The Role of the Dorsolateral Prefrontal Cortex in Age-Related Decline in Fluid Intelligence

Abstract

Fluid intelligence declines in late adulthood. Frontal aging theory posits that this is due to degradation of frontal brain regions, especially the prefrontal cortex, as people age. This study used MRI and Cattell test data of 523 participants from the Cam-CAN data set to examine whether changes in the dorsolateral prefrontal cortex (DLPFC) explain this decline. Exploratory mediation analysis revealed that cortical thickness in the DLPFC does not explain cognitive decline, whereas grey matter volume does. However, neither mediated the age-intelligence relationship. Further research should use longitudinal mediation designs (e.g., cross-lagged panel modelling) to assess the mechanisms of cognitive decline in more detail.

Introduction

Intelligence research often distinguishes between two general types of intelligence, fluid intelligence (Gf) and crystallised intelligence (Gc) (Cattell, 1963). Gf is one's ability to reason flexibly and solve novel problems without reliance on past experiences or knowledge. Gf is typically measured through nonverbal tests such as Ravens Matrices (Raven et al., 1991) and the Culture Fair Intelligence Test (CFIT; Cattell & Cattell, 1973). In contrast, Gc is the ability to apply acquired knowledge, and is assessed through tests of general knowledge and vocabulary.

Research shows changes in both Gc and Gf across the lifespan. Several studies support a nonlinear relationship between age and Gf. For example, Cattell (1943) found that Gf grows rapidly from childhood until mid-twenties where it stabilises and then declines steadily into later adulthood, and finally accelerates in old age. In contrast, trends in Gc are unclear and variable. For example, Persson et al. (2016) found that old age was associated with better vocabulary, whereas Cattell (1987) suggested that Gc trends depend on cultural contexts, sometimes increasing to 18, 28 or beyond depending on the cultural learning period (Cattell, 1963). This implies that Gc may have an environmental cause whereas the more universal trends in Gf suggest that its roots are biological in nature. In accordance with this, research has found that fluid abilities are more sensitive to senescent neurobiological degeneration (Tucker-Drob et al., 2022).

Parieto-frontal integration theory (P-FIT; Jung & Haier, 2007) proposes that variations in intelligence comes down to differences in a defined set of brain regions, including the bilateral DLPFC, inferior and superior parietal lobules and the anterior cingulate gyrus. Many fMRI and PET studies have shown Gf-related activations in these regions (Duncan et al., 2000; Vakhtin et al., 2014). Similarly, there is support from causal brain stimulation methods; Arif et al. (2021) found that transcranial direct current stimulation of the DLPFC modulated performance in logical reasoning tests.

There is some discrepancy about the specific anatomical regions involved, as Yuan et al. (2018) found that changes in cortical thickness but not *volume* (in P-FIT regions) were related to Gf (but not Gc). As cortical thickness reflects cell counts in radial columnar units, whereas volume reflects unit number (Rakic, 2009), they argued that these structural features differentially contribute to cognitive decline, with Gf linked to thickness specifically. However, this is only speculation and is yet to be confirmed by further research.

Understanding why fluid intelligence changes across the lifespan may help us develop early markers for individuals at risk of rapid decline and implement preventative strategies (Kievit et al., 2018). According to the frontal aging hypothesis, deficits in fluid intelligence in older adults are primarily due to deterioration of the frontal lobes (West, 1996). This is supported by evidence that deficits in Gf are highly dependent on the prefrontal cortex (PFC), and that age-related brain atrophy is more pronounced in the PFC than other regions, with grey-matter volume in *lateral* PFC regions showing the fastest and greatest losses (Raz et al., 2003).

