Cognition across the lifespan: Aging and gender differences

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Abstract

Maintaining cognitive health across the lifespan has been the focus of a multi-billion-dollar industry. In order to guide treatment and interventions, a clear understanding of the way that proficiency in different cognitive domains develops and declines across the lifespan is necessary. Additionally, there are gender differences in a range of other factors, such as anxiety and substance use, that are also known to affect cognition, although the scale of this interaction is unknown. Our objective was to assess differences in cognitive function across the lifespan in men and women in a large, representative sample. Over 45,000 individuals were tested on 12 cognitive tasks. Segmented regression was used to model the trajectory of three cognitive domains: short-term memory, verbal abilities, and reasoning. Each domain showed a unique trajectory, suggesting that not all cognitive abilities develop and decline in the same way. Gender differences were found in all three domains; however, after controlling for socio-demographic factors, these differences were greatly reduced or disappeared. These results suggest that the trajectory of cognition across the lifespan differs for men and women, but is greatly influenced by environmental factors. We discuss these findings within a framework that describes gender differences in cognition as likely guided by a complex interplay between biology and environment.

Introduction

By 2020, roughly 22% of the world's population will be over 65, a total of approximately 1.7 billion people [1]. The consequences of our aging population are many, including an increasing focus on maintaining cognitive health; more so than ever before, individuals are seeking ways to keep their minds sharp. This new interest in maintaining cognitive health and reversing, or stalling, normal cognitive decline has led to the creation of billion-dollar industry, promoting products as wide-ranging as "brain training" software and pharmaceutical interventions such as nootropics. Yet, in order to be able to evaluate these approaches as potential tools and treatments, it is important that we first have a clear understanding of how cognition changes across the lifespan in average, healthy individuals. Additionally, because of the often-cited cognitive differences between women and men [2–5], it is important to characterize cognition in each population; if gender differences in cognitive abilities do exist, then men and women may respond differently to cognitive aging interventions.

In healthy individuals, cognitive abilities develop rapidly throughout childhood. By six, most children have developed some degree of inhibitory control, verbal fluency, and task switching [6–8]. By twelve, they are able to plan and organize, and use conceptual strategies and reasoning [9]. In adolescence, these abilities continue to develop, with most teenagers having good attentional control, verbal fluency, and processing speed [6]. By 18, executive function is thought to be mature [10], although research suggests that some processes continue to develop in early adulthood [11]. Young adulthood is where most researchers agree that cognitive abilities peak; however there is large variability within this period across different cognitive functions [6,11]. Mid to late adulthood is then characterized by a slow decline in most cognitive abilities [8,12], and while it can be problematic, this decline is considered part of healthy aging.

Differences in cognitive abilities between men and women are less clear; although several gender disparities in cognitive abilities appear to exist, recent studies have found these differences to be mediated by underlying factors related to gender, rather than being inherent to gender itself. For example, during childhood, girls are thought to develop faster than boys in verbal fluency and information processing [2,3], and boys are thought to develop faster than girls in spatial reasoning, working memory, and number processing [4,13]. However, Tzuriel and Egozi [14] found that gender differences in mental rotation disappeared after visuospatial training. Similarly, Krinzinger and colleagues [15] found that number processing advantages in boys were mediated by attitudes toward mathematics, and similar results have been found in young adults [16]. Differences in verbal processing have been less clear, with some suggesting that they are due to variability in instruction and strategy [17,18], and others suggesting a hormonal link [19,20]. Reports of gender differences in age-related cognitive decline are largely thought to be the result of cohort effects [21–23], although others have found gender-specific links to brain-derived neurotrophic factor [24] and brain metabolic activity [25]. Realistically, the truth likely lies somewhere in between, with a multifaceted interaction of biology and environment [25,26].

Finally, there are a number of sociodemographic factors known to affect cognition. For example, socioeconomic status (SES) and its relationship with cognitive abilities has been widely studied; it is generally agreed that higher SES predicts better performance on cognitive tasks [27,28]. Additionally, anxiety, depression, and substance abuse also have known detrimental effects on cognition, with higher levels of all three being associated with poorer cognitive outcomes [29–31]. Such sociodemographic factors also interact with gender; women tend to experience higher levels of anxiety [32] and depression [33], while men tend to experience higher levels of substance abuse [34], although women may be more at risk specifically for alcohol abuse (35, but see 36). Thus, there is a complex interaction of age, gender, and other sociodemographic variables that must be considered when studying cognitive abilities across the lifespan.

The internet provides a unique opportunity for examining cognition across the lifespan in the general population on a huge scale, allowing data to be sampled from participants from a broad range of SES, geographical, and educational backgrounds. There is a growing body of evidence to suggest that online cognitive assessment is as reliable as in-person pen-and-paper testing [11,37], addressing concerns that data collected in this manner may not be valid. Leveraging the power of the internet provides us with a cross-sectional snapshot of both demographics and cognition from a larger and more diverse sample than would be possible to collect in the laboratory.

The first goal of the present study was to characterize cognitive abilities across the lifespan, ranging from adolescence to late adulthood. Specifically, we sought to address whether differences exist between cognitive domains; do memory and reasoning show the same pattern, or do they peak at different ages? Do reasoning and verbal abilities show the same rate of decline, or does one remain resilient to aging more so than the other? The second goal was to examine whether these age effects differed between genders, and what factors may influence these differences. Specifically, we sought to address whether differences exist in some cognitive domains and not others, whether men and women peak at the same age, and whether they decline at the same rate. Further, we explored the demographic and social factors that affect the genders differently, and whether controlling for these differences affects the observed pattern of cognitive abilities across the lifespan. Based on smaller studies using more limited time windows, we predicted that gender differences would manifest with men outperforming women in memory and reasoning, but with women outperforming men in verbal abilities, and that the pattern of these abilities would show an increase up to early adulthood, and a slow decline into mid and late adulthood. By taking into account studies of the effects of mental health and sociodemographic variables on cognition, we also predicted that controlling for these factors would eliminate gender differences in cognitive abilities.

Materials and methods

Participants

All data for this study were collected with the CBS (www. cambridgebrainsciences.com) online platform, which has previously been used for other large-scale studies of cognition [38,39]. A total of 65,994 participants registered and completed all portions of the study, with a final number of 45,779 being included after removing outliers and rows with missing data (described in the data preprocessing section below). A summary of the final sample's demographics is included in Table 1, broken down by gender. All participants gave informed consent, and ethics approval was obtained through the Cambridge Psychology Research Ethics Committee (2010.62).

Table 1. Comparison of demographic variables across women and men.

