Cohort changes and sex differences after age 50 in cognitive variables in the English Longitudinal Study of Ageing

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Abstract

Objective: This paper models cognitive aging, across mid and late life, and estimates birth cohort and sex differences in both initial-levels and aging trajectories over time in a sample with multiple cohorts and a wide span of ages. Methods: The data used in this study came from the first nine waves of the English Longitudinal Study of Ageing (ELSA), spanning 2002-2019. There were n=76014 observations (proportion Male 45%). Dependent measures were verbal fluency, immediate recall, delayed recall, and orientation. Data were modeled using a Bayesian logistic growth curve model. Results: Cognitive aging was substantial in three of the four variables examined. For verbal fluency and immediate recall, males and females could expect to lose about 30% of their initial ability between the ages of 52 and 89. Delayed recall showed a steeper decline, with males losing 40% and females losing 50% of their delayed recall ability between ages 52 and 89 (although females had a higher initial level of delayed recall). Orientation alone was not particularly impacted by aging, with less than a 10% change for either males or females. Furthermore, we found cohort effects for initial ability level, with particularly steep increases for cohorts born between approximately 1930 and 1950. Discussion: These cohort effects generally favored later born cohorts. Implications and future directions are discussed.

Keywords: Cohort shifts; Flynn effect; ELSA

Introduction

There are two temporal shifts in cognitive functioning that are of particular interest for understanding population aging: changes in cognition related to aging, and secular trends associated with birth cohorts (Clouston et al., 2021). Although aging has long been associated with declines across a wide array of measures of cognitive function, there is also evidence for improvements in cognitive abilities across historical time in recent decades, a process that has been referred to as cohort-period shifts or the Flynn effect (Flynn, 1984, 1987).

For well over 50 years, cross-sectional and longitudinal research has shown that older adults experience declines in cognitive and physical functioning. There has also been acknowledgment that such trends may be related to birth cohort and to various design and methodological confounds (Hofer & Sliwinski, 2001). Some cross-sectional research has suggested that the magnitude of decline attributed specifically to aging has been systematically overestimated, and that actual aging effects are smaller (Dickinson & Hiscock, 2011). Other research has suggested that longitudinal studies underestimate aging effects due to practice effects (Salthouse, 2009); that is, individuals' scores are inflated due to improved performance that results from gaining familiarity with the cognitive tests. In the study by Salthouse, within-person aging effects did not overcome purported practice effects until after age 50. However, the practice effect interpretation (which suggests much higher rates of cognitive decline), and the specific work by Salthouse (2009), has been criticized (e.g., Nilsson, Sternäng, Rönnlund, & Nyberg, 2009; Schaie, 2009).

The interaction of aging-related changes and birth cohort differences remains a particularly challenging, and therefore often ignored, effect. For well over 70 years, it has been known that human cognitive ability has been improving over time (Tuddenham, 1948), and since the (re)discovery of this effect by Flynn in 1984 this knowledge has become mainstream in the scientific community. Cohort differences in cognitive ability and decline have been detected in older aged individuals across a variety of measures and in a variety of contexts (e.g., Brailean et al., 2018; Dodge et al., 2017; Frith & Loprinzi, 2019). Additional research has found Flynn effects in the English Longitudinal Study of Ageing [ELSA; Banks, J., Institute for Fiscal Studies et al. (2021)], which we will use for our analyses, albeit with fewer and earlier, waves than used here (Skirbekk, Stonawski, Bonsang, & Staudinger, 2013). Based on these results, at minimum, we ought to expect later born cohorts to have higher levels of cognitive ability. These higher levels of cognitive ability would be consistent with a cognitive reserve hypothesis (Cadar et al., 2017; Tucker-Drob, Johnson, & Jones, 2009). A variety of research in older aged individuals corroborates the idea that cognitive ability has changed over time, with implications for cognitive aging.