The present study used exploratory mediation analysis to investigate whether decline in Gf with age is mediated by structural changes in the dorsolateral prefrontal cortex. The DLPFC was chosen as the site of interest because of its role in the widely supported P-FIT model of intelligence, the DLPFC's extensive connectivity with other regions (e.g., parietal cortices), and the many studies that endorse the role of the prefrontal cortex in reasoning tests (e.g., Cole et al., 2015; Vakhtin et al., 2014). Using data from the Cambridge Centre for Aging and Neuroscience (Cam-CAN) dataset (Shafto et al., 2014), mediation by the DLPFC was investigated by comparing coefficients in age-only models of fluid intelligence to models incorporating DLPFC measurements. The effects of both cortical volume and thickness in the DLPFC were assessed, to provide further insight into the differential effects found by Yuan et al (2018).

It was hypothesized that (1) fluid intelligence would decrease with age, (2) age would be negatively associated with DLPFC cortical thickness and grey matter volume, (3) these factors would mediate the relationship between age and Gf. Based on previous research (Yuan et al., 2018) it was predicted that cortical thickness would be a better predictor of Gf than cortical volume.

Methods

This was a cross-sectional study examining whether age-related decline in fluid intelligence (Gf) is mediated by either cortical thickness (CT) or grey matter volume (GM) in the dorsolateral prefrontal cortex (DLPFC) using data from the Cam-CAN dataset (Shafto et al., 2014).

Participants

Participants (N= 523, 264 female) aged 18 to 87 were sampled from the Cam-CAN dataset. Twelve individuals were excluded due to missing data. The original study

randomly sampled participants from Primary Care Trust lists in Cambridge (UK). Exclusion criteria included serious psychiatric conditions, MRI contraindications, and insufficient hearing or English proficiency. Full criteria are available in Shafto et al., (2014).

Design and Materials

Gf was measured using the standard form of the Cattell Culture Fair Intelligence Test (CFIT), Scale 2 form A. This is comprised of 4 timed subtests, completed using pen and paper, with a total score range from 0-46. Prior to testing, participants read instructions and were given question examples, to ensure they understood the task.

Brain structure was assessed using MRI. The present study focused on CT and GM in the rostral middle frontal gyrus (RMFG) which was used to approximate of the DLPFC due to anatomical overlap (e.g., Michalski, 2016; Petrides et al., 2012). Values were summed across hemispheres to create total CT and GM measures for each participant.

Statistical Analysis

All inferential models were estimated in R (v.4.4.3) using robust standard errors. Analyses proceeded in two stages: assumption testing and mediation analysis.

Assumption Testing

Prior to interpreting regression results, we examined outliers with boxplots, verified linearity with scatterplots (including LOESS smoothing), evaluated multicollinearity with variance inflation factors (VIF), and checked normality and homoscedasticity using residual plots. Robust standard errors (HC3) were used in all models to prevent against any heteroscedasticity-related bias.

Mediation Analysis

Based on prior evidence that Gf decline is nonlinear, (e.g., Cattell, 1943), all models included both age and age^2 as predictors.

Linear regression models followed Baron and Kenny's (1986) approach to test mediation. This involved fitting three types of regression models, done separately for CT and GM. The first equation ("Path A") checks that the independent variable (age) significantly influences the dependent variable (Cattell scores). The second ("Path B") measures whether age significantly influences the *mediator* (CT/GM). Finally, the mediator must significantly influence the DV while age is controlled for ("Path C"). Partial mediation is present if age's influence on Gf is reduced after the mediator is controlled for, inferred by examining age coefficients.

The models and steps of the analysis were as follows:

1. Path A: Cattell scores were regressed on age and age^2 to confirm that age predicts fluid intelligence.

2. Path B: CT (or GM) were regressed on age and age^2 to confirm that age predicts the mediator.
3. Path C: Cattell scores were modelled on CT (or GM), age and age^2. Coefficients for age and age^2 predictors were compared between paths A and C. Mediation is supported if (a) the mediator significantly predicts Cattell scores (in Path C) and (b) there is a reduction in age coefficients from Path A to Path C.

Finally, we compared models using Akaike's Information Criterion (AIC) rather than Analysis of Variance (ANOVA) because AIC (a) does not assume homoscedasticity and (b) evaluates relative support for each model rather than testing a single 'true' model.

