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Original Report

New Evidence of Healthier Aging: Positive Cohort Effects on Verbal Fluency

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Abstract

Background and Objectives: Cross-sectional studies have shown improvements in cognition in later-born cohorts. However, it remains unclear whether these cohort effects extend beyond cognitive levels and are also detectable in the rate of age-related cognitive decline. Additionally, evidence is scarce on the presence and consistency of cohort effects throughout different segments of the distribution of cognitive trajectories.

Research Design and Methods: This study evaluates the existence and variability of cohort effects across the entire distribution of aging-related trajectories of verbal fluency. With this purpose, we develop sex and education-adjusted longitudinal norms of verbal fluency using data from 9 waves of the English Longitudinal Study of Aging (ELSA) by fitting quantile mixed models. The effect of age was modeled using splines to assess birth cohort effects, after grouping individuals in 5-year groups from 1920 to 1950 according to their age at study entry. To test for possible cohort effects across the 10th, 50th, and 90th quantiles, the coefficients associated with the splines were allowed to vary among cohorts.

Results: Our results suggest that, consistently across longitudinal quantiles, decline in verbal fluency across age is less pronounced for later-born individuals ($p < .001$), supporting the hypothesis of cohort effects. Additionally, we also found that quantiles of verbal fluency at any age are shifted upwards in later-born cohorts compared to those in earlier-born cohorts.

Discussion and Implications: These results enhance our understanding of cognitive decline in older adults by demonstrating that cohort effects on cognition are observable both cross-sectionally and longitudinally, affecting the entire range of verbal fluency trajectories.

Keywords: Cohort effects, Cognition, ELSA, Longitudinal norms

Translational Significance: According to our findings, cohort effects play a significant role in the longitudinal progression of verbal fluency. Compared with the older cohorts, the younger cohorts demonstrated greater verbal fluency and showed less pronounced cognitive decline with age. In the context of health interventions that target the cognitive processes of aging older adults, this result may be clinically useful. Further, the use of verbal fluency may be useful in clinical settings as well. Finally, there are likely medical treatment settings in which knowledge of cohort changes in verbal fluency may inform interaction with patients.

Background and Objectives

The world is undergoing a demographic shift that results in an increasingly older population. As a result, the understanding of aging-related cognitive decline and its associated factors becomes more relevant, as it is a costly and concerning phenomenon that will be experienced by a larger number of individuals.

Cohort trends have generally shown a consistent improvement in general health metrics, notably including neurocognitive functioning. The phenomenon known as the Flynn effect, which describes intergenerational increases in intelligence scores, has been corroborated by meta-analyses in global studies spanning the last century, as highlighted by Pietschnig and Voracek (2015) and Trahan et al. (2014). Members of a given cohort experience shared societal conditions, environmental exposures, and collective experiences that define their generational group. These commonalities may manifest as generational differences in cognitive trajectories (Brailean et al., 2018; Clouston et al., 2021; Dodge et al., 2017; O'Keefe et al., 2023). Indeed, individuals of the same generation share similar exposures to risk and protective factors, along with environmental, cultural, and technological resources that are unique to them. These similar exposures are, therefore,

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expected to have an effect on the development of individuals of the same generation or birth cohort and may help explain observed differences in cognitive function across individuals born at different times. For example, it is possible that the generational change in cognitive performance across life that has been previously reported in the literature may be due to educational improvements (Baker et al., 2015; Clouston et al., 2020; Lynn, 2009) over time. Similarly, researchers (Matthews et al., 2013; Satizabal et al., 2016) have attributed a decrease in the incidence of dementia (a condition derived from cognitive status) to improvements in treatments for cardiovascular disease and diabetes. Other possible causes, such as health, nutrition, and family history in early life, socioeconomic status in adulthood, psychosocial factors, and biological behaviors and diseases have also been considered (Zheng, 2021).

A large body of literature focuses on average changes in cognition in older adults (Campbell et al., 2013; Hall et al., 2007; Hülür et al., 2016; Muniz-Terrera et al., 2013, 2014; Salthouse, 2010; Tucker-Drob, 2011; Wilson et al., 2002) as well as risk factors associated with level and rate of cognitive decline. Instead, others studied the heterogeneity of cognitive trajectories by identifying subgroups of individuals with similar developmental curves (Mungas et al., 2010; Muniz-Terrera et al., 2010; Wang et al., 2023). Although these publications provide important insights about cognitive aging, knowledge about normative cognitive trajectories is limited (Koscik et al., 2019; Liampas et al., 2023; Olaya et al., 2017) despite the use of better normative curves that can be used to provide a benchmark against which individual cognitive change can be compared (to understand whether an individual's decline in cognition is within an expected range or exhibits significant deviations from the expected change). Furthermore, as normative curves facilitate the early detection of abnormal cognitive decline, they can be used in clinical settings to identify individuals at increased risk of impairment. Ignoring the potential presence of cohort differences in normative curves could result in misleading classifications of individuals and therefore, the adequate capture of such effects in models of normative trajectories is highly relevant.