The goal of this paper is to model cognitive aging, across mid and late life, and estimate birth cohort and sex differences in both initial-levels and trajectories over time. By estimating the effect of birth cohort on initial-levels and changes in cognitive ability we test the Flynn effect in the ELSA, while estimating sex differences sheds light on whether age-related differences in cognitive decline varies for males and females. Recent research has suggested that men and women may experience cognitive aging differently, with women having higher cognitive reserve but more rapid rates of decline (Levine et al., 2021). On the other hand, earlier Flynn effect research in children and adolescents found no sex difference in the Flynn effect in a population-level U.S. database (Ang et al, 2010). Whether sex differences exist for cognitive aging is a question with high potential impact for identifying and characterizing the pathogenesis of cognitive decline and impairment in aging populations, which is projected to increase in the future (Rajan et al., 2021). Prior to fitting our models, we assumed that aging results in cognitive declines, at least at the ages we are examining (age range of 52-89). A priori, we did not expect substantial declines in the earliest ages observed based on extant evidence. For example, a review of change point studies suggested that accelerated decline does not begin until at least 15 years before death (Karr et al., 2018), which corresponds to an average of early to mid-sixties for most adults in western countries. Many research studies also find that age-related cognitive declines accelerate in later life and before death, although some studies have observed declines as early as the mid to late-forties (e.g., Singh-Manoux et al., 2012). We fit models that allowed for monotonically decreasing cognitive ability with age, but did not require a constant level of decline year-over-year, and that allow the effect of aging to accelerate over time.

Methods

The data used in this study came from the ELSA study. The data were from the first nine waves of ELSA, spanning 2002-2019 (observations were collected every two years). There were n=76,014 total observations from 16,337 subjects. Independent measures were sex (Proportion Male 0.45), age (M=67.30, SD=9.28), and year of birth (M=1941.94, SD=10.03). Dependent measures were verbal fluency, immediate recall, delayed recall, and orientation. Verbal fluency was measured as the number of animal names that could be produced in a minute (M=20.51, SD=6.94). Memory was measured via immediate (M=5.78, SD=1.80) and delayed (M=4.46, SD=2.13) recall by asking participants to recall as many words as possible from a previously presented 10-word list. Orientation was measured using a four-item questionnaire related to the date (M=3.74, SD=0.62).

Complete case analysis was used. Verbal fluency was not administered during wave six and so had more missingness than the other variables. For the other variables, missingness was assessed on all three variables simultaneously, and only observations with all three variables were included. A plot of the missingness patterns is included in the appendix Figure 1. For orientation and recall missingness is approximately 3%. For verbal fluency, because of the additional unadministered wave of data, there are approximately 11,200 missing observations.

Modeling

Data were modeled using the Stan Bayesian software program and R (Gabry & Češnovar, 2021; R Core Team, 2022). We used a logistic growth curve model. We briefly describe the model here, for a more in-depth review of these models, and alternative methods of fitting them, see work such as Grimm and Ram (2009) and Grimm, Ram, and Hamagami (2011). "Logistic" here describes the function used to describe aging and should not be confused with "logistic regression" where the logistic function is the link function. This function has three parameters estimated from the data: 1) intercept, 2) rate, and 3) inflection-point parameter. Because of the parameterization of our model the inflection point (the age at which the rate of change is greatest) coincides with the age at which half of initial ability has been lost. The logistic model takes the form $y = \frac{intercept}{1+exp(rate \times (Age - Midpoint))}$. The intercept was further modeled as either $intercept = exp(\beta_0 + u_{0i} + u_{0j})$ for verbal fluency or as $intercept = \frac{1}{1+exp(\beta_0+u_{0i}+u_{0j})}$ for the other three dependent variables. Verbal fluency was modeled as a Poisson variable (because it is a count variable that theoretically has no upper limit). The intercept for verbal fluency was therefore constrained to only take values greater than 0 (this was achieved via exponentiation). Recall and orientation were modeled as binomially distributed variables because the values were constrained to integer values between 0 and 10 (for recall variables) or between 0 and 4 (for orientation), and the intercept was constrained to be between 0 and 1. Although researchers may be more familiar with binomial distributions in the case of variables with only binary responses, the binomial distribution is also an appropriate choice when variables can be conceptualized as a count of successes, each with the same probability, from a finite number of trials. In the logistic function the intercept represented the level of ability individuals were expected to maintain throughout adulthood until cognitive decline set in. The intercept (β_0) was allowed to vary randomly between individuals (u_{0i}) and between cohorts (u_{0j}). The rate parameter determined the rate of decline as an individual aged. As decline over time was anticipated the rate parameter was constrained to be positive (as a negative rate would indicate growth over time). The midpoint, or inflection point parameter, determined the age at which ability had declined to half of the intercept. These three parameters were estimated separately for males and females. Overall, the functional form resulted in a decaying function that started with relative stability at the intercept, gradual, but accelerating, decline, followed by a period of decelerating decline, ultimately asymptoting at zero.