Results

Assumption Testing

Residual plots (e.g., QQ plots, residuals vs fitted plots) showed that residuals were approximately normal, with slight heteroscedasticity. The Breusch-Pagan test was significant for both CT and GM models ($BP = 21.52$, $p < .001$; $BP = 20.60$, $p < .001$, respectively) indicating that data violated the homoscedasticity assumption. Given the large sample size, the test may have been overly sensitive to minor violations. Nevertheless, any heteroscedasticity should be accounted for by using robust standard errors.

High VIFs were observed for age and age^2 (e.g., Path A: $VIF = 42.54$ for both). This was expected due to their mathematical relationship and thus was not treated as problematic.

Descriptive Statistics

Descriptive statistics for Cattell scores, GM and CT are presented in Table 1.

Table 1

Descriptive Statistics

Variable	Mean (*SD*)	Min / Max
Cattell Performance Score	32.2 (6.6)	12 / 44
RMFG Grey Matter Volume [mm^3]	34767.2 (5178.6)	23522 / 53345
RMFG Cortical Thickness [mm]	5.7 (0.3)	4.8 / 6.6

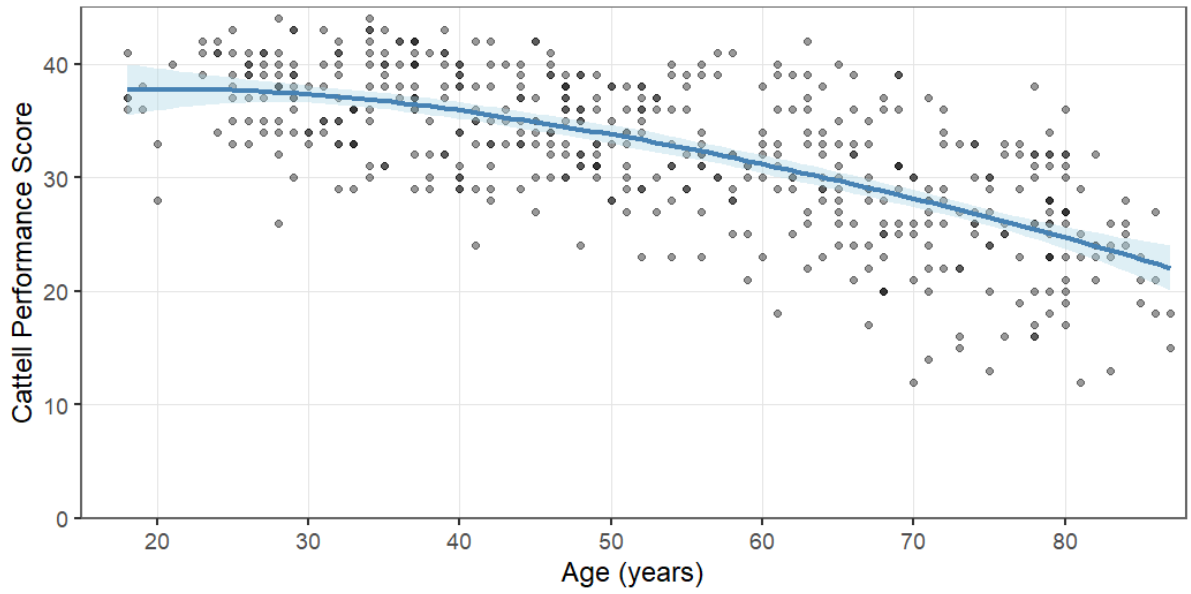
Note. *SD* = standard deviation; RMFG = rostral middle frontal gyrus.

Modelling

A LOESS-smoothed scatterplot of age and Cattell scores (Figure 1) suggested a nonlinear relationship. An ANOVA supported this, indicating that a quadratic model significantly improved fit over a linear model ($F(1, 508) = 14.77$, $p < .001$).