Measure	Mean (SD) or Percentage		t(df), W, χ^2(df, N)[1]	p	Effect size[2]
	Women	Men			
N	13,444	32,335			
Age (years)	28.08 (11.01)	28.22 (10.30)	-1.31(23,696)	0.220	-0.01
Sleep (hours per night)	7.09 (1.64)	6.93 (1.64)	9.51(25,241)	< .001	0.10
Alcohol (units per week)	1.72 (1.85)	1.78 (2.00)	-3.10 (27,022)	.003	-0.03
Caffeine (units per day)	3.24 (4.69)	4.22 (5.53)	-19.36 (29,414)	< .001	-0.19
Cigarettes (per day)	1.48 (4.54)	1.71 (5.06)	-4.68 (27,830)	< .001	-0.05
Highest education completed			$2.17e^{8}$	.989	$6.27e^{-5}$
Some high school	10.20%	9.80%			
High School	8.40%	10.60%			
Some post-secondary	27.80%	30.50%			
Post-secondary degree	27.20%	27.70%			
Professional degree	26.40%	21.40%			

Level of employment			$2.21e^{8}$	.003	0.01
No answer	4.10%	2.70%			
Unemployed	10.30%	12.10%			
Full time student	28.70%	25.40%			
Employed and student	15.50%	11.90%			
Employed part time	10.00%	6.20%			
Employed full time	31.40%	41.80%			
Exercise			$2.18e^{8}$	.974	$5.35e^{4}$
Never	10.60%	11.00%			
Infrequently	37.80%	34.70%			
Weekly	19.90%	18.20%			
Several times a week	25.30%	28.30%			
Every day	6.50%	7.90%			
Depressive feelings			$2.36e^{8}$	< .001	0.07
No answer	1.10%	1.10%			
Never	10.40%	17.50%			
Occasionally	56.80%	54.00%			
Quite often	21.40%	18.20%			
Nearly every day	7.30%	6.40%			
All the time	3.10%	2.80%			
Anxiety			$2.58e^{8}$	< .001	0.15
No answer	1.30%	1.50%			
Never	13.00%	24.00%			
Occasionally	48.80%	49.90%			
Quite often	21.20%	14.80%			
Nearly every day	10.80%	6.50%			
All the time	5.00%	3.20%			
Video games			$2.42e^{9}$	< .001	0.09
Never	38.00%	17.10%			
Monthly	26.00%	20.30%			
Weekly	21.40%	29.40%			
Daily	14.60%	33.20%			
Siblings			$2.19e^{8}$	.111	0.01
Only child	12.40%	10.60%			
Youngest	30.40%	31.00%			
Middle	16.40%	17.40%			
Oldest	40.80%	41.00%			
Religiosity			$2.34e^{8}$	< .001	0.06
Atheist	31.90%	42.40%			
Agnostic	31.50%	31.50%			

Religious lapsed	19.50%	15.10%			
Religious practicing	13.10%	8.10%			
Very religious	3.90%	2.90%			
Political leaning			68.67(2, N = 45,779)	< .001	0.04
Liberal	47.20%	44.90%			
Middle	45.20%	45.10%			
Conservative	7.60%	10.00%			
Tech savvy			2693.40(1, N = 45,779)	< .001	0.24
Yes	64.00%	89.10%			
No	36.00%	10.90%			

[1]Welch's *t*-test used to compare numeric variables, Wilcoxon Rank-Sum used to compare ordinal variables, and χ^2 used to compare categorical variables

[2]Effect sizes used were Cohen's *d* for t-tests, *r* for Wilcoxon Rank-Sum tests, and Cramer's *V* for χ^2 tests

Materials

Sociodemographic questionnaire

The sociodemographic questionnaire included questions about the individual's age and gender, lifestyle such as exercise, substance use, and sleep, mental health such as depressive symptoms and anxiety, and other demographics such as education, employment, and level of technical savviness. Demographics included in the present study are listed in Table 1. Demographic information collected but not of interest here included country of birth, hours slept the night before completing the study, and favourite type of music. The full demographic questionnaire is available in Appendix 1.

Cognitive battery

Prior to filling in the questionnaire, participants completed the 12 tests in the CBS test battery. Test order was fixed across participants. Detailed descriptions of the tests can be found in the Supplementary Material of Hampshire et al. [31], but in brief they are: (1) 'Monkey Ladder' (visuospatial working memory); (2) 'Grammatical Reasoning' (verbal reasoning); (3) 'Double Trouble' (a modified Stroop task); (4) 'Odd One Out' (deductive reasoning); (5) 'Spatial Span' (short-term memory); (6) 'Rotations' (mental rotation); (7) 'Feature Match' (feature-based attention and concentration); (8) 'Digit Span' (verbal working memory); (9) 'Spatial Planning' (planning and executive function); (10) 'Paired Associates' (shape-location associative memory); (11) 'Interlocking Polygons' (visuospatial processing); and (12) 'Token Search' (working memory and strategy).

Factor analysis

Imaging studies have underscored the fact that there is rarely a one-to-one mapping between cognitive functions and the brain areas, or networks, that underpin them. One approach to this issue is to examine the complex statistical relationships between performance on any one cognitive task (or group of tasks), and changes in brain activity to reveal how one is related to the other. In order to do this most effectively, large amounts of data need to be included because of the natural variance in cognitive performance (and brain activity) across tests and across individuals. In the age of computerized internet testing and so-called 'big data', this problem becomes much easier to solve. Hampshire et al. [31] collected data on the 12 CBS tasks from 45,000 participants. These data were then subjected to a factor analysis and 3 discrete factors relating to overall cognitive performance were identified. Each one of these factors represents an independent cognitive function that is best described by a combination of performance on multiple tests, something that no single test can assess, and were labeled as encapsulating aspects of short-term memory, reasoning, and verbal abilities, respectively. This technique allows an individual's performance to be compared to a very large normative database in terms of these descriptive factors rather than performance on a single test.

Here, the same 12 tests were used to create three "composite" scores reflecting performance based on the factor analysis by Hampshire and colleagues , and the three composite scores were calculated as follows. First, the 12 individual test scores were normalized (M = 0.0, SD = 1.0). Then, the three cognitive domain scores were calculated using the formula $Y = X(Ar^{+})^{T}$, where Y is the N × 3 matrix of domain scores, X is the N × 12 matrix of test z-scores, Ar is the 12 × 3 matrix of varimax-rotated principal component weights (i.e., factor loadings) from Hampshire et al. All 12 tests contributed to each domain score, as determined by their component weights. Because scores were demeaned, a domain score of 0.0 is the mean of the population that was used to derive the loadings. Thus, a score above zero indicates that someone is above average.

Data preprocessing

Only data from the participants who completed all questionnaire items and all 12 tests were included in analysis. 65,994 participants met these requirements. Data were then cleaned to remove impossible and improbable questionnaire responses, removing 5,732 participants. Examples of improbable responses include smoking over 60 cigarettes per day, sleeping more than 17 hours the night before, or consuming more than 50 alcoholic drinks per day. Test scores were then filtered for outliers in two passes: scores greater than six standard deviations were assumed to be technical errors and were first removed, eliminating 7,298 participants. Then, scores greater than four standard deviations from the recalculated mean were identified, assumed to be performance outliers, and removed, eliminating 7,157 participants. Finally, individuals younger than 12 and older than 69 were removed because of low numbers outside of this age range, eliminating 28 participants. 45,779 participants were included in the final analysis.