Individual random effects were modeled as simple random effects with a mean of 0 and a standard deviation τ, which was estimated freely. Cohort random effects were modeled as a Gaussian process to account for the fact that individuals born in birth years (cohorts) that are temporally closer are likely to be more similar to one another. The Gaussian process drew random effects from a multivariate normal distribution with a covariance matrix estimated from a distance matrix and two parameters ρ and α. The Gaussian process model we use is intended for data that are stationary, whereas our results suggest that the data are not stationary. However, in small simulations (not reported here) non-stationarity did not affect the ability of the model to capture linear (or other) trends, rather, the non-stationarity would largely impact model based interpolation (which we do not do here). The Gaussian process also appears to increase power by providing additional shrinkage (and commensurately reduced standard errors) compared to completely independent cohort random effects.

As part of the Bayesian model fitting process, prior distributions needed to be chosen for each of the parameters. The priors are tabulated in the appendix in E-Table 2. Because of the exponentiation that occurs in the model, the priors appear more restrictive than they actually were. In certain cases, particularly for delayed recall, model fitting resulted in divergent transitions (a type of model error in Stan), and poorly mixing chains, which required model modification and refitting. The appendix presents a table of the final prior distributions that were used in model fitting, all but the intercept parameter were constrained to be positive (thus the prior distributions were truncated below 0). In the three cases where the parameters were allowed to vary between males and females (the intercept, rate and midpoint parameters), the same priors were used for both males and females. These priors produce a relatively good coverage of plausible values.

Results

To assess whether our basic model is reasonable, we examine Figure 1. This figure displays the model implied aging trajectory for verbal fluency compared to the empirically observed means at each age. This model is highly simplified (it does not account for repeated observations within person, cohort differences, or male and female differences). The model-implied trajectory closely matches the observed empirical means and was equivalent in complexity to a linear regression with a single independent variable in the number of parameters estimated.

Based on trace plots of the posterior draws, and a lack of divergent transitions, the models appeared to have good computational properties. Trace plots and other diagnostics (Rhat), can be found in the appendix. The raw parameter posterior means, as well as 95% credibility intervals are shown in Table 1. These can be compared to the prior distributions to confirm that our models are not merely reproducing informative priors (i.e., the posterior distributions are quite different from the initial prior distributions, suggesting the data had a strong influence on the posterior distribution), but are instead deriving genuine estimates from the data.

Although the posterior means and credibility intervals are useful, a more useful representation of the results is depicted in the following plots (Figures 2 and 3). Males and females were plotted separately, with multiple cohorts plotted for each. For simplicity, we space the cohorts approximately 10 years apart, starting in 1912 and continuing through 1968, and model implied trajectories are shown for each cohort in a ten year window. This allows for comparisons between cohorts without departing far from the actual data.

Figure 4 shows the model-estimated cohort effects. For verbal fluency, the cohort effect is exponentiated and represents the intercept multiplier for each cohort effect. For the other three models, because the cohort effect is included in the exponential term in the intercept logit, there is no clean way to present the effect in isolation. However, if we present the cohort effect as the logit of the cohort effect, we can see the overall pattern in the cohort effects (e.g., Are cohort effects increasing or decreasing? During which periods?). In general, we see that there have been upward trends across cohorts, however, this upward trend tends to level off towards later birth cohorts, and does not immediately appear in the earliest birth cohorts. With the exception of orientation, these cohort effects are significant, both in magnitude and statistically.

To summarize our findings related to sex and aging, for verbal fluency and immediate recall, males and females could expect to lose about 30% of their initial ability between the ages of 52 and 89. Delayed recall showed a steeper decline, with males losing 40% and females losing 50% of their delayed recall ability between ages 52 and 89 (although females had a higher initial level of delayed recall). Orientation alone was not particularly impacted by aging, with less than a 10% change for either males or females. With the exception of verbal fluency, differences in the rate of decline between men and women were consistently statistically significant (i.e., the 95% credibility intervals excluded the estimate for the other sex), however the baseline values for men and women were not significantly different.