Here, we test whether birth cohort effects are present in normative curves of verbal fluency (VF) in older adults. With this aim, we fit additive mixed-effects quantile regression models (Geraci & Bottai, 2014; Koenker, 2004) for longitudinal quantiles 0.1, 0.5, and 0.9 of VF scores from the English Longitudinal Study of Aging (ELSA), and focus on differences between longitudinal norms by birth cohort while accounting for sex and education. By doing this, we evaluate whether later-born cohorts have better VF at study entry than previously born individuals, whether they decline at a slower rate, and if these effects are detected across the entire spectrum of cognitive function or only in some but not all longitudinal quantiles. We focus on VF, a marker of language processing abilities, cognitive flexibility, and executive functions (Henderson et al., 2023; Shao et al., 2014), a measure often included in neuropsychological assessments of older adults. For instance, VF tests support diagnoses of cognitive impairment in people with neurodegenerative diseases, such as Alzheimer's disease or Parkinson's disease (Pettit., 2013; Zhao, 2013). VF tasks have also been used in nonclinical research to measure verbal ability, including lexical knowledge and lexical retrieval ability (Federmeier et al., 2010, 2022) and as a test of executive function (Henry & Crawford, 2004).

Research Design and Methods

Data

The ELSA study is a representative sample of the population aged 50 and older, living in private households in England. It collects data from interviews and self-completion of questionnaires approximately every 2 years since 2002. To date, nine waves of data are available. In our study, we included all available data without exclusion criteria. ELSA is a wide data source including information on sociodemographics, health characteristics, social participation, and biomarkers (Steptoe et al., 2013). To measure VF, the 1-min animal test (Cummings, 2004) is used. In this task, participants are given 60 s to name as many animals as possible and the VF score measure is the total number of animals named.

To assess cohort effects, we divided participants born between 1920 and 1950 into six 5-year groups. Education was measured using the self-reported highest educational qualification. We used the categories "Less than high school," "High school graduate," "Some College," and "College and above." We also adjusted the analysis by sex (Female/Male).

Statistical Approach

Descriptive statistics of continuous variables are expressed in terms of mean and standard deviation and of absolute frequencies and proportions for discrete variables. To compare the distribution of sex, educational attainment, age at baseline, and follow-up period across cohorts, we used Pearson's χ^2 tests and Kruskal–Wallis (KW) tests.

We fitted the following mixed-effects quantile regression to VF scores to derive longitudinal norms

$$Q_{Y_{ij}}(\tau|\ t_{ij}) = F_Y^{-1}(\tau|\ t_{ij}) = b_{\tau,i} + x_{ij}\beta_\tau + s_\tau(t_{ij}) + \varepsilon_{\tau,i} \tag{1}$$

$$i = 1,...,n \quad j = 1,...,n_i$$

where n is the number of individuals (indexed by "i") and n_i is the number of measurements (indexed by "j") of a given subject. Different values of the parameter $\tau \in (0,1)$ specify different quantiles. Additionally, $s_\tau(.)$ is a τ-specific, twice-differentiable smooth function evaluated at subject-specific times t_{ij}, which represents the longitudinal norm of the VF. The value $b_{\tau,i}$ represents an individual-specific random intercept and its distribution is assumed to be a centered Gaussian distribution with a τ-specific variance σ_τ^2.