Statistical analyses

Data were analyzed in R (version 3.5.2, R Core Team, 2018) and RStudio (version 1.1.463). Specific packages included: 'Segmented' [40] for computing regressions with breakpoints, 'MatchIt' [41] for matching samples on demographic variables, 'parallel' for parallel computing, and 'boot' [42] for calculating confidence intervals. Figs were produced using 'ggplot2' [43].

To examine the differences in demographic variables between genders, three different tests were used: Welch's *t*-tests for continuous variables, Wilcoxon Rank Sum tests for ordinal variables, and chi-square tests for categorical variables. *P*-values were corrected for multiple comparisons using a false discovery rate and were considered significant at $p < .05$. Effect size was calculated using the appropriate measures for each test: Cohen's *d* for *t*-tests, *r* for Wilcoxon Rank Sum tests, and Cramer's *V* for chi-square tests. Results are included in Table 1. Measures of skew and kurtosis indicated that domain scores were normally distributed, and histograms are shown in Fig 1.

Fig 1. **Histograms of domain scores by gender.** Dashed lines indicate mean.

Segmented linear regression models were constructed to predict each of the 3 domain scores from participants' reported age and were estimated using maximum likelihood estimation. Segmented regression was used to fit a model in which there is a change in the linear relationship – such as a "peak" that indicates a transition from increasing to decreasing performance with age – without imposing a pre-determined shape (e.g., quadratic or cubic) through adding one or more piecewise linear relationships [40,44]. The value of the independent variable (i.e., age) at which this change occurs is referred to as a breakpoint. The relationship between cognitive performance and age was modeled separately for each gender.

The segmented regression technique used here requires that the number of breakpoints, and (optionally) initial estimates of their locations, are provided. To determine the number of these points in each score, we fit each segmented regression model multiple times with one or more breakpoints and selected the model with the lowest Bayesian Information Criterion (BIC)[40,45]. The number of breakpoints was estimated separately for each domain score and gender. The algorithm converged on consistent breakpoint locations regardless of whether initial estimates were provided (from visual inspection of local regression curves, shown in Fig S1), or not. To confirm that a model with one or more breakpoints predicted the data better than a linear model, the Davies' test [46] was used to determine whether there was a statistically significant change in slope. The estimated breakpoint location was taken as the age at which there was peak performance in all regression models except for two cases. First, in men's verbal scores, in which there were two breakpoints and the breakpoint with the highest score was used as peak age. Second, in women's reasoning scores, in which the highest score was at the lower boundary of our age range. Slopes of the increasing and decreasing segments, as well as the middle segment for men's verbal scores, were obtained using the 'slope' function of the 'segmented' package, and 95% confidence intervals (CIs) were calculated for peak age, score at peak age, and all slopes.

Differences in these parameters between men and women were analyzed by bootstrapping with 10,000 replications the difference of the estimated parameter values from models that were separately estimated for men and women; that is, the sex-by- peak age, peak score, and slope interactions were evaluated using randomized bootstrapping, because estimation of breakpoint parameters in our segmented regression did not allow for interaction with other variables. On each bootstrap iteration, a random sample of 13,444 men were selected in order to match the female sample size. To determine whether these values differed significantly between genders, the lower and upper 2.5% quantiles of the bootstrapped difference values were produced; if these bounds included zero, then it could be interpreted as no significant difference between the genders.

In segmented models where multiple breakpoints were deemed a better solution than a single point as determined using BIC, the increasing or decreasing portion of the curve (i.e., the data to the left or right of the "peak") was characterized by two increasing or decreasing linear segments with different slopes (as can be seen in Fig 2C, women's reasoning scores). In order to compare slopes between the genders in these cases, bootstrapping was conducted by fitting the segmented model, then calculating the average slope to the left (in the case of men's verbal scores) or right (in the case of women's reasoning scores) of the peak. The rest of the bootstrapping parameters were kept the same as described above, with 95% confidence intervals of the difference values being used to detect significant differences between genders.

Post-hoc analyses

Given the differences in demographic variables between the genders, a second set of analyses were run in samples matched across genders for all demographic variables included in Table 1. These follow-up analyses were performed because, although the genders do realistically differ on measures such as anxiety and sleep, such factors are known to affect cognition and may contribute variance to the domain scores. Because it is difficult to account for the strong collinearity between gender and our demographic variables, matching the samples on these variables allowed us to examine gender differences when controlling for differences in socio-demographic variables. Descriptive information for these two new samples is summarized in Table S1, and histograms of domain scores are shown in

Fig S2. Local regression curves are shown in Fig S3. The same set of analyses were performed as outlined in the section above.

Results

Demographics

As reported in Table 1, a total of 13,444 women and 32,335 men completed the relevant demographic questionnaire items and all 12 cognitive tests. Women and men differed on several demographic factors, but not for age, education, exercise, and number of siblings (all *p*s > 0.05). While all significant *p*-values were ≤ .003, the largest effect sizes were seen in hours of sleep (Cohen's *d* = 0.10), units of caffeine per day (Cohen's *d* = -0.19), anxiety level (Wilcoxon's *r* = 0.15), and technical savviness (Cramer's *V* = 0.24).

Cognitive domain scores – unmatched samples

Short-term memory

STM scores for each gender were submitted to segmented regression with age as the sole predictor, entered as a continuous variable. In both cases, the breakpoint corresponded to a peak; that is, a transition from increasing to decreasing performance with increasing age (Fig 2A). Results are reported in Table 2, and slopes with 95% CIs bounds that did not include zero were interpreted as a significant effect of age.

Fig 2. Regression lines for STM, Verbal, and Reasoning scores across the lifespan, ranging from 12 to 69 years of age. 95% simultaneous confidence bands are shown in translucent colour around the line, and 95% confidence intervals for peak age are shown in translucent rectangles.

