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Complexity of Work With People: Associations With Cognitive Functioning and Change After Retirement

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Retirement has been associated with cognitive decline. However, the influence of specific job characteristics like occupational complexity on post-retirement cognitive outcomes is not well understood. Data from the Midlife in the United States (MIDUS) study were used to examine occupational complexity in relation to cognitive performance and cognitive change after retirement. Initial sample included 471 workers between 45 and 75 years of age. At 9-year follow-up (T2), 149 were retired and 322 were still working. All six tasks from the Brief Test of Adult Cognition by Telephone (BTACT) were used. Hierarchical regression with workers at T1 indicated that, controlling for sociodemographic variables, complexity of work with people significantly contributed to explaining variance in overall cognitive performance (1.7%) and executive function (2%). In Latent Change Score (LCS) models, complexity of work with people was the only significant predictor of cognitive change in retirees, with those retiring from high-complexity jobs showing less decline. In conclusion, high complexity of work with people is related to better executive functioning and overall cognition during working life and slower decline after retirement. The finding that more intellectually stimulating work carries cognitive advantage into retirement fits the cognitive reserve concept, where earlier intellectual stimulation brings about lower risks of cognitive problems later. Study results also go along with the unengaged lifestyle hypothesis, whereby people may slip into so-called "mental retirement," leading to post-retirement cognitive loss, which may be most apparent among those retiring from jobs with low complexity of work with people.

Keywords: retirement, occupational complexity, complexity of work with people, cognitive change, executive functioning

Cognitive functioning is influenced by many factors including age, years of education, health, or activity engagement (Brewster et al., 2014). Among these influencing factors, cognitive stimulation associated with environmental complexity during adulthood, including occupational complexity, is often highlighted as a leading contributor to the maintenance of cognitive function during older adulthood (Schooler et al., 1999). In that sense, retirement has been associated with cognitive decline (Bonsang et al., 2012). This decline might be explained according to the "unengaged lifestyle hypothesis" (Rohwedder & Willis, 2010). The hypothesis proposes that the work context provides more cognitively stimulating and challenging conditions than a non-work environment. Workers are more involved in regular "mental exercise" than retired individuals, who sometimes engage in "mental retirement", whereby retirement becomes synonymous with low activity and a drop in cognitive performance (Rohwedder & Willis, 2010). Taken together, there are reasons to believe that there would be a decline in cognitive performance due to retirement and the accompanying loss of stimulation through occupational activities.

Retirement has been associated with accelerated loss in processing speed and spatial skills (Finkel et al., 2009), and a negative lagged effect in memory and working memory (Bonsang et al., 2012). Compared with working peers, retirees show greater loss of learning, memory, and inductive reasoning (Celidoni et al., 2017; Hamm et al., 2020; Roberts et al., 2011; Ryan, 2008; Wickrama et al., 2013; Xue et al., 2018). Thus, it is possible that delayed retirement would relate to better maintenance of cognitive abilities, decreasing the risk of cognitive impairment and cognitive aging and potentially reducing social and health costs (Dufouil et al., 2014; Grotz et al., 2016).

The opposite effect of retirement on cognition has been found, noting that retirees show better verbal memory and abstract reasoning than workers (Bianchini & Borella, 2016; Denier et al., 2017), and a slightly decreased rate of decline in episodic memory post-retirement (Andel et al., 2016; Fisher et al., 2014), especially when paired with preretirement higher mental demands at work or less work-related stress. These positive outcomes have been explained by the effect of mental stimulation at work that acts as a boost for

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cognitive reserve (Andel et al., 2016; Denier et al., 2017; Fisher et al., 2014).

The cognitive reserve hypothesis (Stern, 2009; Stern et al., 2020) suggests that lifetime intellectual activities and other environmental factors, such as occupational tasks, may protect brain function from aging (Barulli & Stern, 2013). Mounting evidence suggests occupational characteristics can play a substantial role in the development and maintenance of cognitive reserve, thus supporting normal cognitive function even in the face of underlying age-associated brain pathology (Stern et al., 2020). These effects seem to persist through older adulthood, as evidenced by research suggesting that work complexity is significantly associated with reduced risk of dementia (Andel et al., 2005; Dekhtyar et al., 2016; Karp et al., 2009; Kröger et al., 2008; Then et al., 2014). Complexity of work refers to the extent to which occupations provide cognitively demanding tasks and incentives to train and improve cognitive skills, as well as promote opportunities for social interaction (Denier et al., 2017). Complexity of work and its three different types—in the management of data, people, or things—might shed light on relationships between occupational activities and cognitive performance during working life and retirement (Nexø et al., 2016). Regarding the effect of occupational complexity on workers, evidence in favor of the environmental complexity theory shows that the more complex the job, the greater the cognitive stimulation (Schooler et al., 1999; Then et al., 2014). Studies have associated high occupational complexities with better specific cognitive performance during working life. For instance, a recent longitudinal study found that, even after controlling for demographics, education, and health, higher occupational complexity was associated with a better processing speed and cognitive flexibility in workers aged between 42 and 56 years (Kraup et al., 2018). A cross-sectional study using the Midlife in United States (MIDUS) study's database found that workers in higher-complexity occupations had better episodic memory and executive function (Grzywacz et al., 2016). In terms of the associations of each type of work complexity and effects on cognition, individuals retiring from jobs with high complexity of work with data showed better general cognition (Andel et al., 2007, 2016; Correa Ribeiro et al., 2013; Finkel et al., 2009) and memory and faster processing speed (Lane et al., 2017) at the moment of retirement. Still, little is known as to how specific work characteristics, like work complexity, affect the various aspects of cognitive function when retirement and complexity are considered within the same longitudinal model.

In a complementary way, the "disuse hypothesis" (Salthouse, 2006) asserts that the rate of age-related decline in cognitive measures is less pronounced for those people that are less mentally active. Given the extent of exposure to work environment across the life course for a large proportion of adults, and the variability of job tasks across different occupations, it is likely that work characteristics, like occupational complexity, contribute substantially to the assumptions that underlie the disuse hypothesis. Specifically, it is possible that high occupational complexity can buffer against age-related decline whereas low occupational complexity can exacerbate decline. What is less known is how retirees respond cognitively when exposure to mentally engaged work environment is removed. Based on the continuity theory of aging (Atchley, 1989), individuals are innately motivated to maintain their behaviors as they get older. The identity continuity and identity crisis theories (Atchley, 1971) further posit that retirement can lead to an identity crisis that can be resolved by engagement in similar activities, or similar activity level, as before retirement. Evidence showing the association between greater work complexity and lower risk of dementia many years after retirement (Andel et al., 2005; Karp et al., 2009) supports this notion.

However, research properly investigating occupational complexity and cognitive aging in the context of retirement is still sparse. Findings show mainly two patterns: the preserved differentiation and the differential preservation (Salthouse, 2006). The preserved differentiation pattern shows that at the time of retirement, individuals with higher complexity of work exhibit higher cognitive performance than those with lower occupational complexity but show similar and parallel rates of cognitive decline over time. On the other hand, a differential preservation pattern shows that, at the time of retirement, individuals with higher complexity of work exhibit higher cognitive performance than those with lower complexity of work and show reduced decline compared with those retiring from less-complex jobs. In terms of types of complexity, higher complexity of work with people has been associated with a faster rate of decline after retirement more consistently, although complexity of work with data shows similar patterns (Finkel et al., 2009; Grotz et al., 2018). Studies that applied an overall measure of complexity without differentiating between the three types of complexity (i.e., data, people, and things) found that higher-complex jobs were associated with slower cognitive aging (Fisher et al., 2014) and lower risk of cognitive impairment (Andel et al., 2017; Boots et al., 2015) post-retirement. For example, spending more than 23 years in a job of high complexity with people and with things was found to reduce the risk for dementia by 64% and 55%, respectively (Kröger et al., 2008).

In summary, more research studying the effect of the different types of occupational complexities on cognition during working life and retirement is needed. In addition, a recent systematic review suggested that factors that explain the association between retirement and cognition should be studied more extensively (Meng et al., 2017). Baldivia et al. (2008) also suggested that complexity of work seems to be one of the main mechanisms as to why occupation may modulate cognitive reserve. Regarding the research designs used to achieve that aim, there is a need for longitudinal studies on the effect of retirement and occupational complexity on cognitive performance, especially on executive functioning (Sörman et al., 2019). Some authors suggest that measurement of cognitive change should be the primary focus of longitudinal aging research (Sliwinski & Buschke, 2004). Moreover, cross-sectional studies comparing retirees with working adults might be needed as well.

To our knowledge, this is the first study using LCS (Latent Change Score) modeling for the purpose of comparing the influence of complexity of work on the rate of cognitive change in the retirement transition compared with older workers, while controlling for covariates commonly associated with cognition such as age, education, and health. The current study selected a specific age range to explore the association between cognitive performance and occupational complexity at a time close to retirement, as a first step to examine the rate of cognitive change. Therefore, our aims were (a) to examine the relationship between cognitive performance and occupational complexity in a sample of workers aged between 45 and 75, and (b) to examine the effect of complexity at work on cognitive change after retirement, while controlling for age, educational level, and health.