Discussion

The goal of this study was to model cognitive aging across mid and late life using a change-point approach to help begin to resolve a question about the rate and timing of cognitive declines. Using the ELSA, we found that cognitive aging was noticeable in three of the four subdomains of cognitive functioning examined. Cognitive aging was not particularly noticeable in orientation, often used as a measure of mental status with many individuals performing above ceiling on the measure. Consistent with their use clinically, these results suggest that changes in orientation score (or low orientation scores) likely represents cognitive shifts unrelated to typical aging. We also found small, but significant, differences between men and women, with the pattern of results partially supporting previous findings (Levine et al., 2021). Women generally had slightly more rapid decline, however we did not find significant differences in women's baseline score relative to men. This was particularly the case for the two recall variables.

We believe that our models represent a method that successfully incorporates theoretical and measurement considerations in a way that more typical linear models could not. Our incorporation of cohort effects, allowing for a fine-grained assessment, and highly non-linear effects, is an additional strength. In principle, our model could allow for the incorporation of cohort effects in the estimation of any of the three primary parameters (the asymptote, rate, and midpoint parameters). We note that this presentation follows Dickinson and Hiscock (2011), who decomposed aging and cohort effects as well, although the current presentation is more expansive and more model-based. Finally, as demonstrated in our first plot, our model is both parsimonious and highly predictive.

Furthermore, we found cohort effects for initial ability level (i.e., there was an effect for cohort on the intercepts in our models). These cohort effects generally favored later born cohorts, with particularly steep increases for cohorts born between approximately 1930 and 1950, with subsequent leveling off in later years. As a function of our modeling choices, this increase in initial ability would imply a greater year-over-year loss in ability in older ages (although the rate of decline, as a proportion of ability, is the same).

Limitations

From a modeling perspective, the Gaussian process model for the cohort effects was computationally difficult to fit. Additionally, we do not address the potential period effects. It is mathematically intractable to simultaneously estimate linear aging, period, and cohort effects without implicitly or explicitly constraining at least one of the three parameter estimates (e.g., Bell & Jones, 2014; Glenn, 1976). In the present analysis we simply make the explicit constraint that period effects are nil. It also proved computationally difficult to estimate cohort effects for parameters in addition to the asymptote parameter. We believe that future simplifications of the cohort model used in this paper will help to resolve this issue. Finally, a reviewer noted that prior work has found that rates of cognitive decline are generally lower for individuals with higher levels of ability. Our current model does not account for that. Our model predicts the same proportion of decline for all individuals, which can result in higher scoring individuals declining faster (albeit always having higher scores). Our model appeared to fit quite well at the population level, but more work should be done at the individual level to account for previous work.

Future Directions

One of the primary future directions for this research is explanation of the cohort effects via the inclusion of covariates. Cohort differences in education or nutrition (for example) may help to explain part of the steady march of cohort improvement. Examining the effects of personal health on the rate of decline may also be fruitful. Due to the design of the model in principle it is possible to incorporate the effects of covariates in any (or all three) of the primary model parameters. We also believe that the application of these models (or similar models) to alternative data sources would be highly illuminating. In particular, we would ask if the clear cohort effects we have observed replicate in other countries with more diverse populations.

Conclusion

In summary, we found significant cohort effects in a direction consistent with a positive Flynn effect (i.e., later born cohorts had higher ability levels), in a longitudinal study and across a variety of cognitive measures. Measures of verbal ability and memory showed the largest losses, particularly memory, although a measure of orientation showed minimal losses. These results suggest that memory loss is a part of normal aging, even significant memory loss, however large losses in orientation are not a function of typical aging in the ELSA, which has high potential impact for identifying and characterizing the pathogenesis of age-related neurodegenerative disorders.

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Data and materials

Data are available to researchers from the UK Data service. Statistical analyses used in the study are available from the first author upon request.

Preregistration

This study was not preregistered.

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Figure 1. Model Implied Trajectory of Simple Verbal Model Against Empirical Means

Note: This figure provides a visualization of the model fit when not accounting for cohort differences, sex differences, or repeated measures. Even lacking certain substantial effects (e.g. cohort effects), we can still see that the model is a good fit to the data.