To account for possible differences in level and rate of change by sex and education, we included a dummy variable for sex (male = 0, female = 1) and three dummy variables indicating whether an individual had completed High School Graduate (HSG), had Some College (SC) education or had complete College and above (CaA). Finally, $\varepsilon_{\tau,i}$ is the error term distributed as a centered asymmetric Laplace distribution with skewness parameter τ and scale parameter ϕ_τ. Its density function is given by the expression:

$$f_\varepsilon^\tau(\varepsilon) = \frac{\tau(1-\tau)}{\phi_\tau}\exp\left\{-\frac{1}{\phi_\tau}\rho_\tau(\varepsilon)\right\} \tag{2}$$

where $\rho_\tau(\varepsilon) = \varepsilon\left[\tau - \mathbb{I}_{(\varepsilon<0)}\right]$ is the loss function and $\mathbb{I}$ denotes the indicator function. To complete the probabilistic description of the model, we assume that errors and random intercepts are independent of each other. Optimization of the

Table 1. Baseline Characteristics of the Overall Sample and by Cohort

Variable	1920–1925	1925–1930	1930–1935	1935–1940	1940–1945	1945–1950	Statistics	Overall
	(*n* = 1,007)	(*n* = 1,370)	(*n* = 1,810)	(*n* = 2,146)	(*n* = 2,415)	(*n* = 2,488)	(*p* Value)	(*n* = 11,315)
Sex							11.101 (.049)	
Female	559 (0.555)	754 (0.550)	930 (0.514)	1,090 (0.508)	1,250 (0.518)	1,304 (0.524)		5,349 (0.476)
Male	448 (0.445)	616 (0.450)	880 (0.486)	1,056 (0.492)	1,165 (0.482)	1,184 (0.476)		5,887 (0.524)
Education							572.35 (<.001)	
Less than high school	628 (0.691)	834 (0.681)	973 (0.593)	976 (0.494)	921 (0.416)	767 (0.341)		5,099 (0.499)
High school graduate	102 (0.112)	116 (0.095)	263 (0.161)	364 (0.184)	463 (0.209)	522 (0.231)		1,839 (0.179)
Some college	115 (0.126)	163 (0.133)	252 (0.154)	405 (0.206)	461 (0.208)	569 (0.252)		1,965 (0.193)
College and above	65 (0.071)	112 (0.091)	150 (0.092)	229 (0.116)	367 (0.167)	398 (0.176)		1,321 (0.129)
Mean follow-up	5.31 (4.69)	6.91 (5.59)	8.17 (5.96)	8.81 (5.99)	9.09 (6.16)	9.48 (6.16)	475.06 (<.001)	10.08 (5.90)
Age at baseline	82.31 (3.81)	78.55 (4.80)	74.63 (5.20)	70.6 (5.42)	65.67 (5.53)	61.61 (5.51)	9722.7 (<.001)	64.8 (7.79)

Notes: For categorical variables frequencies and proportions are shown, whereas for quantitative variables mean and standard deviations are presented. Pearson χ^2 test and Kruskal–Wallis test were used to assess across-cohorts differences for categorical and quantitative variables, respectively.

likelihood function is performed separately for every value of τ as described in Geraci (2007).

Finally, given the nonlinear nature of the norms specified in model (1), to obtain a better interpretation of the rate of change, average marginal effects (AME) with respect to time were calculated. The AME are interpreted as the average population rate of change of the outcome (VF) throughout the period of study (Onukwugha & Bergtold, 2015). In comparison to a linear model, the AME can be interpreted as the average slope of the $s_\tau(.)$ term with respect to time.

To test the equality of norms across cohorts, we conducted tests based on the likelihood ratio test (LRT). We compared the fit of the model described in Equation (1), which we call the global model (GM), with a cohort-specific model (CSM) for each cohort. The statistic used to quantify evidence against the global model was:

$$\Lambda = 2\log\frac{\max_{\theta\in\Theta}\ell(Y_1,\ldots,Y_n|\theta)}{\max_{\theta\in\Theta_0}\ell(Y_1,\ldots,Y_n|\theta)} \quad (3)$$

where $\ell(Y_1,\ldots,Y_n|\theta)$ is the likelihood of the model as a function of the parameter θ. Supposing that Θ_0 and Θ are the parameter spaces under the GM and the CSM of dimension r_0 and r respectively, according to Wilk's theorem (Wilks, 1938) Λ asymptotically follows a χ^2 distribution with $r - r_0$ degrees of freedom as the sample size tends to infinity.

All statistical procedures were performed in the R environment (R Core Team, 2021). In particular, the routines of the *lqmm* (Geraci, 2014; Geraci & Bottai, 2014), *splines*, and *ggplot2* (Wickham, 2009) packages were used.

Results

Descriptive Analysis

The sample included a total of 11,236 individuals (see Table 1 for descriptive characteristics of the sample). This large sample size supports the use of asymptotical theory needed for Wilks statistic. There were differences in the distribution of men and women across cohorts (KW = 11.1, p = .049) and earlier-born cohorts had a higher proportion of individuals with lower educational attainment (KW = 572.3, p < .001). Similarly, individuals from earlier-born cohorts had a shorter follow-up period (χ^2 = 475.0, p < .001) and younger average age at study-entry (p < .001).