Method

Participants and Procedure

The MIDUS study (http://midus.wisc.edu/) was the first North American longitudinal study conceived to investigate the role of psychological, behavioral, and social factors in health and well-being in midlife. The first wave, MIDUS-1 (1995–1997), was the baseline and included demographics, psychosocial, and information about daily life health information. MIDUS-2 [M2; Time 1 (2004–2009)] was the follow-up and added cognitive, biomarker, and neuroscience assessments. MIDUS-3 [M3; Time 2 (2013–2019)] was the second follow-up. The current study was conducted with samples from the MIDUS-2 and 3 (Figure 1). In order to select a suitable sample for both study aims (i.e., to explore the association of cognitive performance and complexity of work in workers and to study how occupational complexity influences change in cognition during the retirement transition), an age range eligibility criteria had to be set at Time 1 (T1), so part of the sample were retired at Time 2 (T2). Age criteria for M3 sample was set 15 years above and below the average retirement age (60 ± 15; Gallup Inc, 2013). Therefore, the following inclusion criteria were applied in M2: being employed and aged between 45 and 75 at T1.

The exclusion criteria were (a) previous history of stroke, Parkinson’s disease, head injury, or other neurological disorders, (b) current clinical depression, (c) incomplete cognitive assessment in M2, (d) incomplete occupational information in order to obtain the complexity of work scores, and (e) incomplete cognitive assessment in M3.

From the initial population of 4,512 people in T1, 2,652 people did not meet the inclusion criteria, and 1,389 met the exclusion criteria, leaving a sample for analysis of 471 subjects. Mean age was 54.12 ($SD = 6.07$) and 54% were women (Table 1). In T2, the majority of participants ($n = 315$) were still working, whereas the remaining were retired ($n = 144$) (Table 2).

Measures

The Brief Test of Adult Cognition by Telephone

The Brief Test of Adult Cognition by Telephone (BTACT) was administered by interviewers in M2 and M3 to assess cognitive performance. This instrument, administered over the phone, allows valid assessment of cognitive areas that are sensitive to aging, so it can be administered to large population-based studies (Lachman et al., 2014).

BTACT has an administration time of ≈20 min and includes six tests: the Rey Auditory-Verbal Learning Test (RAVLT; Lezak, 1995) for assessing episodic verbal memory, the Backward Digit Span subtest from the WAIS-III (Weschler, 1997) for working memory, the Category Fluency test (Tombauh et al., 1999) for verbal category fluency, the Number Series (Salthouse & Prill, 1987) for reasoning, the 30 s and Counting task (Backward Counting) for processing speed, and the Stop and Go Switch task (Switching task) for switching control. An exploratory analysis of the battery suggested two factors: Memory and Executive Functioning and with good test-retest reliability (Lachman et al., 2014). The Memory factor includes the immediate and delayed recalls of the RAVLT. The remaining tests composed the Executive Function factor. Every factor is calculated as the mean of z scores of the tests. A BTACT composite score, for general cognitive performance, is also available using the mean of z scores of all tasks. The BTACT composite and the two factors were standardized as well ($M = 0$, $SD = 1$).

Occupational Complexity

Complexity of work scores have been widely used in research (Andel et al., 2005; Feldberg et al., 2016; Kröger et al., 2008; Smart et al., 2014). In the MIDUS study, respondent occupations were derived from three open questions in the M2 phone interview: (a) what kind of business or company is this? (b) what is your

Figure 1
Flow Chart of the Sample Selection

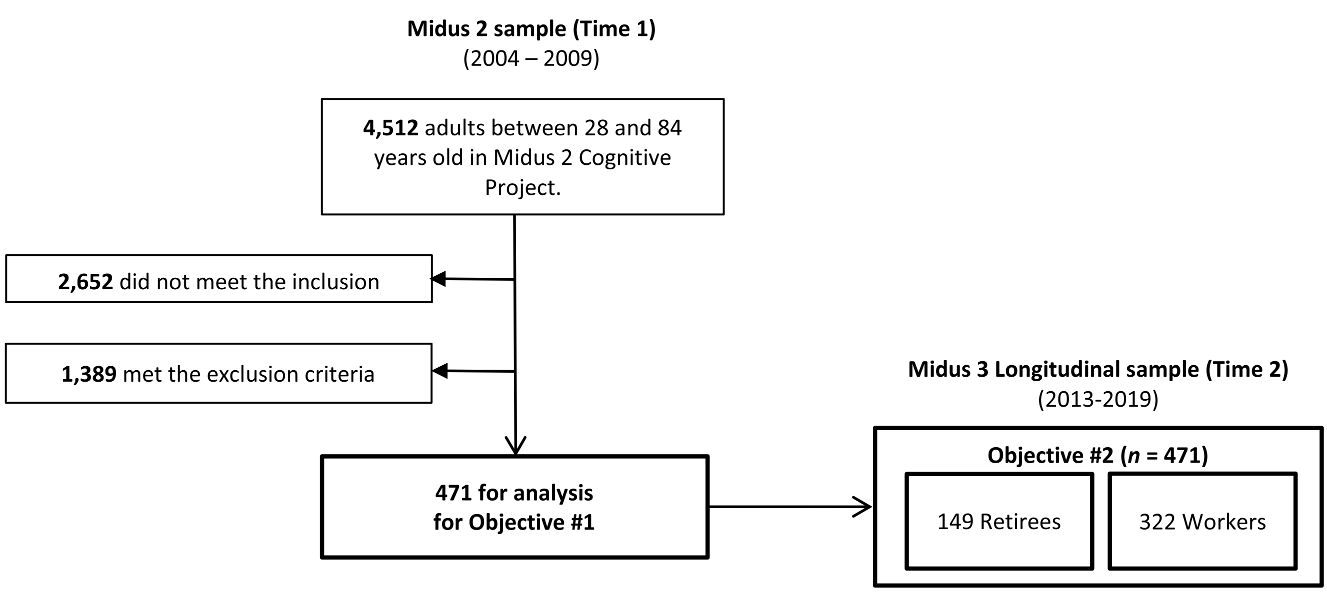


Table 1
Descriptive Data of the Sample for Objective #1 (Time 1)

	Workers $n = 471$ M (SD) or n (%)	Skewness	Kurtosis
Age	54.15 (6.09)	.56	−.16
Age range	45–75		
Gender			
Male	217 (46.1%)		
Female	254 (53.9%)		
Educational level (U.S. Department of Education)			
Less than high school	9 (1.9%)		
High-school competition	114 (24.2%)		
Some college, no degree	81 (17.2%)		
Associate degree	34 (7.2%)		
Bachelor's or higher degree	233 (49.5%)		
Complexity of work with data	4.18 (1.34)	−1.49	2.16
Complexity of work with people	3.65 (2.49)	.25	−1.46
Complexity of work with things	1.88 (2.39)	.69	−1.19
Physical health	3.88 (.82)	−.45	.11
BTACT composite at T1	0 (1)	−.01	.12
Memory factor at T1	0 (1)	.52	.43
Executive function factor at T1	0 (1)	.00	.37

Note. M = Mean; SD = Standard Deviation.

job title? and (c) what are your most important activities or duties? Interviewers were trained to code occupations and worked in pairs to agree to the final occupation code. Each respondent was assigned an occupation code using the 1990 Census Bureau occupational classification scheme from the U.S. Department of Labor. This scheme was developed by job analysts based on their observation of jobs and it is available in the Occupational Information Network (O*NET; http://www.onetonline.org/).

Table 2
Descriptive Data for Objective #2 (Time 2)

	Retirees $n = 149$ M (SD) or n (%)	Workers $n = 322$ M (SD) or n (%)	t (p) or χ^2 (p)	Skewness	Kurtosis
Age at T2	67.27 (5.32)	61.35 (5.49)	10.97 (<.001)	.56	−.16
Gender			2.31 (.128)		
Male	61 (40.9%)	156 (48.4%)			
Female	88 (59.1%)	166 (51.6%)			
Physical health	3.73 (.82)	3.95 (.82)	−2.58 (.010)	−.45	.11
Educational level (MIDUS interviews)			20.65 (.037)		
No school/some grade school	2 (1.3%)	1 (.3%)			
Eighth grade/junior high school	2 (1.3%)	2 (.6%)			
Some high school	47 (31.5%)	3 (.9%)			
GED	23 (15.4%)	1 (.3%)			
Graduated from high school	3 (2%)	64 (19.9%)			
1–2 years of college, no degree yet	14 (9.4%)	42 (13%)			
3 or more years of college, no degree yet	22 (14.8%)	13 (4%)			
Graduated from 2-year college or associate degree	3 (2%)	20 (6.2%)			
Graduated from 4- or 5-year college or bachelors degree	25 (16.8%)	79 (24.5%)			
Some graduate school	7 (4.7%)	11 (3.4%)			
Master's degree	2 (1.3%)	54 (16.8%)			
PhD, EDD, MD, DDS, LLB . . . , or other professional degree	2 (1.3%)	32 (9.9%)			
Complexity of work with data	3.84 (1.52)	4.34 (1.23)	−3.55 (<.001)	−1.49	2.16
Complexity of work with people	3.38 (2.54)	3.78 (2.46)	−1.64 (.101)	.25	−1.46
Complexity of work with things	1.84 (2.34)	1.91 (2.42)	−.29 (.767)	.69	−1.19
BTACT composite at T1	−.28 (1.00)	.13 (.97)	−4.15 (<.001)	−.01	.12
Memory factor at T1	−.09 (1.01)	.04 (.99)	−1.38 (.170)	.52	.43
Executive function factor at T1	−.29 (.99)	.13 (.97)	−4.75 (<.001)	0	.37
BTACT composite at T2	−.31 (.97)	.14 (.98)	−4.75 (<.001)	.03	.02
Memory factor at T2	−.18 (.99)	.08 (.99)	−2.69 (.008)	.61	.12
Executive function factor at T2	−.29 (.96)	.14 (.99)	−4.49 (<.001)	.05	.16

Note. M = Mean; SD = Standard Deviation.