Table 2: Segmented regression parameter estimates for age, from regression models estimated for each composite score, for models estimated with N = 45,779

Score	Gender	Coef	SE	*t*	*p*
STM	Women	0.03	0.01	3.83	< .001
	△Age	-0.05			
	Men	0.04	0.01	6.48	< .001
	△Age	-0.07			
Verbal	Women	0.04	0.01	8.16	< .001
	△Age	-0.05			
	Men	0.10	0.01	8.44	< .001
	△Age1	-0.09			
	△Age2	-0.02			
Reasoning	Women	-0.01	0.001	-9.62	< .001
	△Age	-0.01			
	Men	0.003	0.004	0.73	.468
	△Age	-0.03			

Note: *p*-values for delta parameters measured by Davies' test

A model with one breakpoint was found to best estimate women's memory scores. The peak in women's STM scores occurred at age 20.47 [95% CI = 19.39, 21.55], with a score of 0.02 [95% CI = -0.01, 0.05]. The slopes of the segments to the left and right of the breakpoint were 0.03 [95% CI = 0.02, 0.05] and -0.02 [95% CI = -0.02, -0.02], respectively, indicating that age was a significant predictor of STM performance in these age ranges; specifically, increasing age was associated with increasing scores up to the age of 20 years, after which it was associated with decreasing performance. Davies' test for a change in slope was significant ($p < .001$), indicating that the linear relationship changed at the breakpoint, as can be seen in Fig 2A.

Men's memory scores were also best estimated by a segmented model with one breakpoint. The peak in men's STM score occurred at age 20.48 [95% CI = 19.85, 21.12], with a score of 0.30 [95% CI = 0.29, 0.32]. Slope of the increasing segment was 0.04 [95% CI = 0.03, 0.05], and slope of the decreasing segment was -0.024 [95% CI = -0.03, -0.02], showing a significant effect of age on STM score in men. The change in slope was significant, as measured by the Davies' test ($p < .001$).

In order to determine whether women and men differed in peak age, peak score, or increasing and decreasing slopes, 95% quantiles of bootstrapped difference values were calculated for each parameter. As can be seen in Table 3, there was no significant difference in the age at which women and men peaked in STM performance. However, men reached a significantly higher overall score than women at their peak ages, a difference of 0.28 standard deviations. When comparing how STM scores increased leading up to peak age and how quickly they declined afterward, women and men did not differ significantly.

Table 3: Comparisons between genders on key measures of cognitive performance over the lifetime

Score	Measure	Women [95% CI]	Men [95% CI]	Difference [95% CI]
STM	Peak age	20.471 [19.388, 21.553]	20.482 [19.845, 21.119]	-0.011 [-4.696, 3.441]
	Peak score	0.021 [-0.007, 0.049]	0.304 [0.286, 0.323]	-0.283 [-0.331, -0.219]
	Increasing slope	0.032 [0.015, 0.048]	0.042 [0.029, 0.054]	0.010 [-0.071, 0.036]
	Decreasing slope	-0.023 [-0.025, -0.021]	-0.024 [-0.025, -0.023]	0.001 [-0.002, 0.005]
Verbal	Peak age	23.206 [21.996, 24.418]	39.202 [35.986, 42.428]	-15.996 [-26.362, -3.858]
	Peak score	0.067 [0.033, 0.101]	0.116 [0.074, 0.157]	-0.049 [-0.145, -0.002]
	Increasing slope	0.042 [0.032, 0.052]	0.014 [0.007, 0.027][a]	0.028 [0.012, 0.176]
	Decreasing slope	-0.006 [-0.008, -0.004]	-0.013 [-0.017, -0.009]	0.007 [-0.001, 0.019]
Reasoning	Peak age	12	23.512 [22.248, 24.777]	-11.512 [-16.956, -4.221]
	Peak score	0.208 [0.168, 0.249]	0.196 [0.163, 0.228]	0.012 [-0.136, 0.046]
	Increasing slope	–	0.003 [-0.004, 0.009]	–
	Decreasing slope	-0.019 [-0.021, -0.018][a]	-0.027 [-0.029, -0.026]	0.008 [0.004, 0.012]

Note: Values are missing for women's reasoning increasing slope as both segments were negative

[a] Combined slope across two segments is reported. Slopes of the individual segments are reported in-text.

Verbal abilities

Results of segmented regression of verbal scores are also summarized in Table 2. A model with one breakpoint was again found to best estimate women's verbal scores. The peak in women's verbal scores occurred at age 23.21 [95% CI = 22.00, 24.42] with a score of 0.07 [95% CI = 0.03, 0.10], as can be seen in Fig 2B. Slope of the increasing segment was 0.04 [95% CI = 0.03, 0.05], and slope of the decreasing segment was -0.006 [95% CI = -0.008, -0.004], showing a significant relationship between age and verbal abilities. Davies' test for a change in slope was significant (p < .001), indicating that the linear relationship changed at the breakpoint.

Men's verbal scores were best estimated by a segmented model with two breakpoints. As can be seen in Fig 2B, men first had a breakpoint at age 18.85, at which point the rate at which scores were increasing, slowed. The peak in men's verbal score occurred at age 39.20 [95% CI = 35.99, 42.42], with a score of 0.12 [95% CI = 0.07, 0.16]. Slope of the initial increasing segment was 0.10 [95% CI = 0.07, 0.12], the slope of the second increasing segment was 0.005 [95% CI = 0.002, 0.007] and slope of the decreasing segment was -0.01 [95% CI = -0.02, -0.009], indicating a significant relationship between age and verbal abilities in all three sections. The change in slope was significant, as measured by the Davies' test (p < .001).

As summarized in Table 3, men reached a peak in verbal abilities at a significantly later age than women. Men also had significantly higher scores at peak age, with a difference of 0.05 standard deviations. When comparing how scores increased up to peak age, women's scores improved at a faster rate than men's, however there was no difference when comparing the rate of decline from peak age to age 69.

Reasoning

A model with one breakpoint was again found to best estimate women's reasoning scores. However, this breakpoint occurred at age 38.24 years, and indicated a transition from a gradual to steeper decline: scores declined with a slope of -0.014 [95% CI = -0.017, -0.011] from age 12 to age 38.24, at which point the negative slope increased to -0.029 [95% CI = -0.034, -0.023]. Davies' test for a change in slope was significant ($p < .001$), indicating that the linear relationship changed. As can be seen in Fig 2C, the highest predicted scores for women occurred at age 12 with a score of 0.21 [95% CI = 0.12, 0.25]. However, because this is the cut-off age of our sample, it is not possible to determine whether this is indeed a true peak, or if scores are higher at earlier ages.

Men's reasoning scores were best estimated by a segmented model with one breakpoint. The breakpoint in men's reasoning score occurred at age 23.51 (95% CI = 22.25, 24.78), with a score of 0.20 [95% CI = 0.16, 0.23]. The change in slope was significant, as measured by the Davies' test ($p <$ .001), however the slope of the initial segment was 0.002 [95% CI = -0.004, 0.010], and slope of the decreasing segment was -0.027 [95% CI = -0.029, -0.026], indicating that only the second segment showed a significant effect of age. Similar to women, this suggests that we did not capture a developmental increase in reasoning abilities within the current sample, and it is possible that the true peak occurs earlier than age 12.