Table 2. Differences Across Cohorts in the Quantiles τ = 0.1, 0.5, and 0.9

Variable	Log-likelihood	*df*	LRT	*p* Value
τ = 0.1			478.48	<.001
GM	−150,649.8	8		
CSM	−150,410.6	32		
τ = 0.5			608.97	<.001
GM	−140,987.9	8		
CSM	−140,683.4	32		
τ = 0.9			822.58	<.001
GM	−148,011.9	8		
CSM	−147,600.6	32		

Notes: CSM = cohort-specific model; *df* = degrees of freedom; GM = global model; LRT = Likelihood ratio test.

Longitudinal Norms of Verbal Fluency

As stated earlier, the model presented in Equation (1) was adjusted both globally (GM) and by cohort (CSM). The results presented in Table 2 indicate that, in the three quantiles considered, the effect of at least one of the components (age, education, or form of the longitudinal norm) differs between cohorts.

As the results in Table 2 suggest that the fit of the CSM is better than that of the GM, from this point on all the following results presented refer to the CSM. The results of the CSM adjustment suggest a slight effect of sex in the older cohort and a stronger effect of education. Figure 1 presents the estimated coefficients (and their 95% confidence interval) for sex and education on longitudinal norms of VF for the six considered cohorts. It illustrates that the coefficient associated with sex only had a significant negative effect in the oldest cohort in the 50th and 90th quantiles and that among the education coefficients, the one associated with individuals with college stands out and shows a positive trend in both the 50th and 90th quantiles.

As part of the variability of VF within and between cohorts is due to sex and education, we next present the longitudinal norms after adjusting for the effect of these variables. The