Subsequently, for this study, codes of current occupations were assigned to the 2000 Dictionary of Occupational Titles (DOT) classification scheme, because the three middle digits in the codes represent complexity of work with data (4th digit), people (5th digit), and things (6th digit). The work complexity classification is composed of a list of particular skills that are required in every occupation and reflects the level of complexity in the management of data, people, and things. Categories of the three dimensions of complexities at work are shown in Table 3. This scoring system makes it possible to quantify the complexity of working tasks required in a certain job, with lower scores indicating more complexity. For instance, counseling psychologist (code 045.107-026) has a complexity of work with data score of 1 (*Coordinating*), a complexity of work with people score of 0 (*Mentoring*), and a complexity of work with things score of 7 (*Handling*). This would mean that a counseling psychologist would determine the sequence of actions to be taken on the basis of analysis of data, guide individuals to solve problems based on clinical principles, and handle devices with no responsibility to accomplish tasks. As in previous studies, in order to facilitate the interpretation of the analysis, each complexity score was reversed so a higher score reflects higher complexity.

Demographic and Health Measures From MIDUS

Age, highest educational level, and subjective physical health were extracted from MIDUS dataset. The highest educational level was recorded by interviewers and coded into 12 categories. In order to use dummy coding in the regression analysis, the 12 categories were recoded to 5 categories (Table 1), used by the U.S. Department of Education. The reference group for dummy coding was less than high-school completion. The original 12 educational-level variables were used for the second objective (Table 2).

To obtain a measure of health status, the interviewers in the MIDUS study asked the participants to rate their physical health. Respondents rated their health from 1 to 5 as (1) excellent, (2) very good, (3) good, (4) fair, and (5) or poor. A score of this kind of assessment has been considered a good indicator of general objective health (Wu et al., 2013). For this study, health scores were reversed so higher scores reflect a better subjective health (5-excellent, 1-poor).

Table 3

Rating Scores and Categories of Occupational Complexity With Data, People, and Things From the Dictionary of Occupational Titles

Data		People		Things	
0	Synthesizing	0	Mentoring	0	Setting up
1	Coordinating	1	Negotiating	1	Precision working
2	Analyzing	2	Instructing	2	Operating-controlling
3	Compiling	3	Supervising	3	Driving-operating
4	Computing	4	Diverting	4	Manipulating
5	Copying	5	Persuading	5	Tending
6	Comparing	6	Speaking-signaling	6	Feeding-offbearing
		7	Serving	7	Handling
		8	Taking instructions-Helping		

Note. For this study, ratings were reversed, meaning that the higher the score is, the higher the complexity.

Statistical Analyses

For the first objective, bivariate correlations were calculated to assess associations between cognitive outcomes and complexity of work, demographics, and health. Hierarchical linear regression analyses were conducted to estimate which complexity of work indices predicted better cognition. Age, dummy variables for education, and subjective health were introduced in the first block. Complexity of work with people, data, and things were included in the following blocks separately according to an evidence-based order. That is, both complexity of work with data and people have significant associations with cognition. However, complexity of people was entered in the first block after covariates due to the fact that there is greater evidence supporting the importance of complexity of work with people (Andel et al., 2005, 2016; Boots et al., 2015; Finkel et al., 2009; Karp et al., 2009; Kröger et al., 2008; Smart et al., 2014).

To accomplish the second objective, we fit two Latent Change Score (LCS) models for the general cognitive functioning (Kievit et al., 2018; Figure 2). The LCS (Δ) represents the rate of change between two measures in different times. This score is estimated in the model as a latent variable, allowing to attenuate influences of measurement error and variances and to reduce task-specific variance. According to the specifications of a multiple-indicator univariate LCS model (Kievit et al., 2018), variance of cognition at T1 was constrained to zero, cognition at T2 was regressed onto T1 (COG_T1) and Δ, and a covariance was set between same measures at different times. Parameters for Δ were set to one. Loadings of indicators of cognition variables were set to be equal over time in order to ensure obtain measurement invariance (Eid et al., 2012).

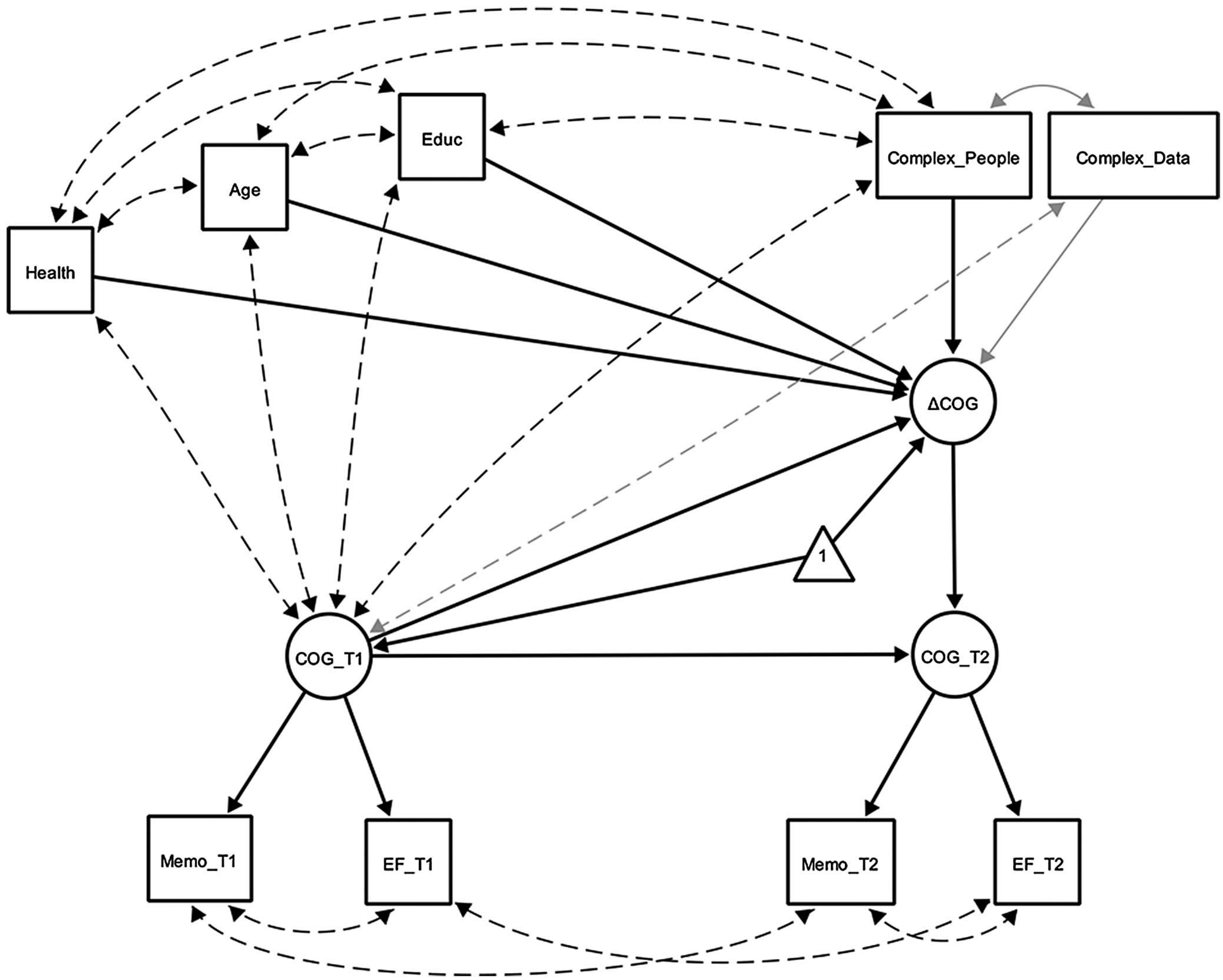
The first latent construct of general cognition was composed by the Memory and Executive factors in MIDUS-2 (T1), and the second latent construct included the same measures at MIDUS-3 (T2). In Model 1, change in cognition (Δ) was regressed on age, educational level, subjective health, and complexity of work with people. Covariances between all the independent variables and between cognition at T1 were set (Figure 2). Then, we tested the same model including complexity of work with data (Model 2). Complexity of work with things was not included because it was not significant in the cross-sectional prediction of cognitive performance, and it has previously shown weak reliability (Cain & Treiman, 1981; Kröger et al., 2008).

Models were tested in a multigroup framework for workers ($n = 322$) and retirees ($n = 149$) simultaneously. Differences across groups were tested by comparing an equality-constrained model with a model where parameters were freely estimated in each group. If the model constrained to be equal in loadings, intercepts and regressions fit worse, this would mean that there are differences between groups.

Model fit was assessed by standards of χ^2 test ($\chi^2/df < 2$; $p > .05$), Comparative fit index (CFI; >.95), Root Mean Square Error of Approximation (RMSEA; <.05), and Standardized Mean Square Residual (SRMR; <.07) and Goodness of Fit (GFI; >.09). For this purpose, RStudio (v. 1.2.5042; 2020) and lavaan package (Rosseel, 2012) were used, applying the robust Maximum

Figure 2

Simplified Path Diagram of the Multivariate Latent Change Score Model Testing for Latent Change in General Cognitive Performance



Note. There is a latent variable at each time (T1 and T2) (represented by circles) and they are indicated by scores on each of the two BTACT factors: Memory (Memo_T1 and Memo_T2) and Executive Function (EF_T1 and EF_T2) and a latent change score (ΔCOG) is derived from them. The variables age, education, health, and complexity of work with people are regressed on the change factor. Dashed lines are covariances. Grey lines represent the addition in Model 2.