Figure 1

LOESS Smoothed Curve for Age and Cattell Score



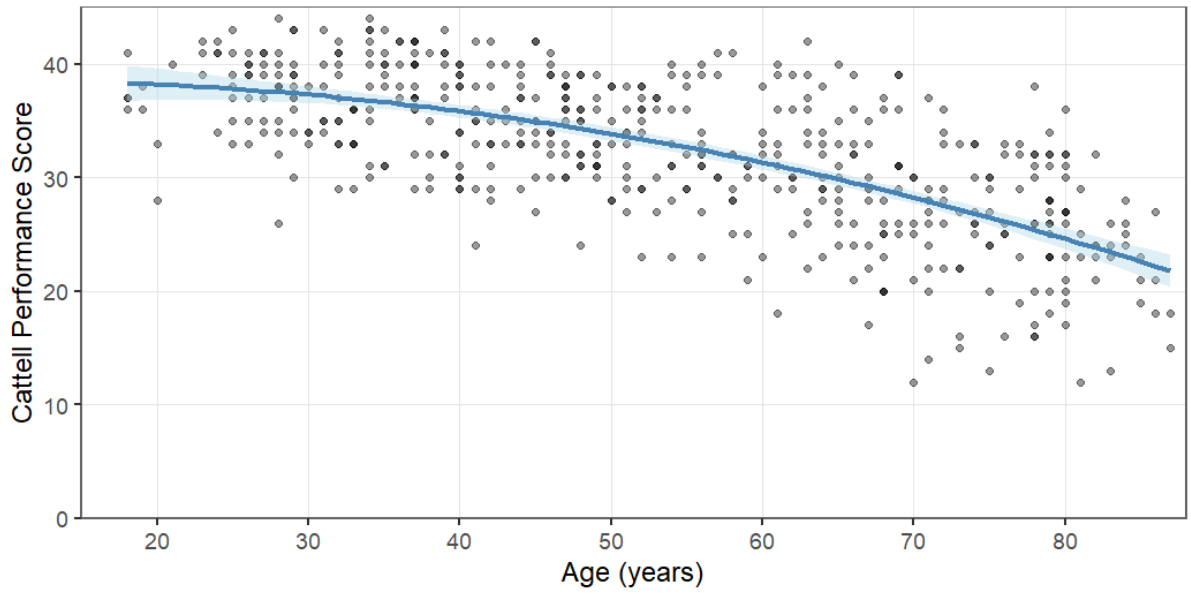
Regression Analysis

age^2 revealed a non-linear decline in Gf. The linear term was non-significant (b = 0.046, p = .502)[1], but the quadratic term was highly significant (b = -0.003, p < .001), indicating that performance decline accelerates with advancing age (Figure 2).

[1] Coefficients are reported to 2 decimal places unless extremely small, in which case greater precision is used to avoid misinterpretation.