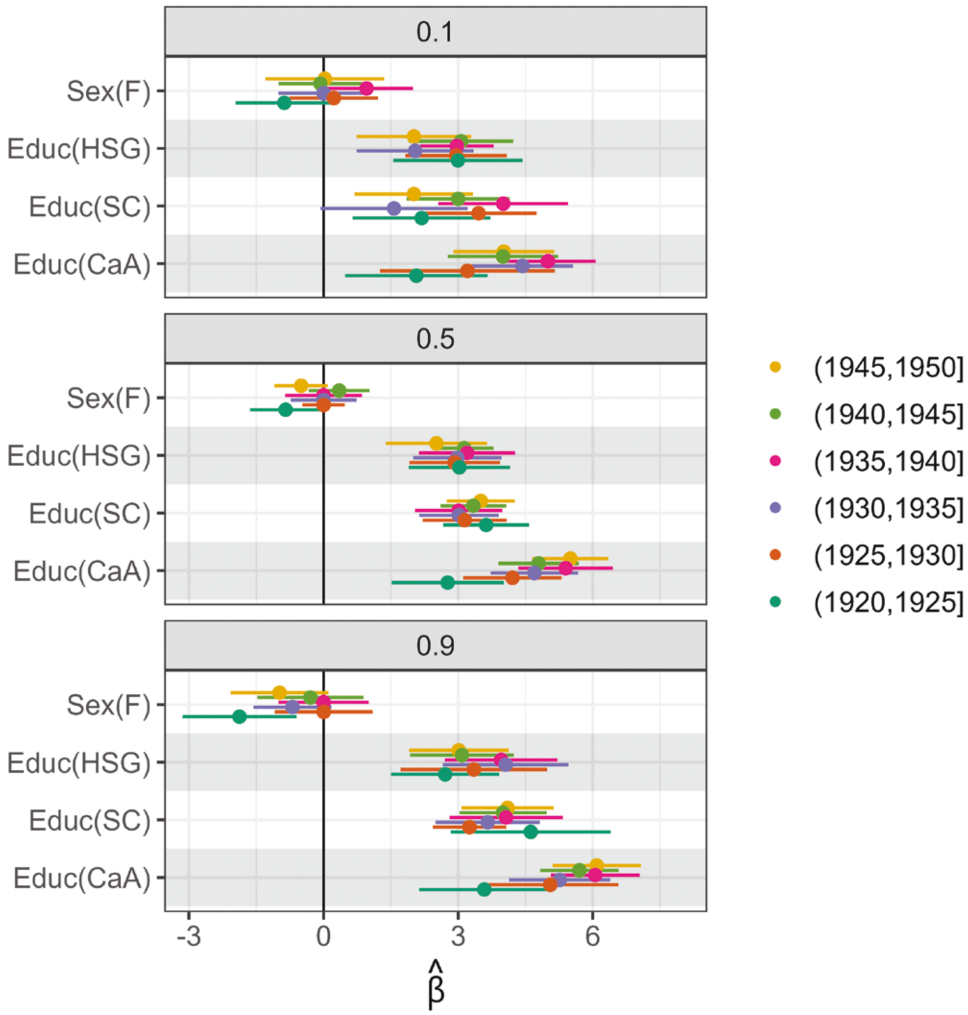

Figure 1. Estimated coefficients for the longitudinal norms of verbal fluency in the cohort-specific model. CaA = College and above; Educ = Education; F = Female; HSG = High School Graduates; SC = Some College.

longitudinal norms of VF presented in Figure 2 were generated using the estimated coefficients of CSM and marginalizing over sex and education.

By comparing the fitted curves presented in Figure 2, it can be seen that individuals in the earlier-born cohorts (left-hand panels) had poorer VF performance at 50 years old than individuals in the later-born cohorts. Additionally, a more pronounced decline was observed in the 1920s, 1925s, 1930s, and 1935s cohorts compared to that observed in the 1940s and 1945s cohorts, as depicted in Figure 2, which shows that the 10th and 50th quantile have a more pronounced decline with age than the 90th quantile. The differences in the rate of change of the quantiles are more pronounced for individuals in the earlier-born cohorts, that is, for individuals born from 1920s to 1940s. Individuals born since the 1940s present less pronounced rates of change across the different quantiles.

To simplify the interpretation of the longitudinal standards, Table 3 presents the values of the AME.

Upon inspection of the AME, it is evident that there not only is a higher value of VF in younger cohorts (across the considered quantiles) but it also indicates that the observed marginal change in VF becomes less pronounced in successive cohorts. Both statements point to heterogeneity in VF between cohorts in both level (Intercepts) and evolution (AME).

Sensitivity Analyses

We performed sensitivity analyses of the results. First, we perform this analysis changing the covariate education to reduce the categories in which the individuals are classified. We collapsed the categories “Some college” and “College or above” into one category so that the education variable has only three categories. The results obtained under this setup do not differ from those obtained with the education variable with four categories.

Second, we fitted the models using different definitions of the cohorts. Particularly, we grouped the individuals in three cohorts, specifically individuals born in the 1920s, 1930s, and 1940s. The main results remain unchanged using this different definition of cohorts.

Thirdly, since older cohorts only contributed data for individuals older than 72 years, we conducted the analysis using only the last four cohorts. The results obtained from this case showed significant differences between the GM and the CSM.

Discussion and Implications

By *using cohort-specific models, we estimated* normative trajectories for VF using data from participants aged 50 and older from ELSA. We specifically analyzed changes across

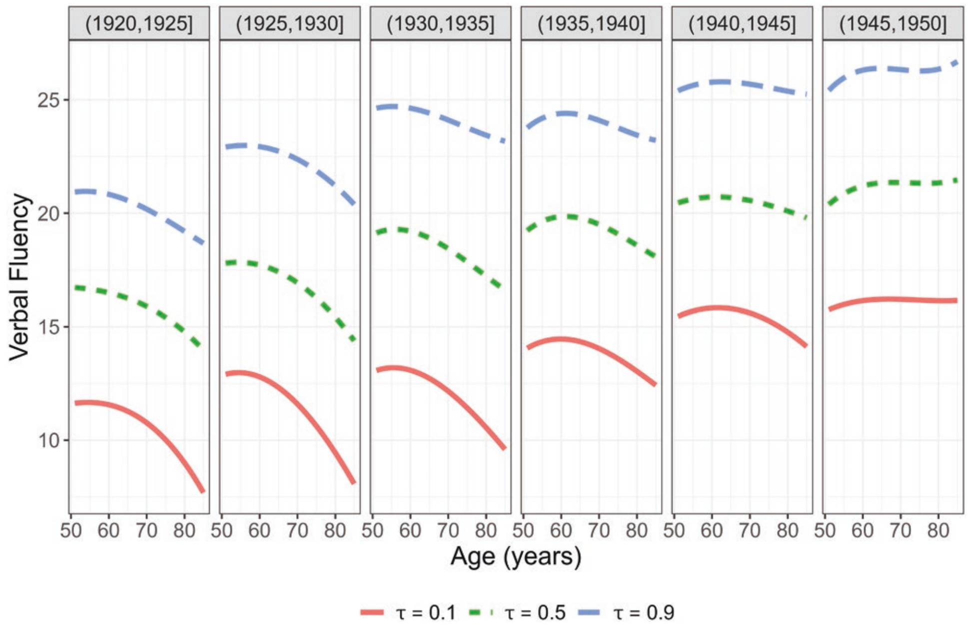

Figure 2. Longitudinal norms of verbal fluency by cohort, adjusting for sex and education.