Likelihood Estimator (MLR). This estimator introduces corrections to offset the bias produced by non-normal distributions (Li, 2016). Moreover, the mean LCS ($\mu\Delta$) indicates reliable change between the two different times; variance of the change ($\sigma^2\Delta$) represents the extent to which individuals differ in the change; and β can be assessed to interpret the extent to which change is dependent, or proportional, to the scores at T1 (Kievit et al., 2018).

Results

Association Between Complexity of Work and Cognitive Performance in Workers

Results for the first objective showed significant correlations between cognitive measures and complexity of work and sociodemographic factors (Table 4). The highest correlation, though moderate, was between education and the BTACT composite and Executive Function factor ($r = .37$ and $r = .36$, respectively) (Cohen, 1988). Complexity of work with data correlated significantly with the three cognitive measures, as well as complexity of work with people. Complexity of work with things had significant correlations ($p < .05$) with the BTACT composite and the Executive Function factor.

Hierarchical regression analyses showed that complexity of work with people explained variance of the models of BTACT general composite and the Executive Function factor (Table 5). The models, including complexity with people, age, educational level, and health, accounted for 21% and 19% of the variance, respectively. Additionally, a model with complexity of work with data was significant for the Executive factor ($R^2 = .20$, $p < .001$).

Table 4
Descriptive Data and Correlations of Sociodemographics (a–c), Complexity of Work Indices (d–f), and the Brief Telephone Adults Cognitive Testing (BTACT) Measures (1–3)

	a	b	c	d	e	f	1	2
a. Age	—							
b. Educational level	−.10*	—						
c. Physical health	−.02	.21**	—					
d. Complexity with data	−.16**	.31**	.13*	—				
e. Complexity with people	−.09	.46**	.07	.45**	—			
f. Complexity with things	.05	−.21**	−.04	−.21**	−.50**	—		
1. BTACT composite	−.18**	.37**	.20**	.28**	.29**	−.12*	—	
2. Memory factor	−.10**	.22**	.10**	.12**	.15**	−.06	.53**	—
3. Executive function factor	−.17**	.36**	.20**	.27**	.29**	−.12*	.97**	.30**

Note. Spearman rho bivariate correlations (*n*) were calculated for educational level. Remaining refers to Pearson correlations (*r*).
* $p < .05$. ** $p < .01$.

Effect of Complexity of Work on Cognitive Change for Retirees and Workers

Regarding the second objective, the first model describing the influence of complexity with people on cognitive change between T1 and T2 showed optimum fit indices (Model 1: $\chi^2/df = 1.32$, $p = .175$, CFI = .994, robust RMSEA = .037, SRMR = .048, GFI = 1.00; Table 6). Estimates of rate of change were significant for the retiree group (μΔCOG = 1.80, $p = .037$). Additionally, educational level and complexity of work with people showed significant covariance with cognition at T1. On the other hand, workers did not show a significant change ($p = .097$) and all covariates showed a significant association with cognition at T1. Multigroup differences for retirees and workers showed that the model did fit the data significantly better than the one with loadings, intercepts and regressions constrained to be equal across groups [$\chi^2(13) = 183.68$, $p < .001$].

In the retiree group, the regression of complexity of work with people on the latent cognitive change was significant ($p = .044$), indicating better cognitive performance with increasing complexity of work with people. This association is illustrated in Figures 3 and 4. Specifically, Figure 3 shows means of cognitive scores of retirees at T1 and T2 by the level of complexity of work with people. Subgroups of level of complexity were made for illustrative purposes based on one standard deviation above the mean (high) and below the mean (low). Figure 3 shows that those retiring from jobs with higher complexity of work showed better cognitive performance than those retired from low-complexity jobs, both at T1 and T2. Moreover, it depicts that the latter showed a steeper cognitive decline.

Figure 4 illustrates the regression slope for the association between the continuum of complexity of work with people scores (*X*-axis) and cognitive change scores (*Y*-axis) (β = .38). The results are shown separately for retirees and workers at T2. Among retirees, those who retired from jobs with higher complexity of work with people showed less negative change (i.e., less cognitive decline) than those who retired from jobs with lower level of complexity of work with people. Complexity of work with people did not influence cognitive change significantly among those still working at T2 ($p = .803$).

Fit indices were also acceptable for the same model including complexity of work with data (Table 7; Model 2: $\chi^2/df = 1.21$, $p < .232$, CFI = .995, RMSEA = .030, SRMR = .048). In this case, retirees also showed a significant rate of change (μΔCOG = 1.91, $p = .045$), but none of the independent variables were significant predicting the change. All covariates showed a significant association with cognition at T1 for workers and retirees, as well as complexity of work with people and with data. Multigroup differences showed that the model did fit the data significantly better than the constrained model ($\chi^2(15) = 200.21$, $p < .001$).

Discussion

Association of Occupational Complexity With Cognitive Performance

The first objective of the study was to determine the relationship between cognitive performance and occupational complexity in workers between 45 and 75 years old. Correlation results showed significant and positive associations between workers' general cognitive ability, Memory and Executive Function factors, and the complexity of work indices with data and people. Complexity of work with things showed a negative significant correlation with the BTACT composite and the Executive factor. However, the correlation between complexity of work with people and the general composite and executive performance was the closest to the critical level of .30 to be considered a moderate association (Cohen, 1988). These results are consistent with other observational studies that found a positive association between complexity with people and with data and better general status (Andel et al., 2016; Finkel et al., 2009).

However, the results of prediction models of workers' cognitive functioning showed that just complexity of work with people acts as a significant predictive factor for the BTACT composite. Age, educational level, self-rated physical health, and complexity of work with people accounted for 21% of the variance. This finding is supported by previous studies which have found that complexity with people is the type of occupational complexity that is most associated with general cognitive performance, even after correcting for education (Finkel et al., 2009; Smart et al., 2014).

Some authors discuss that complexity of work is associated with better cognition because people who possess high cognitive skills, and so higher educational levels, might have better access to jobs rated as more complex by the DOT (Hyllegard & Lavin, 1992).

Table 5
Hierarchical Regression Model Results for Cognitive Measures at Time 1

	Step	Predictor	*B*	*SE B*	β	R^2	ΔR^2
BTACT composite	1	Constant	−.38	.49		.19***	.19**
		Age	−.02	.01	−.14**		
		Educ_2	.82	.32	.36*		
		Educ_3	.90	.32	.35**		
		Educ_4	.97	.35	.26**		
		Educ_5	1.34	.32	.77***		
		Health	.12	.05	.10*		
	2	Constant	−.56	.49		.21***	.02**
		Age	−.02	.01	−.14**		
		Educ_2	.81	.31	.35*		
		Educ_3	.83	.32	.32**		
		Educ_4	.90	.34	.24**		
		Educ_5	1.28	.32	.68***		
		Health	.13	.05	.10*		
		Complexity with people	.06	.02	.15**		
Memory factor	1	Constant	−.79	.51		.09***	.09***
		Age	−.02	.01	−.10*		
		Educ_2	1.30	.33	.58***		
		Educ_3	1.45	.34	.57***		
		Educ_4	1.22	.36	.33***		
		Educ_5	1.65	.33	.86***		
		Health	.03	.06	.03		
Executive function factor	1	Constant	−.14	.50		.18***	.18***
		Age	−.02	.01	−.14**		
		Educ_2	.49	.33	.21		
		Educ_3	.54	.33	.20		
		Educ_4	.71	.35	.18*		
		Educ_5	1.17	.32	.59***		
		Health	.14	.05	.11*		
	2	Constant	−.33	.50		.19***	.02**
		Age	−.02	.01	−.13**		
		Educ_2	.47	.32	.20		
		Educ_3	.48	.33	.18		
		Educ_4	.64	.35	.17		
		Educ_5	1.00	.33	.50**		
		Health	.14	.05	.12**		
		Complexity with people	.06	.02	.15**		
	3	Constant	−.61	.52		.20***	.01*
		Age	−.02	.01	−.12**		
		Educ_2	.45	.32	.19		
		Educ_3	.43	.33	.16		
		Educ_4	.57	.35	.15		
		Educ_5	.94	.33	.47**		
		Health	.14	.05	.11*		
		Complexity with people	.05	.02	.11*		
		Complexity with data	.08	.04	.10*		

Note. *B* = Unstandardized beta; *SE* = Standard error; β = Standardized beta; ΔR^2 = Change in R^2; Educ_2 = Dummy variable for high-school completion; Educ_3 = Dummy variable for some college, no degree; Educ_4 = Dummy variable for associate degree; Educ_5 = Dummy variable for bachelor's or higher degree. Models with no significant complexity of work with data or things are not shown in the table.
* $p < .05$. ** $p < .01$. *** $p < .001$.

In relation to this, few studies have controlled for previous cognitive ability variables. For instance, Smart et al. (2014), controlling for childhood intelligence, education, and social deprivatio, found that complexities of work with people and data were associated with better cognitive ability in older age. In the present model, the highest educational level had the greatest weight in the explained variance (bachelors or higher degree [β = .68, $p < .001$]), while complexity with people showed a β = .15 ($p < .01$). However, recent evidence suggests that the complexity of work mediates the protective effect of education by 11%–22% (Fujishiro et al., 2019). Hence, as it has been suggested in previous research (Karp et al., 2009), it may be that the effect of work complexity is greater in low educational levels.