Because we do not have a reliable measure of peak age in either gender, we compared between genders the age at which reasoning scores began to decline. In this sample, women began to decline in reasoning abilities significantly earlier than men, however reasoning scores at that age did not differ between genders (Table 3). Because women did not show an increase in reasoning scores within our age range, we could not compare men and women on this measure. However, when comparing how scores declined after peak age, men declined significantly faster than women.

Cognitive domain scores – matched samples

In the matched samples, the general pattern of results was similar to the unmatched samples in both STM and reasoning. However, the previously found gender differences in verbal abilities disappeared in the matched sample. Segmented regression lines for the matched sample are shown in Fig 3.

Fig 3. **Regression lines for STM, Verbal, and Reasoning scores across the lifespan, ranging from 12 to 69 years of age, in a socio-demographically matched sample.** 95% simultaneous confidence bands are shown in translucent colour around the line, and 95% confidence intervals for peak age are shown in translucent rectangles.

Short-term memory

Results of the segmented regression for STM scores of both genders in the socio-demographically matched sample are reported in Table 4. Both women and men again showed a significant change in slope as measured by the Davies' test (p < .001 for both genders). As can be seen in Table 5, after matching women and men on sociodemographic variables, no significant differences were found in the age at which women and men peaked in STM, nor in the slopes of the increase and decrease in scores surrounding peak age. However, men still reached a higher overall score than women at their peak ages by a standard deviation of 0.21.

Table 4: Segmented regression parameter estimates for age, from regression models estimated for each composite score in a demographically matched sample

Score	Gender	Coef	SE	*t*	*p*

STM	Women	0.04	0.01	4.10	< .001
	△Age	-0.06			
	Men	0.05	0.01	3.61	< .001
	△Age	-0.07			
Verbal	Women	0.05	0.01	7.58	< .001
	△Age1	-0.13			
	△Age2	-0.03			
	Men	0.14	0.03	5.36	< .001
	△Age1	-0.13			
	△Age2	-0.02			
Reasoning	Women	-0.01	0.001	-8.83	< .001
	△Age	-0.02			
	Men	0.01	0.01	1.10	.272
	△Age	-0.04			

Table 5: Comparisons between genders matched on socio-demographic variables

Score	Measure	Women [95% CI]	Men [95% CI]	Difference [95% CI]
STM	Peak age	20.423 [19.365, 21.482]	19.651 [18.609, 20.693]	0.772 [-2.089, 4.319]
	Peak score	0.046 [-0.009, 0.101]	0.259 [0.187, 0.330]	-0.213 [-2.63, -0.159]
	Increase	0.036 [0.019, 0.053]	0.049 [0.022, 0.075]	-0.013 [-0.132, 0.028]
	Decrease	-0.023 [-0.025, -0.022]	-0.025 [-0.027, -0.023]	0.002 [-0.001, 0.005]
Verbal	Peak age	24.889 [22.263, 27.515]	28.423 [25.330, 31.517]	-3.534 [-20.490, 6.098]
	Peak score	0.071 [0.033, 0.108]	0.104 [0.050, 0.158]	-0.033 [-0.091, 0.019]
	Increase	0.035 [0.016, 0.048][a]	0.022 [0.006, 0.045][a]	0.013 [-0.012, 0.036]
	Decrease	-0.006 [-0.008, -0.003]	-0.008 [-0.011, -0.005]	0.002 [-0.003, 0.014]
Reasoning	Peak age	12	19.623 [17.804, 21.542]	-7.623 [-12.816, -2.226]
	Peak score	0.223 [0.187, 0.271]	0.131 [0.060, 0.201]	0.092 [-0.047, 0.151]
	Increase	–	0.015 [-0.012, 0.041]	–
	Decrease	-0.020 [-0.021, -0.018][a]	-0.025 [-0.027, -0.023]	0.005 [0.003, 0.008]

[a] Combined slope across two segments is reported.

Verbal abilities

Both women and men again showed a significant change in slope as measured by the Davies' test ($p < .001$ in all tests). There were no significant differences in the age at which women and men peaked in verbal abilities, scores at peak age, nor in the slopes of the increase and decrease in scores surrounding peak age (Table 5).

Reasoning

Reasoning scores in our sample of women began to decrease at a significantly earlier age than men, however scores at that age did not differ between genders. While we did not capture an increase in reasoning abilities in either gender in our sample, reasoning scores decreased significantly faster in men than women (Table 5).

Discussion

After creating three cognitive domain scores from the 12 CBS tests based on their underlying factor structure, we were able to replicate previous findings suggesting that not all cognitive domains develop and decline in the same way. Specifically, STM increased rapidly from age 12 to the early 20s, at which point it decreased at a steady rate until age 69, the upper limit of our sample's age range. Verbal abilities also peaked in early adulthood, while reasoning did not show a clear peak in scores, instead being characterized by either a decline from age 12, or a plateau followed by a decline. These results were consistent with previous studies showing that cognition is not a unitary concept, and different cognitive abilities have separable developmental trajectories [11,12]. However, they extend the results of those studies in several important ways:

First, when examining the progression of STM, verbal abilities, and reasoning in men and women separately, all three cognitive domains also showed unique gender differences. Although men and women peaked in STM performance at the same age, men reached a slightly higher score than women. In verbal abilities, women reached their peak faster and earlier, but men again reached higher scores. While women's reasoning began to decline earlier than men's, men declined at a faster rate. These results extend what is known from previous gender research. For example, there is evidence that men lose grey matter volume more rapidly with age than women, especially in fronto-temporal regions [47]; this in turn may lead to a faster rate of decline in cognitive function, fitting the pattern we see here in the reasoning domain. In contrast, women are thought to have better verbal processing than men; however we see the opposite here, with men reaching a higher peak score than women. One possible explanation for this discrepancy could be the age at which verbal abilities are tested. For example, Burton and colleagues (19) tested a sample of university students, which is common in Psychology research. Looking at the pattern of verbal abilities in men and women in the current unmatched sample, women seem to outperform men at age 23, which, if we were to only examine individuals around this age, may lead to the erroneous conclusion that women have superior verbal abilities. Similarly, men are frequently reported to be better at mental rotation than women [19], a test included in our reasoning domain. In our sample, we found that peak reasoning scores did not differ between genders, but women declined much earlier than men. Again, comparing genders within a limited age range would have led to the erroneous conclusion that men outperform women in this domain, when in reality it is a difference in trajectory of reasoning abilities. The present results underline the need to take the progression of cognitive abilities across the lifespan into account when studying gender differences.

While these results are presumed to be reflective of the cognitive performance of the population, they are complicated by the differences in socio-demographic factors. Several of the factors showing the largest differences, such as sleep and anxiety, have known effects on cognitive function [38], making it difficult to determine what is driving the observed gender differences. Further complicating the matter is that because these socio-demographic factors are gender-dependent, it is not possible to include them in the model due to issues with multicollinearity. By matching men and women on these factors, however, we were able to limit their effect on the data as much as possible and the results show that this greatly reduced the differences in cognitive performance and aging. Of course, there are numerous demographic factors that we did not control for, and it is impossible to truly capture all of them. Additionally, there are some socio-demographic differences that may have biological underpinnings. For example, depression is more prevalent in women, and this may be in part due to the presence of sex-specific forms such as premenstrual dysphoric disorder [48]. It is therefore difficult to disentangle the environment from biological sex differences, however accounting for these differences, regardless of their origin, is necessary for describing gender differences in cognition alone.