Figure 2

Quadratic Fit of Cattell Score on Age

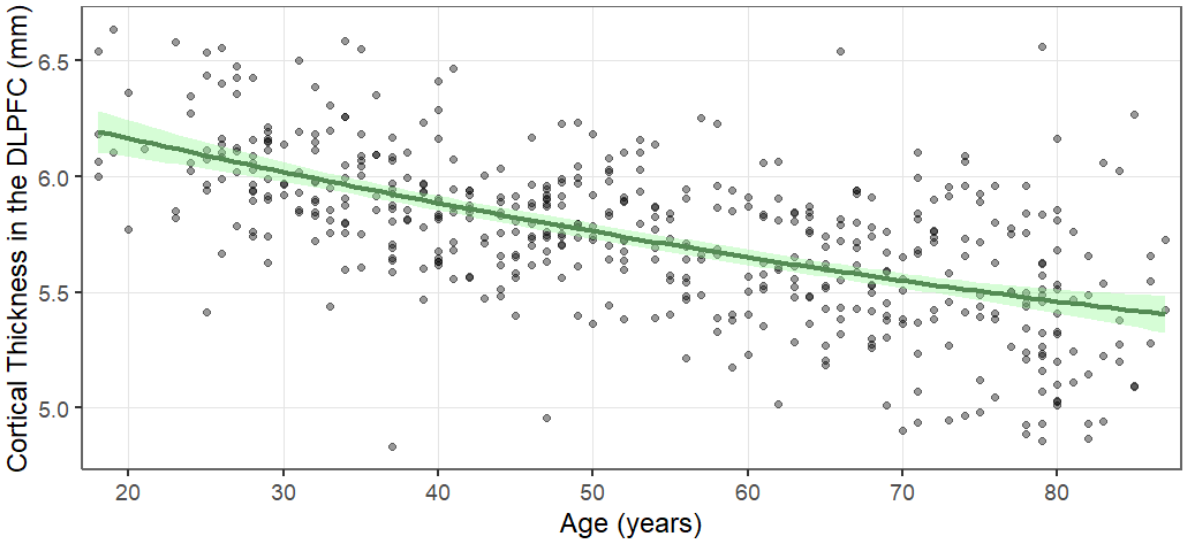


Analysis of Cortical Thickness

Age significantly predicted CT (Path B: $b = -0.017$, $p < .001$), and Figure 3 presents the decline in CT across the age range. However, CT was not a significant predictor of Cattell scores when controlling for age (Path C: $b = 0.15$, $p = 0.858$); this lack of association is shown in Figure 4. Furthermore, the age and age^2 coefficients did not change substantially from the baseline model (age: $b = 0.046$; age^2: $b = -0.003$) to the model including CT (age: $b = 0.048$; age^2: $b = -0.003$). This suggests no evidence for mediation via cortical thickness.