Our results show that no type of complexity of work explained variance of the Memory factor. Findings from another MIDUS study showed that occupational complexity was a significant predictor of the BTACT Memory factor (Grzywacz et al., 2016). However, that study is not directly comparable because it used a general complexity measure instead of the DOT categorization and did not differentiate between working with data, people, and things. Additionally, the sample consisted of adults aged 32–84, so it might be that complexity of work accounts for episodic memory in the broad

Table 6
Model 1. Latent Change Scores Estimates by Groups (Retirees and Workers)

		B	*SE B*	β	*z* value	*p*
Retirees (n = 149)						
	Estimates of change					
	μΔCOG	.57	.28	1.80	.28	.037
	σ^2ΔCOG	.07	.10	.71	.70	.483
	Prediction of ΔCOG					
	Cognition at Time 1	−.28	.16	−.52	−1.73	.083
	Age	−.02	.01	−.26	−1.82	.069
	Education	−.00	.02	−.01	−.08	.939
	Health	.02	.05	.04	.38	.708
	Complexity with people	.05	.02	.38	2.01	.044
	Covariance with COG_T1					
	Age	−.26	.34	−.08	−.76	.449
	Education	.72	.16	.48	4.58	<.001
	Health	.11	.06	.23	1.82	.069
	Complexity of work with people	.73	.16	.50	4.58	<.001
Workers (n = 322)						
	Estimates of change					
	μΔCOG	.34	.21	.77	1.66	.097
	σ^2ΔCOG	.18	.06	.93	5.62	<.001
	Prediction of ΔCOG					
	Cognition at Time 1	−.18	.03	−.20	−5.70	<.001
	Age	−.01	.01	−.15	−2.44	.015
	Education	−.02	.01	−.09	−1.22	.224
	Health	.05	.04	.09	1.26	.209
	Complexity of work with people	.00	.01	.02	.25	.803
	Covariance with COG_T1					
	Age	−.60	.24	−.22	−2.49	.013
	Education	.68	.12	.53	5.72	<.001
	Health	.11	.04	.27	2.98	.003
	Complexity of work with people	.40	.11	.33	3.79	<.001

Note. ΔCOG = Rate of change; COG_T1 = Cognition at Time 1; *B* = Unstandardized coefficient; *SE* = Standard error; β = Standardized coefficient. Fit indices: χ^2 = 21.1 (χ^2 Retirees = 8.2, χ^2 Workers = 12.8), *df* = 16, *p* = .175. CFI = .994, RMSEA = .037, SRMR = .048, GFI = 1.00, R^2 ΔCOG_R = .30, R^2 ΔCOG_W = .07.

spectrum of adulthood and not in older adults. Another possible reason as to why no indicator of complexity was shown to be significant in the prediction of the Memory factor may be that all levels of education are associated with memory, but only the highest level is associated with executive functions, as shown in Table 5. This finding might suggest that memory is more required and influenced by educational level, while the unfolding of executive functioning is greater at highest educational levels (O'Shea et al., 2018; Ritchie et al., 2015).

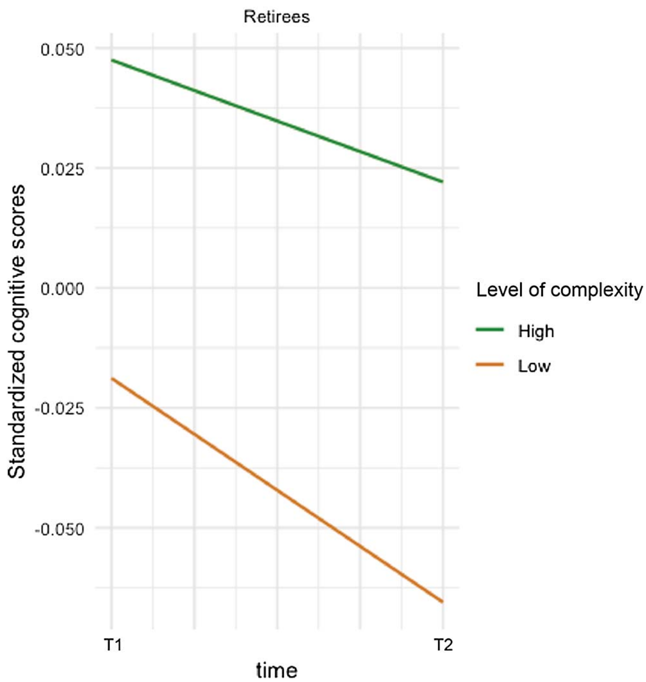
In our study, the weight of education is less important for executive functioning, where the highest category is the only significant one (β = .47, p < .01). In addition, complexity of work with people and with data, age, and health were all significant (People β = .11, p < .05; Data β = .10, p < .05). As far as we know, just one study has previously found complexity with people to be associated with executive function (Sörman et al., 2019). Their sample had similar ages (50–75 y/o) and structural modeling analysis showed similar findings as complexity of work with people was related to the main executive components (working memory and switching), as well as complexity with data (working memory). Other findings have also associated complexity of work with data with a better performance in executive functions and attention (Feldberg et al., 2016).

Some mechanisms could be considered about these associations. On the one hand, it seems that social networks influence general cognition, memory performance, and executive functioning (Ybarra et al., 2008). It would be expected that people in more social occupations have larger social networks and more complex interactions with people. Likewise, occupations with higher social participation are among the more complex occupations, because they entail constant interpretation of social cues and selection and inhibition of appropriate responses (Cramm et al., 2013). These characteristics are inherently related to executive functioning. Processes as working memory, switching, or reasoning are enhanced when interacting with other people (e.g., in negotiation or mentoring), as one needs to access, maintain, and manipulate social information.

In that context, the concept of social working memory has recently emerged (Meyer et al., 2015). Research on this topic has found that social working memory tasks recruit two neurocognitive networks: the medial frontoparietal system or mentalizing system (associated with mental state reasoning) and the lateral frontoparietal system (associated with traditional working memory and general intelligence). At the same time, jobs with higher complexity with data, as researchers or accountants, imply a high level of processing speed, working memory, or task switching, because they have to manipulate many sources of information simultaneously. Consequently, it would be expected that more complex occupations with people and data promote the activation of working memory systems, improving its performance. Thus, stimulation of working memory may transfer to an improvement in fluid intelligence (Zinke et al., 2014).

Figure 3

Means of Standardized Cognitive Scores From Time 1 (T1) to Time 2 (T2) by Level of Complexity of Work With People in Retirees



Note. Levels of complexity of work with people were calculated by scores one standard deviation above the mean (high complexity) and one standard deviation below the mean (low complexity). See the online article for the color version of this figure.

Effect of Complexity of Work on Intraindividual Cognitive Change After Retirement

The second objective was to determine the effect of complexity of work on long-term change in cognition by employment status. Results show that complexity of work with people was the only significant predictor of intraindividual cognitive change in retirees ($\beta = .38$, $p = .044$), compared with workers. Also, higher levels of preretirement complexity of work with people were associated with less decline in cognition compared with lower levels of complexity of work with people (Figure 3). That is, a less negative rate of change was found in those retiring from higher-complex occupations (Figure 4).

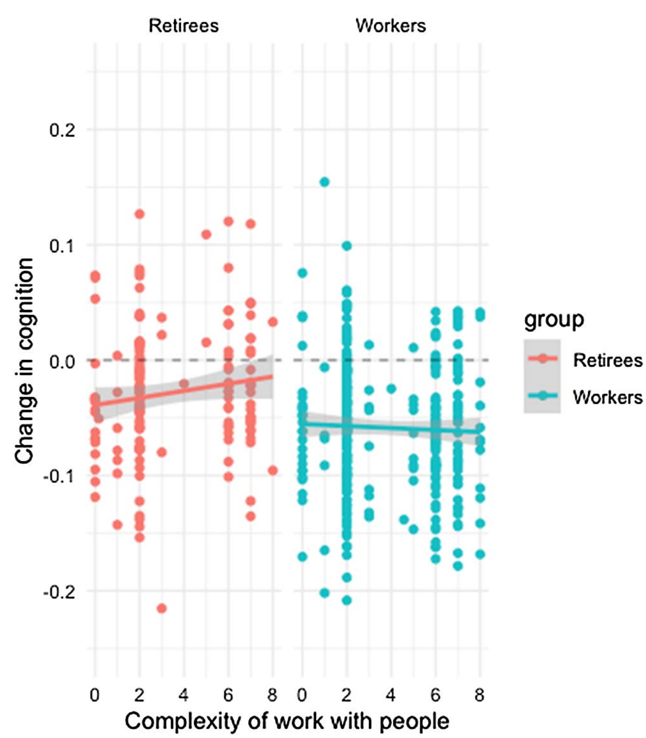
This finding is in line with a previous study that found that higher levels of mental demands at work were associated with a slower rate of memory decline in older adults after retirement (Fisher et al., 2014). Moreover, it fits the differential preservation pattern (Salthouse, 2006), which was observed previously (Finkel et al, 2009). Thus, individuals in high-complexity occupations had the advantage of achieving higher cognitive performance up to retirement plus showed less cognitive change than those who retired from lower-complexity jobs (see Figure 3), suggesting that the cognitive advantage presumably attributable to work complexity remains after retirement. Additional research is needed to understand the mechanism of the effect.

The effect of retirement on cognitive decline can be explained by the "unengaged lifestyle hypothesis" (Rohwedder & Willis, 2010), which states that people after retirement lose their exposure to work environment and the engagement and routine that come with it, which may accelerate cognitive aging. These results provide support for Rohwedder and Willis' proposition that retirement represents a crucial life event that can lead to "mental retirement" or the tendency to significantly reduce intellectual activity. In that sense, Hamm et al. (2020) found in the same MIDUS sample that retirees who disengaged from challenging activities showed a steeper cognitive decline.