As noted above, controlling for gender-specific differences in socio-demographic factors greatly reduced the differences in cognitive performance and aging. While men still reached a higher peak score than women, the difference between peak scores decreased from .28 SDs to .21 SDs. Notably, all differences in verbal abilities disappeared, with women appearing more like men in the nature of their progress, having no differences in peak age, score, or the rate of improvement or decline. However, although the gender gap was smaller (or absent) in the matched sample, this does not mean that differences in the unmatched sample should be ignored. While they may not necessarily be inherent to biology, environmental influences are a part of life, and they do drive gender differences in cognitive abilities. Thus, it is reasonable to conclude that gender differences in cognitive abilities, based on biological sex alone, are minimal; however, there are notable effects of environmental factors that in turn drive gender differences in cognition.

One large area of disparity that remained even when controlling for environmental factors was with respect to the age at which reasoning abilities began to decline. Women declined significantly earlier than men, even when controlling for demographic factors. We were also not able to capture a reliable measure of the age at which reasoning abilities peak in either gender. In women, in both the full and matched samples, scores declined from 12 years of age, onward. This could be because 12 is the age at which women's reasoning abilities do indeed peak. However, it is also possible that women peak earlier, but due to lack of data we were unable to determine the true peak from the current sample. Similarly, both unmatched and matched samples of men showed a plateau in reasoning scores, rather than an increase, until the point at which they began to decline. There are several possible explanations here. First, it is possible that men do peak in early adulthood, somewhere between 18 and 24 years of age, but the increase in reasoning abilities was not captured due to too small a sample size or noisy data. Second, they could follow a similar trajectory to women, with a slow decline before a steeper one, again not captured due to a lack of data. Because our sample of men was very large (over 32,000 in the unmatched sample), it is unlikely that either of these options are the case. Third, this plateau could be a true peak in reasoning, lasting several years, before beginning to decline. Previous research does suggest that reasoning abilities are relatively mature by age 12 [6,9], and another large-scale study has shown that by age 18, reasoning abilities have begun to decline [12]. Thus, although it is not possible to confirm that decline begins around age 12 in the current sample of women, the data follow a pattern that fits previous research and supports this claim.

The results presented here offer some insight into how to tailor interventions for cognitive decline appropriately for each gender. For example, women are known to experience more anxiety than men [32], a fact reflected in the current sample. Anxiety is known to correlate negatively with working memory [49]. Thus, to improve working memory, or protect against its decline, therapies should perhaps focus on reducing anxiety in everyone, with a targeted focus on women. Another example is substance abuse, which is more prevalent in men [34]. Because substance abuse negatively affects cognition [30], especially with respect to aging [50], a focused campaign aimed to reduce drug and alcohol consumption in men may yield a slowing in cognitive decline at the male population level. These gender-focused interventions can be combined with other treatments known to provide protection from cognitive decline, such as frequent exercise [51] for a well-rounded defence against cognitive aging.

Conclusions

By examining a sample of over 45,000 individuals, ranging from 12 to 69 years of age, we showed how different cognitive abilities vary across the lifespan. Each domain had a unique relationship with age, demonstrating that not all cognitive processes follow the same pattern. Importantly, we found differences in the way women and men cognitively age, and showed that these disparities are reduced when controlling for socio-demographics such as sleep and anxiety. Nevertheless, some gender differences remained, supporting the notion that gender differences in cognition are likely guided by a complex interplay of both biology and environment.

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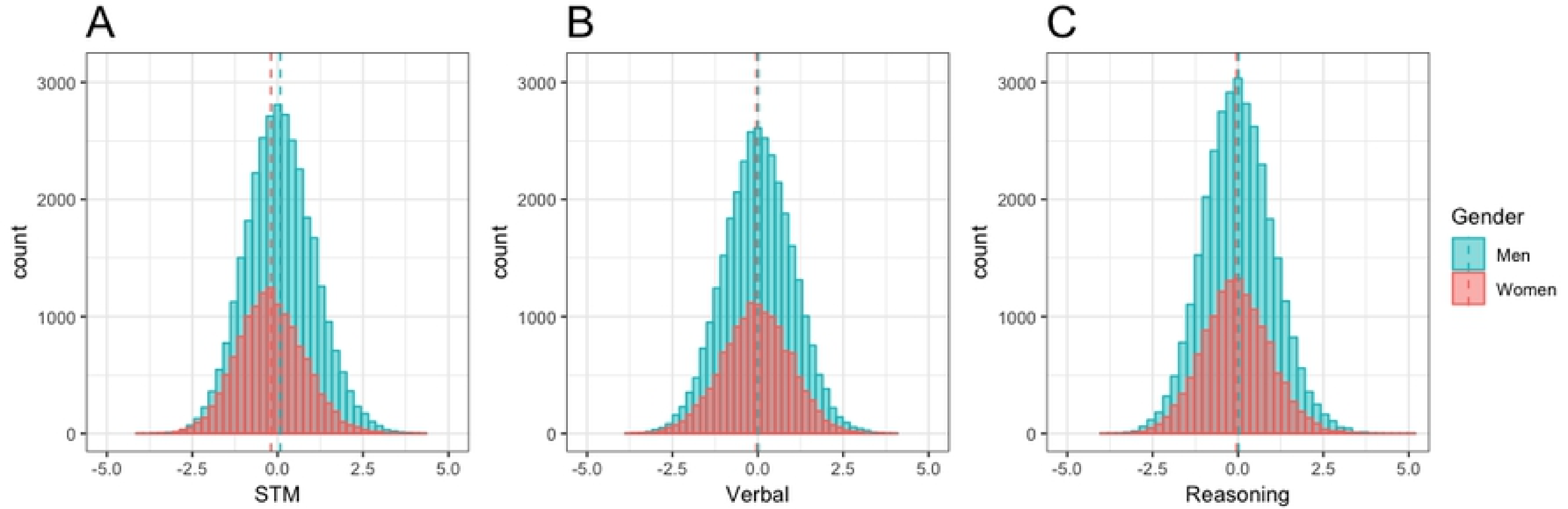
Supporting information

S1 Fig. Local regression curves for STM, Verbal, and Reasoning scores across the lifespan, ranging from 12 to 69 years of age. 95% confidence bands are shown in translucent colour around the line.

S2 Fig. Histograms of cognitive domain scores by gender, in a socio-demographically matched sample. Dashed lines indicate mean.

