptability.

(b) Forest plot displaying the standardized indirect effects (β) of occupational data complexity on eight cognitive domains. Estimates and 95% confidence intervals are shown for three specific pathways, distinguished by color and shape: Light blue circles: Indirect effects via the CR pathway (residual-based score), representing functional reserve. Royal blue squares: Indirect effects via the BR pathway mediated specifically by the left hippocampus. Navy blue triangles: Indirect effects via the BR pathway mediated specifically by the right inferior temporal gyrus. Error bars indicate 95% bias-corrected bootstrap confidence intervals. Intervals that do not cross the vertical dashed line (x=0) are statistically significant ($p < 0.05$). The right-hand column lists the precise standardized point estimates and [95% CI] for each path. Note that while CR mediates effects across most domains, structural BR mediation is domain-specific, and a negative indirect effect is observed for executive function.