Table 3. Average Marginal Effects (and Standard Deviations) of Verbal Fluency Norms by Cohort Across Quantiles

Cohort	$\tau = 0.1$		$\tau = 0.5$		$\tau = 0.9$	
	Intercept	AME	Intercept	AME	Intercept	AME
1920–1925	10.42 (0.45)	−0.40 (0.07)	15.32 (0.46)	−0.27 (0.05)	20.10 (0.46)	−0.12 (0.05)
1925–1930	11.22 (0.41)	−0.34 (0.03)	16.05 (0.35)	−0.24 (0.03)	20.97 (0.51)	−0.19 (0.04)
1930–1935	11.97 (0.45)	−0.20 (0.04)	17.38 (0.38)	−0.14 (0.04)	22.61 (0.59)	−0.08 (0.04)
1935–1940	11.64 (0.46)	−0.10 (0.03)	17.41 (0.41)	−0.07 (0.02)	21.43 (0.64)	−0.03 (0.03)
1940–1945	13.71 (0.48)	−0.08 (0.04)	18.40 (0.35)	−0.04 (0.05)	23.64 (0.52)	−0.01 (0.04)
1945–1950	13.81 (0.78)	0.01 (0.02)	19.04 (0.34)	0.07 (0.02)	24.16 (0.46)	0.09 (0.03)
% change	32.46%	−103.23%	24.26%	−125.54%	20.21%	−146.89%

Notes: AME = average marginal effects.

different points of the distribution: the median trajectory (quantile $\tau = 0.5$), the trajectory representing individuals with minimal cognitive decline (quantile $\tau = 0.9$), and the trajectory for those experiencing the most significant cognitive deterioration (quantile $\tau = 0.1$). Our results revealed a significant cohort effect on VF trajectories among the ELSA participants aged 50 and older. These findings align, to some extent, with previous research (Baker et al., 2015; Lynn, 2009), which attributed such cohort effects to various factors, notably the incremental improvements in education over time. Our analysis confirmed that educational attainment has indeed increased among later-born cohorts. Nevertheless, our results demonstrated that even after accounting for educational differences, individuals from more recent cohorts exhibited less pronounced declines in VF compared to their earlier-born counterparts.

The results of our study highlighted the possible existence of greater heterogeneity in the cognitive progression of the younger cohorts in relation to older cohorts. This result may be clinically useful for health interventions that address the cognitive processes of the aging older adults. This analysis allowed us to assess differences in cognitive impairment according to the level of the VF indicator for the different cohorts. Thus, it is observed that the younger cohorts have higher levels of VF and a less pronounced cognitive decline with age than the older cohorts. In addition, the deterioration of individuals with lower levels of VF (those in the 10th quantile) is more pronounced than the deterioration of individuals with higher levels of VF (those in the 90th quantile).

Our work is not without limitations. In our methodological approach, we do not account for missing data or death. The presence of missing data in longitudinal studies (especially in studies of older adults) could lead to biased and inefficient estimates that can threaten the validity of study inferences, especially if not properly addressed. This poses a new challenge for future work analyzing cognitive trajectories in aging studies. *Further research on cognitive trajectories would benefit from considering methodologies that account for missing data and death*. In addition, it would be interesting to perform analyses similar to those carried out in this study with other cognitive markers not only to corroborate the existence of cohort effects but also to determine whether they are equally strong.

In summary, even after adjusting the analysis for educational attainment, the presence of a cohort effect is observed. We believe that the cohort-effect observed in this study can be attributed to the fact that older cohorts experienced significant traumatic historical events (the Great Depression, World War II, the Cold War, among others) that probably had profound effects on their cognition and general mental health. We conclude this study by asserting that the presence of this effect in both the level and rate of decay with age affect differently across the VF quantiles.

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Conflict of Interest

None.

Data Availability

To obtain ELSA data from all waves, including wave 0 (Health Survey from England) contact the UK Data Service. The code used to generate the simulated data sets and obtain the results presented in this paper can be obtained by request to the main author.

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