S3 Fig. Local regression curves for STM, Verbal, and Reasoning scores across the lifespan, ranging from 12 to 69 years of age, in a socio-demographically matched sample. 95% simultaneous confidence bands are shown in translucent colour around the line.

S1 Table. Comparison of demographic variables across women and men in a matched sample.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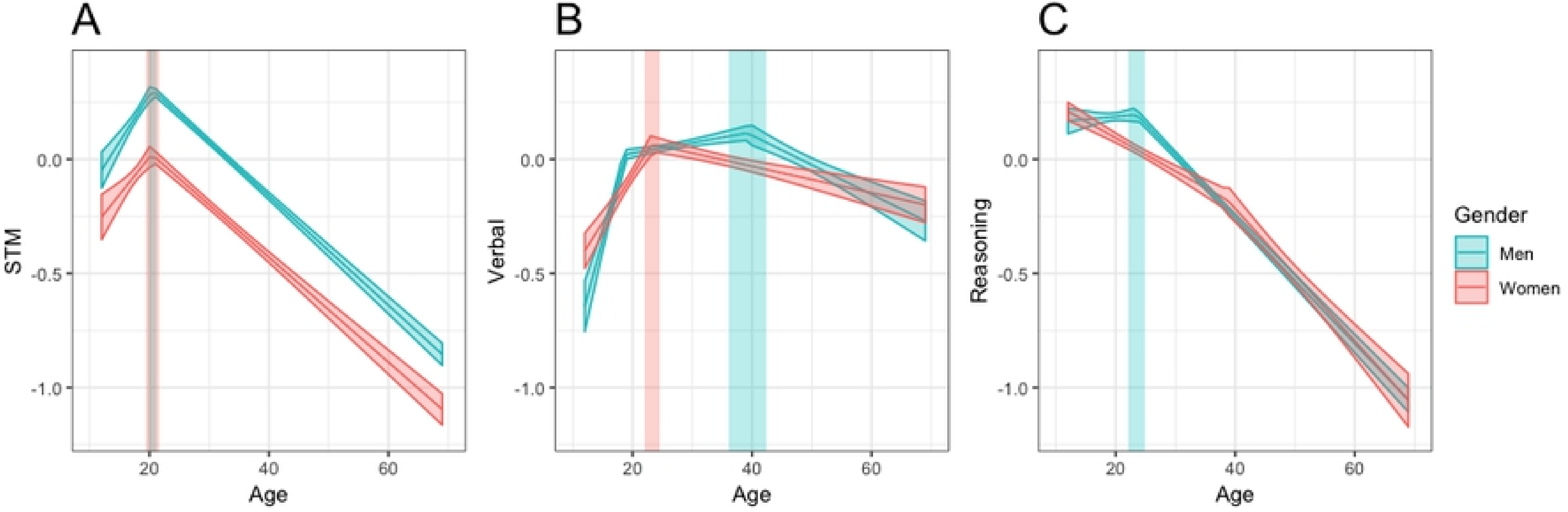
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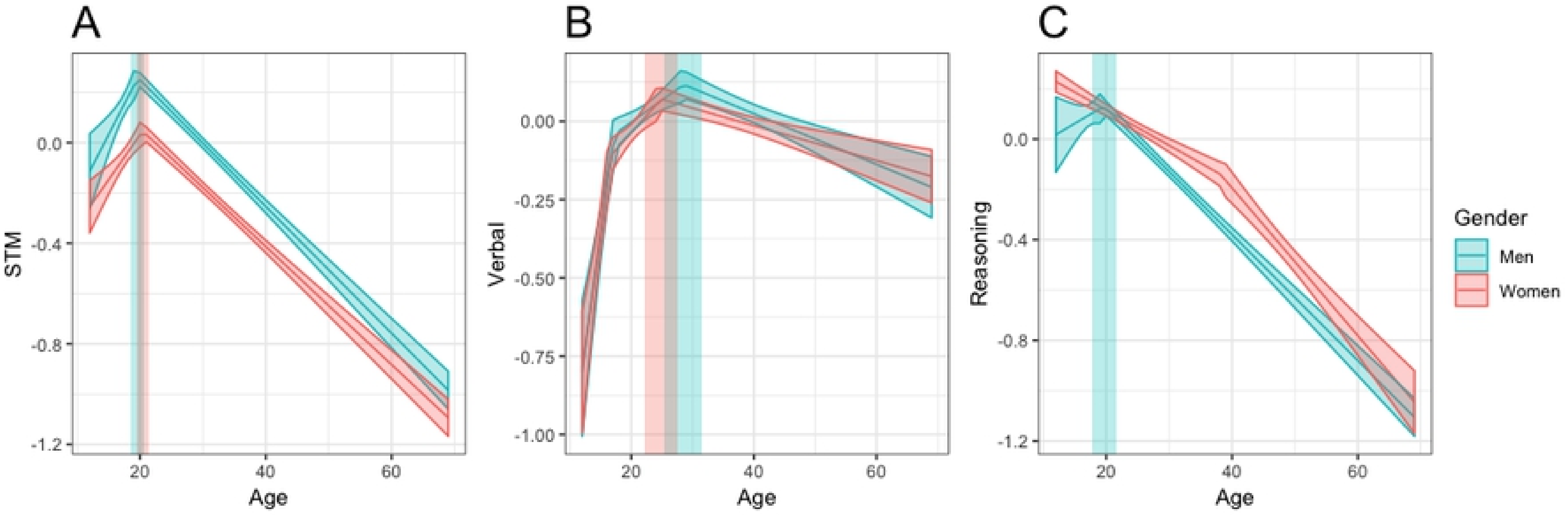