Figure 3

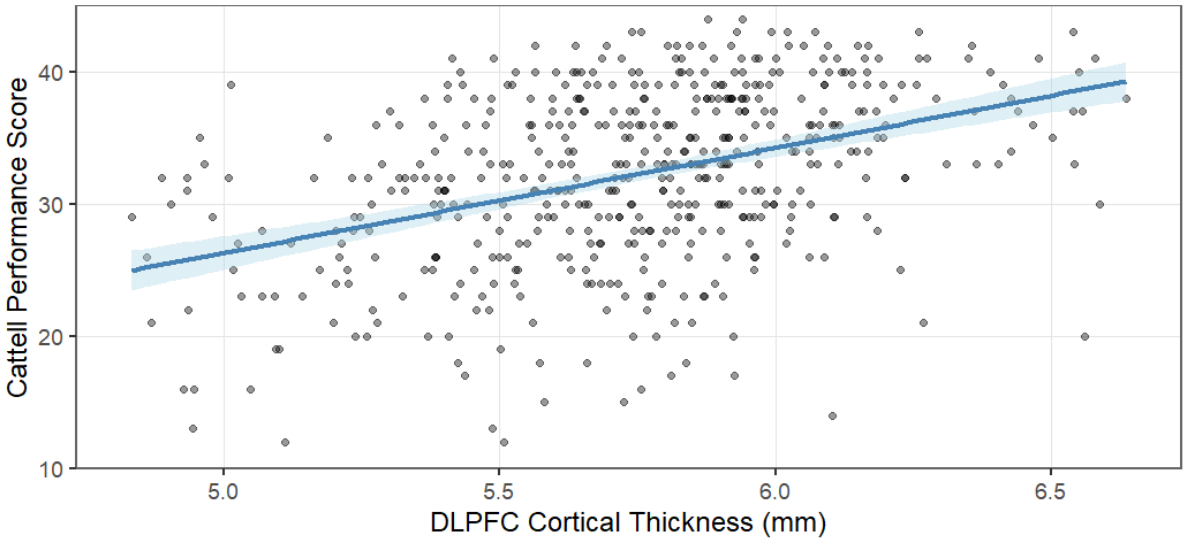
DLPFC Cortical Thickness vs. Age



Note: DLPFC: dorsolateral prefrontal cortex

Figure 4

Cattell Score vs. DLPFC Cortical Thickness



Note: DLPFC: dorsolateral prefrontal cortex

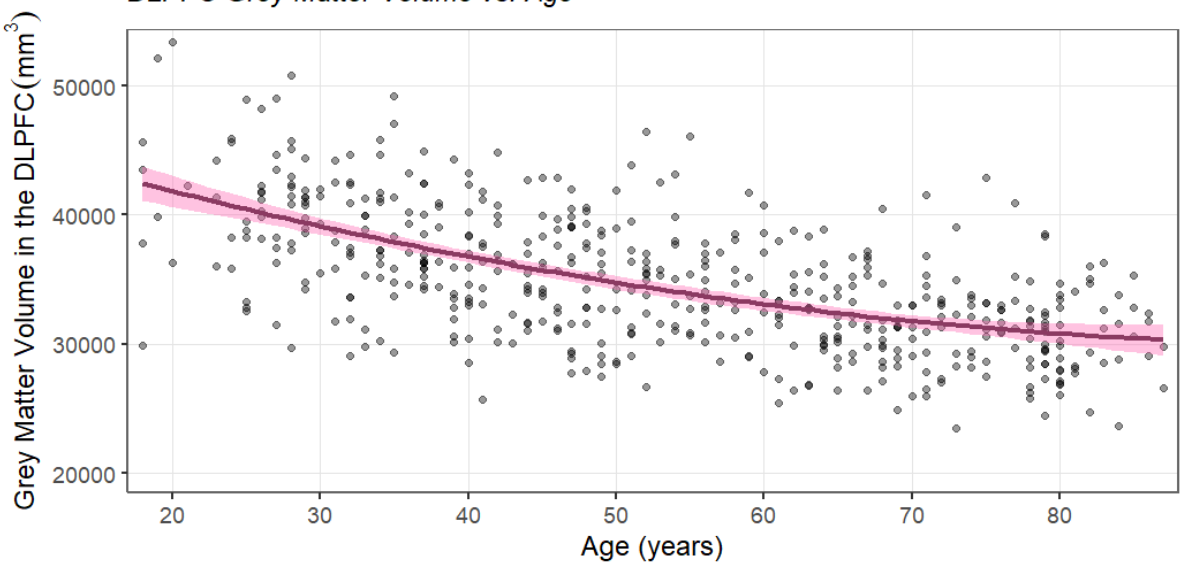
Analysis of Grey Matter Volume

Age significantly predicted GM (Path B: b = -357.20, p < .001), with volume decreasing as age increased, as illustrated in Figure 5. Furthermore, GM significantly predicted Cattell scores when age was controlled (Path C: b = 0.00024, p < .001), indicating that greater GM volume is associated with better performance (Figure 6).

While the age coefficient increased from Path A to C (from $b = 0.046$ to $b = 0.13$), it remained statistically non-significant in both cases. The quadratic age coefficient (age^2) was significant in both models, however the coefficient showed minimal change (refer to Tables 2a and 2b for all model coefficients). These findings suggest that GM does not appear to mediate the effects of age and may instead operate as an independent predictor of Gf.