Furthermore, the fact that higher complexity of work has an effect on cognitive aging post-retirement is also supported by the cognitive reserve theory (Stern, 2009; Stern et al., 2020), which argues that complexity of work provides a range of cognitive benefits that protect against decline at older ages. Our findings support the notion that mental stimulation offered specifically by higher complexity of work with people relates to better cognitive function. In addition, this aspect of work also relates to less age-related cognitive decline, indicating that the reserve gained from complex work continues to provide cognitive advantage into older adulthood.

Figure 4

Regression of Complexity of Work With People on the Cognitive Change Between T1 and T2 by Retirement Status at T2



Note. Change score = Time 2 cognitive scores minus Time 1 scores (ΔCOG). Change scores above zero mean positive change and scores below zero mean negative change (i.e., cognitive decline). The colored line in the center represents the linear regression slope. *Y*-axis depicts the magnitude of individual cognitive change scores and the *X*-axis shows the continuum of complexity of work with people scores. Among T2 retirees, complexity of work with people had a positive effect on change in cognition between T1 and T2, where those retiring from high-complexity jobs showed less negative change scores. Among T2 workers, complexity of work with people had an insubstantial negative effect on change in cognition. See the online article for the color version of this figure.

Table 7
Model 2. Latent Change Scores Estimates by Groups (Retirees and Workers)

		B	*SE B*	β	*z* value	*p*
Retirees (n = 149)						
	Estimates of change					
	μΔCOG	.54	.27	1.91	2.01	.045
	σ^2ΔCOG	.05	.10	.67	.51	.609
	Prediction of ΔCOG					
	Cognition at Time 1	−.25	.17	−.51	−1.45	.143
	Age	−.02	.01	−.29	−1.80	.071
	Education	−.01	.02	−.06	−.26	.793
	Health	.02	.05	.05	.34	.733
	Complexity of work with people	.04	.03	.33	1.40	.162
	Complexity of work with data	−.03	.03	.17	1.13	.257
	Covariance with COG_T1					
	Age	−.26	.34	−.10	−.76	.447
	Education	.72	.16	.50	4.59	<.001
	Health	.11	.06	.23	1.82	.069
	Complexity of work with people	.73	.16	.50	4.59	<.001
	Complexity of work with data	.27	.08	.31	3.19	.001
Workers (n = 322)						
	Estimates of change					
	μΔCOG	.40	.21	.89	1.94	.052
	σ^2ΔCOG	.19	.03	.93	5.56	<.001
	Prediction of ΔCOG					
	Cognition at Time 1	−.17	.05	−.19	−3.12	.002
	Age	−.01	.01	−.16	−2.23	.026
	Education	−.02	.01	−.09	−1.12	.261
	Health	.05	.04	.09	1.33	.184
	Complexity of work with people	.01	.01	.04	.47	.640
	Complexity of work with data	−.02	.03	−.10	−.85	.395
	Covariance with COG_T1					
	Age	−.60	.24	−.22	−2.48	.013
	Education	.68	.12	.52	5.73	<.001
	Health	.11	.04	.27	2.99	.003
	Complexity of work with people	.41	.11	.33	3.80	<.001
	Complexity of work with data	.21	.06	.35	3.43	.001

Note. ΔCOG = Rate of change; COG_T1 = Cognition at Time 1; *B* = Unstandardized coefficient; *SE* = Standard error; β = Standardized coefficient. Fit indices: χ^2 = 24.2 (χ^2 Retirees = 9.6, χ^2 Workers = 14.7), df = 20, p = .232. CFI = .995, RMSEA = .030, SRMR = .048, GFI = 1.00, R^2 ΔCOG_R = .34, R^2 ΔCOG_W = .07.

The finding that benefits of complex work appear to span throughout retirement deserves attention in the context of the possibility that mental stimulation through work may be the mechanism. Beyond the possibility that mental stimulation provided by high-complex jobs helps build cognitive reserve, having a high-complexity job may have other benefits. Although we could not test the possibility directly, it may be that those retiring from high-complexity jobs have an easier time maintaining their preretirement levels of intellectual activity. Based on Atchley's continuity theory (Atchley, 1989), which posits that individuals aspire to remain at the same level of engagement throughout the life course, we can speculate that those retiring from high-complexity jobs transfer into intellectually engaging post-retirement activities. The identity continuity theory (Atchley, 1971), which posits that retirement can lead to identity crisis, which is best resolved by transition into activities that map well onto previous work activities, also supports this notion.

The fact that complexity of work with people specifically emerged as the stronger factor in reducing cognitive aging than complexity of work with data is of interest in terms of designing work-related interventions to promote cognitive health. Previous research also suggests that complexity of work with people may be particularly useful in buffering against cognitive decline (Andel et al, 2016; Finkel et al., 2009) and risk of dementia (Andel et al., 2005). It may be that the specific work tasks reflected in the complexity of work with people provides particularly distinct cognitive benefits. In addition, retirement also tends to bring about reduction in social networks (Kemperman et al., 2019), which has been found to accelerate cognitive decline in older adulthood. It may be that for people retiring from jobs with high complexity of work with people, staying socially engaged is somewhat easier. Regardless, complexity of work with people appears to hold promise in terms of cognitive health promotion.

Of note is that complexity of work with people did not influence the cognitive change in retirees (β = .33, p = .162), when complexity with data was added into the same model, although both were related to the level before retirement. This finding is likely to be explained by collinearity between complexity of work with people and data, whereby some aspects of intellectual stimulation are shared between the two constructs, as reflected in a relatively high correlation ($r = .45$, see Table 4). This may also be due to the influence of education on these associations. In a previous study, the association between complexity of work with data and cognition was substantially attenuated when education was included (Finkel et al., 2007).

Limitations and Strengths

This study has some limitations. First, we had available only one measurement of complexity of current work in a specific time. Ideally, a complexity of work index should be calculated for every job in which the individual has been employed, building a composite score. Second, this study only included two waves of data from the MIDUS study. Ideally, accounting for more longitudinal data would determine the rate of cognitive change in a longer period of time. Additionally, although the DOT has been widely used to determine level of complexity of work, it assigns levels according occupation, failing to characterize individual differences in complexity and perceptions of complexity. However this may also be a strength as characterizing complexity as high subjectively may be a reflection of either actual work complexity or cognitive difficulties. Despite the fact that the BTACT cognitive battery has shown good reliability and concurrent validity (Lachman et al., 2014), telephone testing has relevant limitations. Namely, there are restrictions to auditory stimuli and tasks, and lack of control over distractors, and interferences due to the quality of connection or other technical problems. Hence, results would benefit from the use of a face-to-face administered battery.

This research has several strengths. First of all, the data from MIDUS is recent, so information about complexities is more likely to be representative of tasks in current jobs. Additionally, the entire sample resides in the same country, which suggests that institutional retirement conditions are similar across the sample. Finally, we selected the exclusion criteria so that we could exclude noncognitively healthy individuals, as well as those with a previous history of stroke or clinical depression. As a result, we presented the association between complexity of work and executive functioning in older workers and its association with cognitive aging in healthy retired and working people.

In summary, the current study brings to light that complexity of work with people may play an important role in cognitive functioning, especially in executive function, a crucial domain in terms of everyday activities and overall cognitive function, both before and after retirement. The contrast to complexity of work with data, where the results were more obscure, along with the inclusion of multiple cognitive domains, provides a uniquely detailed look at a modifier of cognitive aging before and after retirement in MIDUS. This evidence implies that, when assessing the effect of occupational complexity, the types (i.e., people, data, and things) should be specified, as they show different effects. Second, to our knowledge, this is the first longitudinal study to use a LCS model to determine the influence of complexity of work with people on cognitive change, comparing individuals who retire in a 9-year period with those who continue to work. This kind of analysis is a type of structural equation model that allows researchers to assess patterns, causes, and consequences of intraindividual change (Ferrer & McArdle, 2010; Kievit et al., 2018). These outcomes continue to support the role of occupational complexity with people in cognitive functioning after the end of working life. Thus, only this type of complexity is shown to play a significant role in age-related cognitive decline after retirement, being slightest for those in more complex jobs.

Present findings have some theoretical implications for the cognitive reserve hypothesis. This study highlights the need for inclusion of specific measures of complexity of previous work in studies assessing the impact of cognitive reserve on normal and pathological aging trajectories. The lack of specification of the types of complexities, as well as the omission of occupational complexity measures, could lead to inaccurate conclusions. Furthermore, these findings have implications for the environmental complexity hypothesis and the disuse hypothesis, because not all types of complexity of work have the same effect on cognition in the short and long term.

Additionally, our findings provide a thorough look at a potential important factor, contributing to slowing age-related cognitive decline in the early years following retirement, jobs with high complexity of work with people. Previous studies have shown that a higher complexity of work is also associated with a lower risk of developing Alzheimer's disease and other dementias (Karp et al., 2009). Thus, these findings showing that complexity of work with people is associated with cognitive abilities and that high levels might protect against cognitive decline have substantial implications to health and design of preventive interventions, as recommended by the World Health Institution (2019). Interventions should therefore be focused on fostering cognitively engaging activities after retirement. Retirees from low-complexity jobs may need to pay particular attention to the maintenance of their cognitive function post-retirement. Given that complexity of work with people stood out in the results as especially important, social engagement at work may operate as an overarching construct to slow cognitive aging, offering a clear target for intervention at the workplace (i.e., to increase social engagement in jobs low on complexity of work with people). Particularly, executive function stimulation is recommended because it is associated with less functional decline in instrumental activities of daily life in older people (Rebok et al., 2014).