Figure 2. Model implied trajectories for verbal fluency and orientation for males and females

Note: This figure shows the model implied trajectories for men and women across multiple cohorts on verbal fluency and orientation. These plots show the magnitude of the cohort differences on these variables, and allow for visual comparisons between men and women. While there are clear differences in cohort baseline ability, there are not equally clear differences in baseline ability for men and women. There are visually distinguishable differences between the rate of decline for men and women, particularly at the oldest ages.

Figure 3. Model implied trajectories for immediate and delayed recall for males and females

Note: This figure shows the model implied trajectories for men and women across multiple cohorts on immediate and delayed recall. These plots show the magnitude of the cohort differences on these variables, and allow for visual comparisons between men and women. While there are clear differences in cohort baseline ability, there are not equally clear differences in baseline ability for men and women. There are visually distinguishable differences between the rate of decline for men and women, particularly at the oldest ages.

Figure 4. Plots of cohort random effects and posterior credibility intervals

Note: This figure provides a visual reference for the cohort effects. In these figures a higher cohort score indicates a higher baseline ability level for that cohort. For every measure except orientation there is a clear upward trend in cohort ability, with leveling in recent years.

Table 1: Posterior mean and 95% credibility interval for parameters

effects	verbal	immediate	delayed	orientation
Asymptote-Male	2.97 (2.87,3.05)	-0.24 (-0.42,-0.03)	0.32 (0.05,0.59)	-0.62 (-1.41,0.13)
Rate-Male	1.62 (1.4,1.86)	1.05 (0.88,1.23)	0.92 (0.71,1.11)	0.67 (0.49,0.9)
Midpoint-Male	4.61 (4.47,4.77)	4.91 (4.69,5.17)	4.39 (4.2,4.63)	8.86 (7.27,10.9)
Asymptote-Female	2.95 (2.85,3.03)	-0.32 (-0.5,-0.12)	0.24 (-0.02,0.51)	-0.75 (-1.53,0)
Rate-Female	1.58 (1.44,1.74)	1.53 (1.37,1.7)	1.66 (1.52,1.8)	1.95 (1.48,2.49)
Midpoint-Female	4.48 (4.39,4.57)	4.5 (4.4,4.62)	3.99 (3.93,4.05)	5.11 (4.76,5.59)
Random Effect SD	0.25 (0.24,0.25)	0.46 (0.45,0.47)	0.69 (0.67,0.7)	1.21 (1.15,1.27)
rho[a]	4.02 (2.95,5.24)	4.27 (3.25,5.42)	4.16 (3.24,5.29)	4.73 (3.82,5.81)
alpha[a]	0.11 (0.07,0.16)	0.24 (0.16,0.37)	0.34 (0.23,0.54)	1.67 (1.11,2.39)

[a]rho and alpha are control parameters affecting the variation and smoothness of the Gaussian process model