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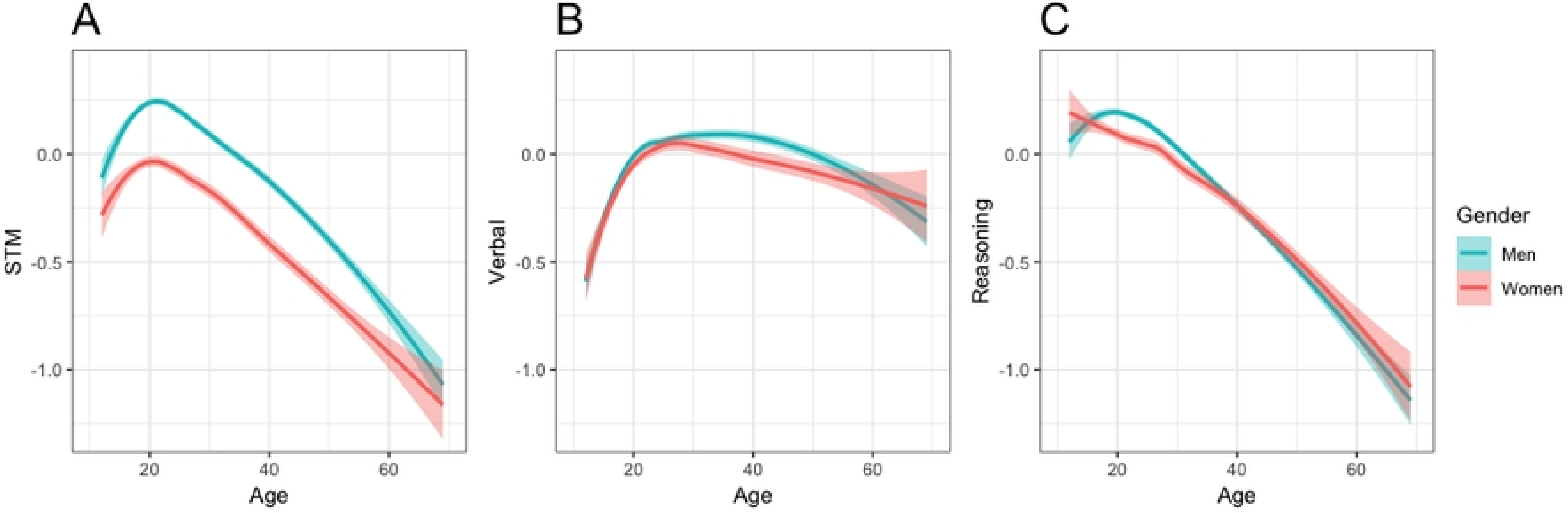
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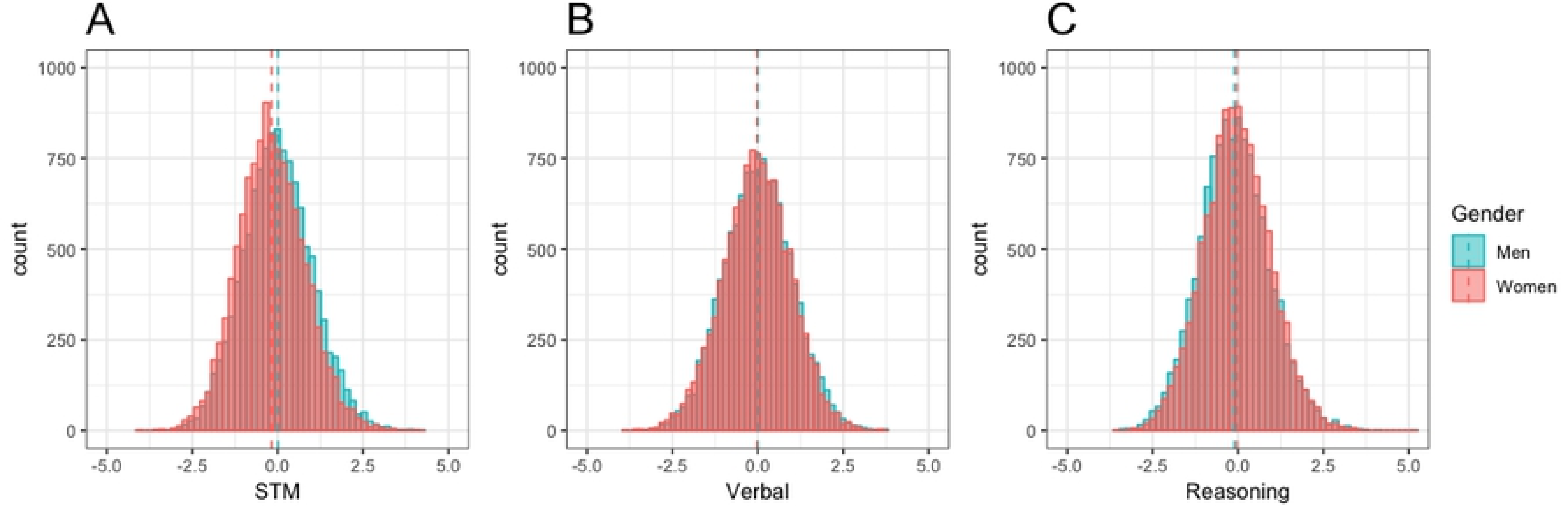
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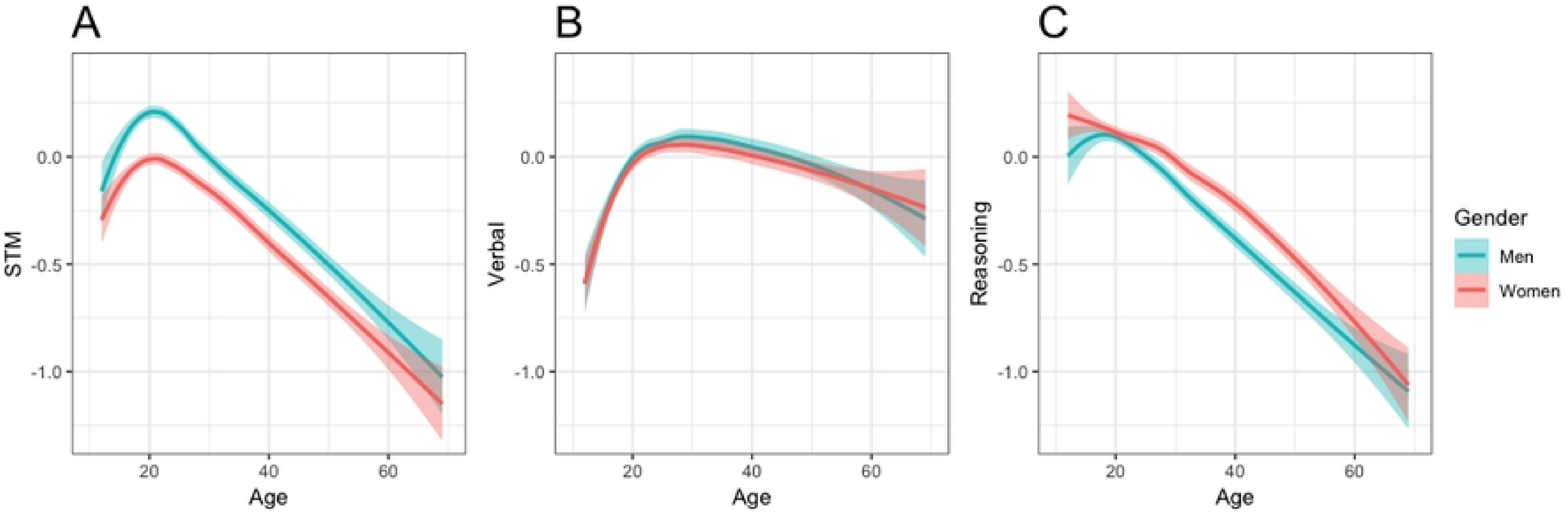
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