Conclusion

Findings have shown an association between higher complexity of work with people and better general cognition and complexity with data and people with executive functioning. This association persisted after retirement, with those who retired from jobs with high complexities of work with people showing less cognitive decline. During working life, occupational complexity was associated with better general cognitive performance and, specifically, better executive functioning. Further research on associations between retirement, complexity of work with people, and executive functioning is needed. In particular, the field would benefit from knowing what characteristics of managing people are associated with executive processes, and how they contribute to general cognitive functioning. Additionally, research assessing the implications of complexity of work on cognitive reserve is still required. In this sense, more neuroimaging studies would help to discern compensation in cognitive performance and real brain atrophy.

References

Andel, R., Crowe, M., Pedersen, N. L., Mortimer, J., Crimmins, E., Johansson, B., & Gatz, M. (2005). Complexity of work and risk of Alzheimer's disease: A population-based study of Swedish twins. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *60*(5), P251–P258. https://doi.org/10.1093/geronb/60.5.P251

Andel, R., Dávila-Roman, A. L., Grotz, C., Small, B. J., Markides, K. S., & Crowe, M. (2017). Complexity of work and incident cognitive impairment in Puerto Rican older adults. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *74*(5), 785–795. https://doi.org/10.1093/geronb/gbx127

Andel, R., Finkel, D., & Pedersen, N. L. (2016). Effects of preretirement work complexity and postretirement leisure activity on cognitive aging. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *71*(5), 849–856. https://doi.org/10.1093/geronb/gbv026

Andel, R., Kareholt, I., Parker, M. G., Thorslund, M., & Gatz, M. (2007). Complexity of primary lifetime occupation and cognition in advanced old age. *Journal of Aging and Health*, *19*(3), 397–415. https://doi.org/10.1177/0898264307300171

Atchley, R. C. (1971). Retirement and leisure participation: Continuity or crisis? *The Gerontologist*, *11*(1), 13–17. https://doi.org/10.1093/geront/11.1_Part_1.13

Atchley, R. C. (1989). A continuity theory of normal aging. *The Gerontologist*, *29*(2), 183–190. https://doi.org/10.1093/geront/29.2.183

Baldivia, B., Andrade, V. M., & Bueno, O. F. A. (2008). Contribution of education, occupation and cognitively stimulating activities to the formation of cognitive reserve. *Dementia and Neuropsychologia*, *2*(3), 173–182. https://doi.org/10.1590/S1980-57642009DN20300003

Barulli, D., & Stern, Y. (2013). Efficiency, capacity, compensation, maintenance, plasticity: Emerging concepts in cognitive reserve. *Trends in Cognitive Sciences*, *17*(10), 502–509. https://doi.org/10.1016/j.tics.2013.08.012

Bianchini, L., & Borella, M. (2016). Retirement and memory in Europe. *Ageing and Society*, *36*(7), 1434–1458. https://doi.org/10.1017/S0144686X15000434

Bonsang, E., Adam, S., & Perelman, S. (2012). Does retirement affect cognitive functioning? *Journal of Health Economics*, *31*(3), 490–501. https://doi.org/10.1016/j.jhealeco.2012.03.005

Boots, E. A., Schultz, S. A., Almeida, R. P., Oh, J. M., Koscik, R. L., Dowling, M. N., Gallagher, C. L., Carlsson, C. M., Rowley, H. A., Bendlin, B. B., Asthana, S., Sager, M. A., Hermann, B. P., Johnson, S. C., & Okonkwo, O. C. (2015). Occupational complexity and cognitive reserve in a middle-aged cohort at risk for Alzheimer's disease. *Archives of Clinical Neuropsychology*, *30*(7), 634–642. https://doi.org/10.1093/arclin/acv041

Brewster, P. W. H., Melroes, R. J., Marquine, M. J., Johnson, J. K., Napoles, A., MacKay-Brandt, A., Farias, S., Reed, B., & Mungas, D. (2014). Life experience and demographic influences on cognitive function in older adults. *Neuropsychology*, *28*(6), 846–858. https://doi.org/10.1037/neu0000098

Cain, P. S., & Treiman, D. J. (1981). The dictionary of occupational titles as a source of occupational data. *American Sociological Review*, *46*(3), 253. https://doi.org/10.2307/2095059

Celidoni, M., Dal Bianco, C., & Weber, G. (2017). Retirement and cognitive decline. A longitudinal analysis using SHARE data. *Journal of Health Economics*, *56*, 113–125. https://doi.org/10.1016/j.jhealeco.2017.09.003

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge.

Correa Ribeiro, P. C., Lopes, C. S., & Lourenço, R. A. (2013). Complexity of lifetime occupation and cognitive performance in old age. *Occupational Medicine*, *63*(8), 556–562. https://doi.org/10.1093/occmed/kqt115

Cramm, H. A., Krupa, T. M., Missiuna, C. A., Lysaght, R. M., & Parker, K. H. (2013). Executive functioning: A scoping review of the occupational therapy literature. *Canadian Journal of Occupational Therapy*, *80*(3), 131–140. https://doi.org/10.1177/0008417413496060

Dekhtyar, S., Wang, H. X., Fratiglioni, L., & Herlitz, A. (2016). Childhood school performance, education and occupational complexity: A life-course study of dementia in the Kungsholmen project. *International Journal of Epidemiology*, *45*(4), 1207–1215. https://doi.org/10.1093/ije/dyw008

Denier, N., Clouston, S. A. P., Richards, M., & Hofer, S. M. (2017). Retirement and cognition: A life course view. *Advances in Life Course Research*, *31*, 11–21. https://doi.org/10.1016/j.alcr.2016.10.004

Dufouil, C., Pereira, E., Chêne, G., Glymour, M. M., Alpérovitch, A., Saubusse, E., Risse-Fleury, M., Heuls, B., Salord, J. C., Brieu, M. A., & Forette, F. (2014). Older age at retirement is associated with decreased risk of dementia. *European Journal of Epidemiology*, *29*(5), 353–361. https://doi.org/10.1007/s10654-014-9906-3

Eid, M., Courvoisier, D. S., & Lischetzket, T. (2012). Structural equation modeling of ambulatory assessment data. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 384–405). Guilford Press.

Feldberg, C., Hermida, P. D., Tartaglini, M. F., Dorina, S., Somale, V., & Allegri, R. F. (2016). Cognitive reserve in patients with mild cognitive impairment: The importance of occupational complexity as a buffer of declining cognition in older adults. *AIMS Medical Science*, *3*(1), 77–95. https://doi.org/10.3934/medsci.2016.1.77

Ferrer, E., & McArdle, J. J. (2010). Longitudinal modeling of developmental changes in psychological research. *Current Directions in Psychological Science*, *19*, 149–154. https://doi.org/10.1177/0963721410370300

Finkel, D., Andel, R., Gatz, M., & Pedersen, N. L. (2009). The role of occupational complexity in trajectories of cognitive aging before and after retirement. *Psychology and Aging*, *24*(3), 563–573. https://doi.org/10.1037/a0015511

Finkel, D., Andel, R., & Pedersen, N. L. (2007, November). The role of occupational complexity in trajectories of cognitive aging. In S. Reed & T. Rantanen (Chairs), *Psychological aging in twins*. Symposium presented at the annual meeting of the Gerontological Society of America.

Fisher, G. G., Stachowski, A., Infurna, F. J., Faul, J. D., Grosch, J., & Tetrick, L. E. (2014). Mental work demands, retirement, and longitudinal trajectories of cognitive functioning. *Journal of Occupational Health Psychology*, *19*(2), 231–242. https://doi.org/10.1037/a0035724

Fujishiro, K., MacDonald, L. A., Crowe, M., McClure, L. A., Howard, V. J., & Wadley, V. G. (2019). The Role of occupation in explaining cognitive functioning in later life: Education and occupational complexity in a U.S. national sample of black and white men and women. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *74*(7), 1189–1199. https://doi.org/10.1093/geronb/gbx112

Gallup Inc. (2013). *In U.S., average retirement age up to 61 younger age*.

Grotz, C., Meillon, C., Amieva, H., Andel, R., Dartigues, J. F., Adam, S., & Letenneur, L. (2018). Occupational social and mental stimulation and cognitive decline with advancing age. *Age and Ageing*, *47*(1), 101–106. https://doi.org/10.1093/ageing/afx101

Grotz, C., Meillon, C., Amieva, H., Stern, Y., Dartigues, J. F., Adam, S., & Letenneur, L. (2016). Why is later age at retirement beneficial for cognition? Results from a French population-based study. *The Journal of Nutrition, Health and Aging*, *20*(5), 514–519. https://doi.org/10.1007/s12603-015-0599-4

Grzywacz, J. G., Segel-Karpas, D., & Lachman, M. E. (2016). Workplace exposures and cognitive function during adulthood: Evidence from national survey of midlife development and the O*NET. *Journal of Occupational and Environmental Medicine*, *58*(6), 535–541. https://doi.org/10.1097/JOM.0000000000000727

Hamm, J. M., Heckhausen, J., Shane, J., & Lachman, M. E. (2020). Risk of cognitive declines with retirement: Who declines and why? *Psychology and Aging*, *35*(3), 449–457. https://doi.org/10.1037/pag0000453

Hyllegard, D., & Lavin, D. E. (1992). Higher education and challenging work: Open admissions and ethnic and gender differences in job complexity. *Sociological Forum*, *7*(2), 239–260. https://doi.org/10.1007/BF01125042

Karp, A., Andel, R., Parker, M. G., Wang, H. X., Winblad, B., & Fratiglioni, L. (2009). Mentally stimulating activities at work during midlife and dementia risk after age 75: Follow-up study from the kungsholmen project.