Figure 1

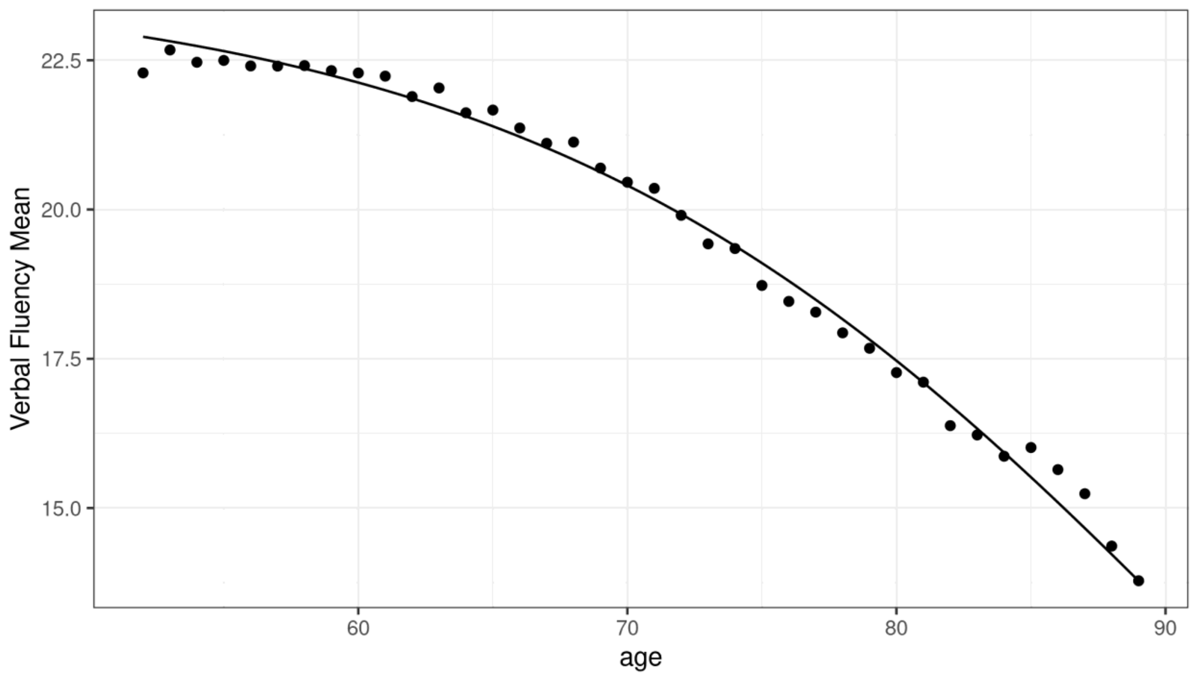


Figure 2

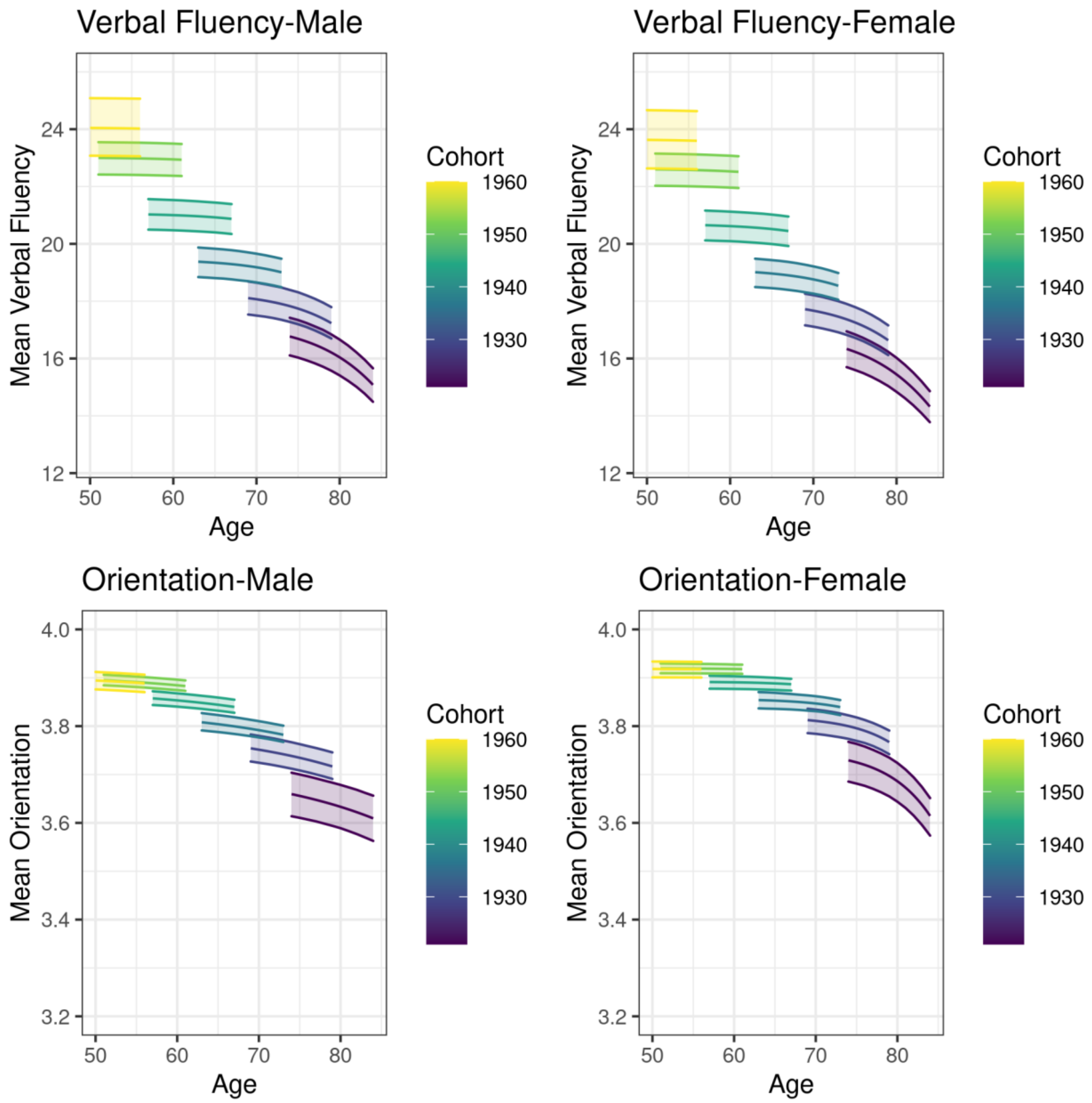
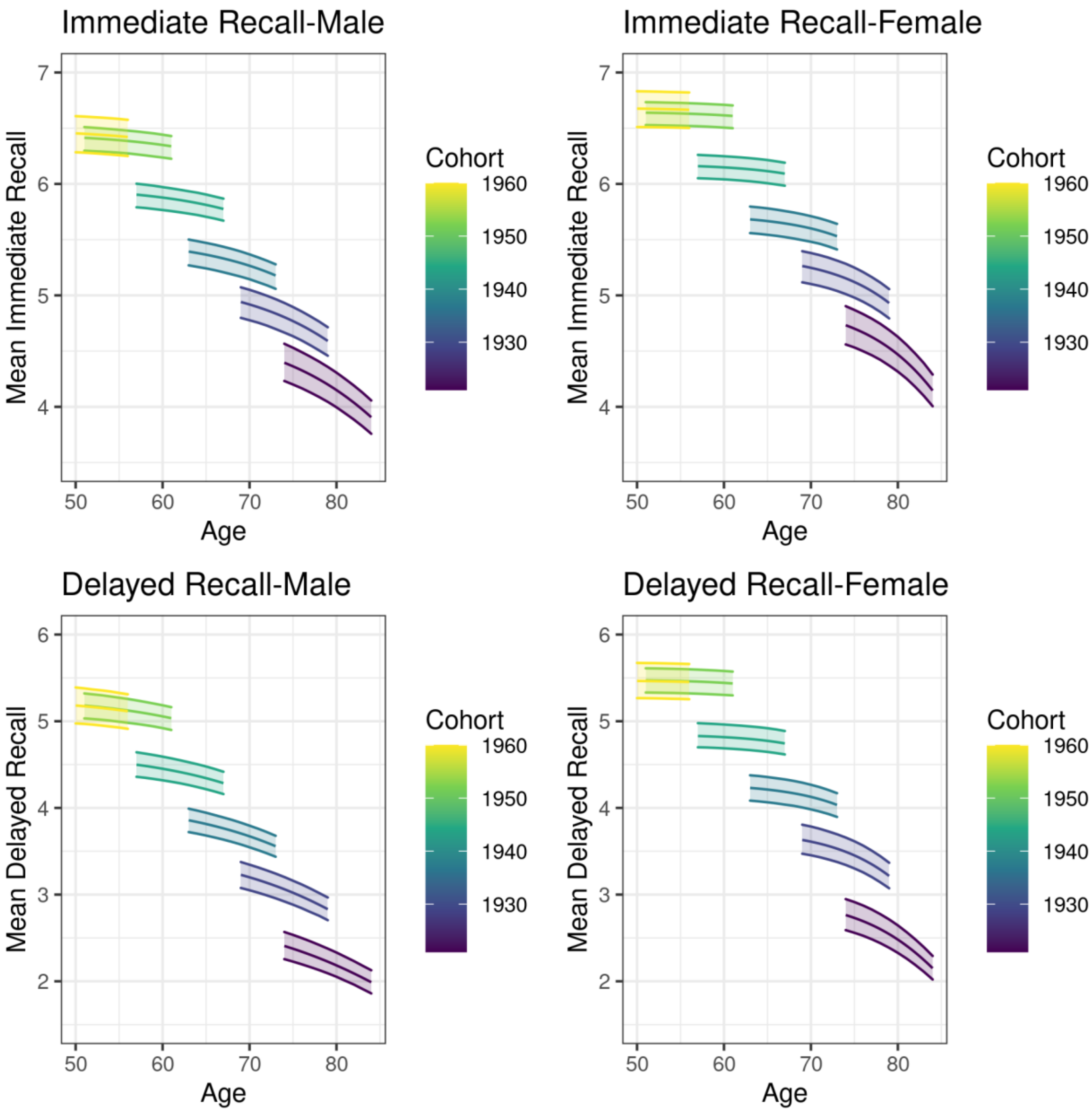
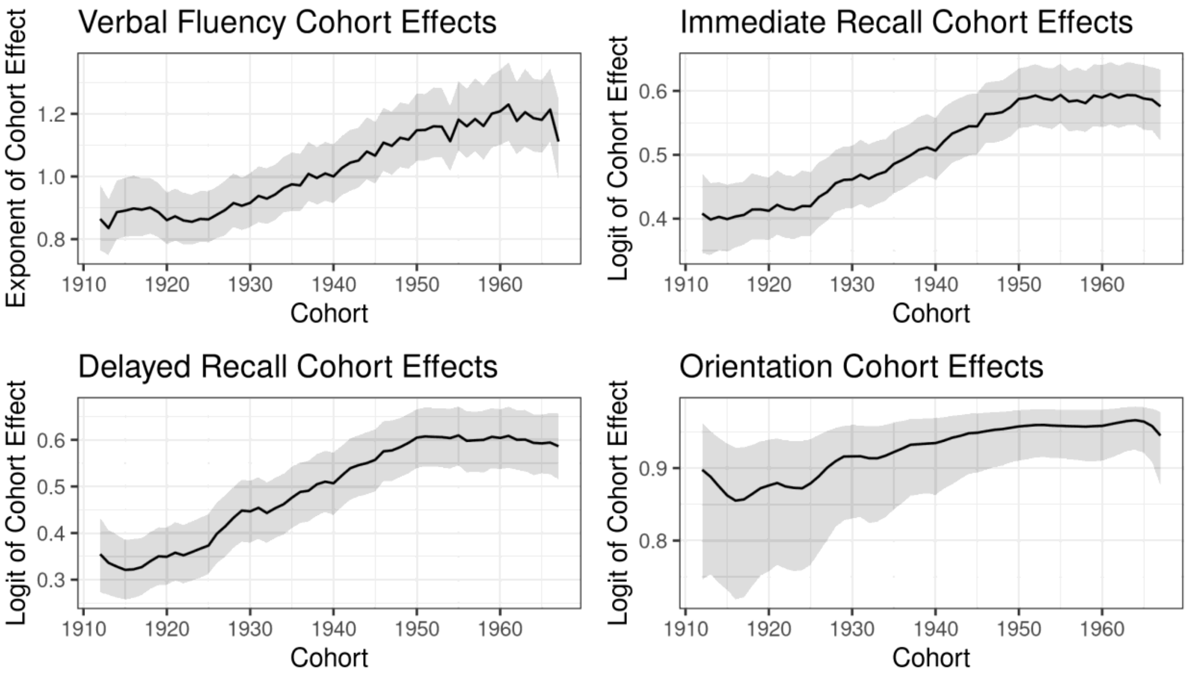

Verbal Fluency-Male
Mean Verbal Fluency
Age
Cohort
1960
1950
1940
1930
Verbal Fluency-Female
Orientation-Male
Mean Orientation
Orientation-Female

Figure 3



Immediate Recall-Male
Mean Immediate Recall
Age
Cohort
1960
1950
1940
1930
Immediate Recall-Female
Mean Immediate Recall
Age
Cohort
Delayed Recall-Male
Mean Delayed Recall
Age
Delayed Recall-Female
Mean Delayed Recall
Age

Figure 4


Verbal Fluency Cohort Effects
Exponent of Cohort Effect
1.2
1.0
0.8
1910
1920
1930
1940
1950
1960
Cohort
Immediate Recall Cohort Effects
Logit of Cohort Effect
0.6
0.5
0.4
1910
1920
1930
1940
1950
1960
Cohort
Delayed Recall Cohort Effects
Logit of Cohort Effect
0.6
0.5
0.4
0.3
1910
1920
1930
1940
1950
1960
Cohort
Orientation Cohort Effects
Logit of Cohort Effect
0.9
0.8
1910
1920
1930
1940
1950
1960
Cohort