The American Journal of Geriatric Psychiatry, *17*(3), 227–236. https://doi.org/10.1097/JGP.0b013e318190b691

Kemperman, A., Van Den Berg, P., Weijs-Perrée, M., & Uijtdewillegen, K. (2019). Loneliness of older adults: Social network and the living environment. *International Journal of Environmental Research and Public Health*, *16*(3), 1–16. https://doi.org/10.3390/ijerph16030406

Kievit, R. A., Brandmaier, A. M., Ziegler, G., van Harmelen, A. L., de Mooij, S. M. M., Moutoussis, M., Goodyer, I. M., Bullmore, E., Jones, P. B., Fonagy, P., the NSPN Consortium, Linderberger, U., & Dolan, R. J. (2018). Developmental cognitive neuroscience using latent change score models: A tutorial and applications. *Developmental Cognitive Neuroscience*, *33*, 99–117. https://doi.org/10.1016/j.dcn.2017.11.007

Kraup, A. R., Xia, F., Launer, L. J., Sidney, S., Nasralllah, I., Erus, G., Allen, N., & Yaffe, K. (2018). Occupational cognitive complexity in earlier adulthood is associated with brain structure and cognitive health in midlife: The CARDIA study. *Neuropsychology*, *32*(8), 895–905. https://doi.org/10.1037/neu0000474

Kröger, E., Andel, R., Lindsay, J., Benounissa, Z., Verreault, R., & Laurin, D. (2008). Is complexity of work associated with risk of dementia? The Canadian study of health and aging. *American Journal of Epidemiology*, *167*(7), 820–830. https://doi.org/10.1093/aje/kwm382

Lachman, M. E., Agrigorei, S., Tun, P. A., & Weaver, S. L. (2014). Monitoring cognitive functioning: Psychometric properties of the Brief Test of Adult Cognition by Telephone (BTACT). *Physiology & Behavior*, *21*(4), 404–417. https://doi.org/10.1016/j.physbeh.2017.03.040

Lane, A. P., Windsor, T. D., Andel, R., & Luszcz, M. A. (2017). Is occupational complexity associated with cognitive performance or decline? Results from the Australian longitudinal study of ageing. *Gerontology*, *63*(6), 550–559. https://doi.org/10.1159/000475559

Lezak, M. (1995). *Neuropsychological assessment* (3rd ed.). Oxford University Press.

Li, C. H. (2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, *48*(3), 936–949. https://doi.org/10.3758/s13428-015-0619-7

Meng, A., Nexø, M. A., & Borg, V. (2017). The impact of retirement on age related cognitive decline—A systematic review. *BMC Geriatrics*, *17*(1), Article 160. https://doi.org/10.1186/s12877-017-0556-7

Meyer, M. L., Taylor, S. E., & Lieberman, M. D. (2015). Social working memory and its distinctive link to social cognitive ability: An fMRI study. *Social Cognitive and Affective Neuroscience*, *10*(10), 1338–1347. https://doi.org/10.1093/scan/nsv065

Nexø, M. A., Meng, A., & Borg, V. (2016). Can psychosocial work conditions protect against age-related cognitive decline? Results from a systematic review. *Occupational and Environmental Medicine*, *73*(7), 487–496. https://doi.org/10.1136/oemed-2016-103550

O'Shea, D. M., Langer, K., Woods, A. J., Porges, E. C., Williamson, J. B., O'Shea, A., & Cohen, R. A. (2018). Educational attainment moderates the association between hippocampal volumes and memory performances in healthy older adults. *Frontiers in Aging Neuroscience*, *10*, 361. https://doi.org/10.3389/fnagi.2018.00361

Rebok, G. W., Ball, K., Guey, L. T., Jones, R. N., Kim, H. Y., King, J. W., Marsiske, M., Morris, J. N., Tennstedt, S. L., Unverzagt, F. W., & Willis, S. L. (2014). Ten-year effects of the advanced cognitive training for independent and vital elderly cognitive training trial on cognition and everyday functioning in older adults. *Journal of the American Geriatrics Society*, *62*(1), 16–24. https://doi.org/10.1111/jgs.12607

Ritchie, S. J., Bates, T. C., & Deary, I. J. (2015). Is education associated with improvements in general cognitive ability, or in specific skills? *Developmental Psychology*, *51*(5), 573–582. https://doi.org/10.1037/a0038981

Roberts, B. A., Fuhrer, R., Marmot, M., & Richards, M. (2011). Does retirement influence cognitive performance? The Whitehall II study. *Journal of Epidemiology and Community Health*, *65*(11), 958–963. https://doi.org/10.1136/jech.2010.111849

Rohwedder, S., & Willis, R. J. (2010). Mental retirement. *The Journal of Economic Perspectives*, *24*(1), 119–138. https://doi.org/10.1257/jep.24.1.119

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

RStudio Team. (2020). *RStudio: Integrated development for R*. http://www.rstudio.com

Ryan, L. H. (2008). *The work environment and cognitive function across adulthood: Reciprocal relations and meaningful outcomes*. The Pennsylvania State University.

Salthouse, T. A. (2006). Mental exercise and mental aging: Evaluating the validity of the "Use it or lose it" hypothesis. *Perspectives on Psychological Science*, *1*(1), 68–87. https://doi.org/10.1111/j.1745-6916.2006.00005.x

Salthouse, T. A., & Prill, K. (1987). Inferences about age impairments in inferential reasoning. *Psychology and Aging*, *2*, 43–51. https://doi.org/10.1037/0882-7974.2.1.43

Schooler, C., Mulatu, M. S., & Oates, G. (1999). The continuing effects of substantively complex work on the intellectual functioning of older workers. *Psychology and Aging*, *14*(3), 483–506. https://doi.org/10.1037/0882-7974.14.3.483

Sliwinski, M., & Buschke, H. (2004). Modeling intraindividual cognitive change in aging adults: Results from the Einstein aging studies. *Neuropsychology, Development, and Cognition. Section B, Aging, Neuropsychology and Cognition*, *11*(2–3), 196–211. https://doi.org/10.1080/13825580490511080

Smart, E. L., Gow, A. J., & Deary, I. J. (2014). Occupational complexity and lifetime cognitive abilities. *Neurology*, *83*(24), 2285–2291. https://doi.org/10.1212/WNL.0000000000001075

Sörman, D. E., Hansson, P., Pritschke, I., & Ljungberg, J. K. (2019). Complexity of primary lifetime occupation and cognitive processing. *Frontiers in Psychology*, *10*, 1861. https://doi.org/10.3389/fpsyg.2019.01861

Stern, Y. (2009). Cognitive reserve. *Neuropsychologia*, *47*(10), 2015–2028. https://doi.org/10.1016/j.neuropsychologia.2009.03.004

Stern, Y., Arenaza-Urquijo, E. M., Bartrés-Faz, D., Belleville, S., Cantilon, M., Chetelat, G., Ewers, M., Franzmeier, N., Kempermann, G., Kremen, W. S., Okonkwo, O., Scarmeas, N., Soldan, A., Udeh-Momoh, C., Valenzuela, M., Vemuri, P., Vuoksimaa, E. & the Reserve, Resilience and Protective Factors PIA Empirical Definitions and Conceptual Frameworks Workgroup. (2020). Whitepaper: Defining and investigating cognitive reserve, brain reserve, and brain maintenance. *Alzheimer's and Dementia*, *16*(9), 1305–1311. https://doi.org/10.1016/j.jalz.2018.07.219

Then, F. S., Luck, T., Luppa, M., Thinschmidt, M., Deckert, S., Nieuwenhuijsen, K., Seidler, A., & Riedel-Heller, S. G. (2014). Systematic review of the effect of the psychosocial working environment on cognition and dementia. *Occupational and Environmental Medicine*, *71*(5), 358–365. https://doi.org/10.1136/oemed-2013-101760

Tombauh, T., Kozak, J., & Rees, L. (1999). Normative data stratified by age and education for two measures of verbal fluency: FAS and animal naming. *Archives of Clinical Neuropsychology*, *14*, 167–177. https://doi.org/10.1016/S0887-6177(97)00095-4

Weschler, D. (1997). *Weschler adult intelligence scale-III (WAIS-III) manual*. The Psychological Corporation.

Wickrama, K., O'Neal, C. W., Kwag, K. H., & Lee, T. K. (2013). Is working later in life good or bad for health? An investigation of multiple health outcomes. *The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences*, *68*(5), 807–815. https://doi.org/10.1093/geronb/gbt069

World Health Institution. (2019). *Risk reduction of cognitive decline and dementia: WHO guidelines*. https://www.who.int/mental_health/neurology/dementia/guidelines_risk_reduction/en/

Wu, S., Wang, R., Zhao, Y., Ma, X., Wu, M., Yan, X., & He, J. (2013). The relationship between self-rated health and objective health status: A population-based study. *BMC Public Health*, *13*(1), Article e320. https://doi.org/10.1186/1471-2458-13-320

Xue, B., Cadar, D., Fleischmann, M., Stansfeld, S., Carr, E., Kivimäki, M., McMunn, A., & Head, J. (2018). Effect of retirement on cognitive function: The Whitehall II cohort study. *European Journal of Epidemiology*, *33*(10), 989–1001. https://doi.org/10.1007/s10654-017-0347-7

Ybarra, O., Burnstein, E., Winkielman, P., Keller, M. C., Manis, M., Chan, E., & Rodriguez, J. (2008). Mental exercising through simple socializing: Social interaction promotes general cognitive functioning. *Personality and Social Psychology Bulletin*, *34*(2), 248–259. https://doi.org/10.1177/0146167207310454

Zinke, K., Zeintl, M., Rose, N. S., Putzmann, J., Pydde, A., & Kliegel, M. (2014). Working memory training and transfer in older adults: Effects of age, baseline performance, and training gains. *Developmental Psychology*, *50*(1), 304–315. https://doi.org/10.1037/a0032982

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