Figure 5

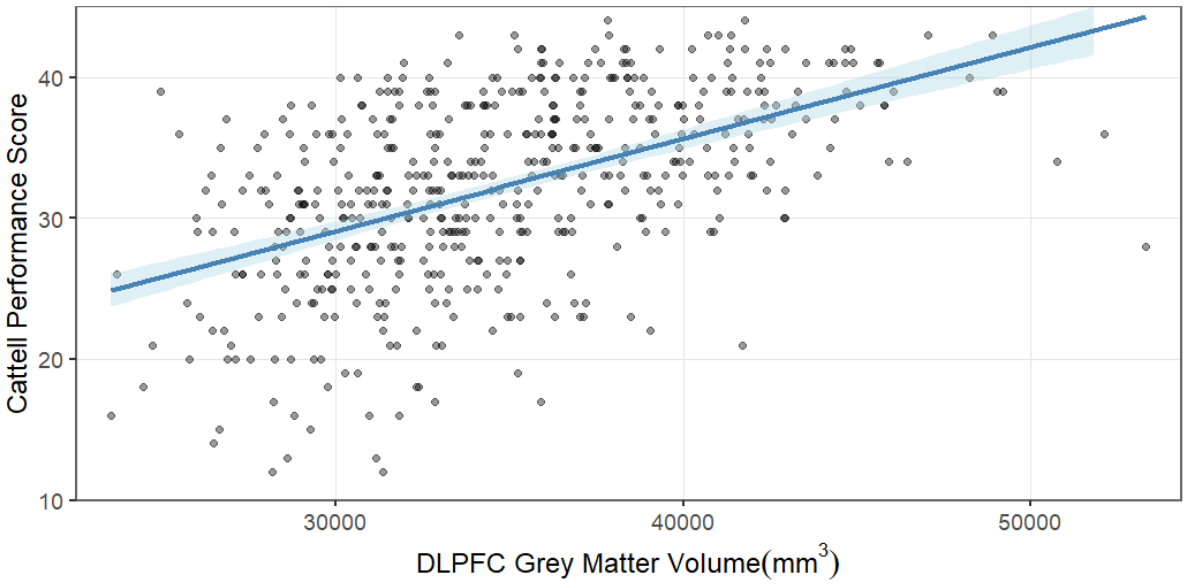
DLPFC Grey Matter Volume vs. Age



Note: DLPFC: dorsolateral prefrontal cortex

Figure 6

Cattell Score vs. DLPFC Grey Matter Volume



Comparing AICs revealed that the GM model fit the data best ($AIC = 3043.41$) followed by the age-only model ($AIC = 3062.53$), and the CT model ($AIC = 3064.50$).

These results indicate that GM is a better predictor of cognitive decline than CT and contributes unique explanatory power beyond chronological age.

Table 2a

Regression Coefficients for Cortical Thickness Models

Model	Age; *b*, *p*	Age^2; *b*, *p*	CT; *b*, *p*	Adjusted R^2
Path A: Cattell ~ age + age²	0.046, .502	-0.003, *	N/A	.467
Path B: CT ~ age + age²	-0.017, *	†, .188	N/A	.368
Path C: Cattell ~ age + age² + CT	0.049, .072	-0.003, *	0.152, .857	.466

Note. Values are given to three decimal places to provide greater precision and facilitate comparison.
CT = cortical thickness in the rostral middle frontal gyrus;
† $b < 0.001$, * $p < .001$.

Table 2b

Regression Coefficients for Grey Matter Volume Models

Model	Age; *b*, *p*	Age^2; *b*, *p*	GM; *b*, *p*	Adjusted R^2
Path A: Cattell ~ age + age²	0.046, .502	-0.003, *	N/A	.467
Path B: GM ~ age + age²	-357.196, *	1.733, .011	N/A	.370
Path C: Cattell ~ age + age² + GM	0.131, .068	-0.003, *	†, *	.488

Note. Values are given to three decimal places to provide greater precision and facilitate comparison.
GM = grey matter volume in the rostral middle frontal gyrus;
† $b < 0.001$, * $p < .001$.
Path A is identical in Tables 2a and 2b.

Discussion

This study found that older participants performed more poorly on measures of fluid intelligence, and the age-Gf relationship is nonlinear. Similar relationships have been found in other studies, which suggest that Gf initially stabilises in early adulthood before declining slowly, and then rapidly in very late life (e.g., Kievit et al., 2018; Persson et al., 2016).

Furthermore, as expected, age was shown to predict decreasing cortical thickness and grey matter volume in the DLPFC. However, unlike the relationship between age and Gf, age was a *linear* predictor of CT and GM, as the age^2 coefficient was nonsignificant in both models. This alone indicates that CT and GM are not full mediators of the age-Gf relationship, as age differentially predicts GM/CT and Gf.

Cortical thickness did not significantly predict changes in Gf, but grey matter volume did. This contradicts the findings of Yuan et al., (2018) that only CT (not GM) predicted Gf. This may be because the current study focused on the DLPFC whereas Yuan et al. (2018) looked at multiple P-FIT regions. Therefore, CT may be more

relevant in other P-FIT regions. Future research should investigate CT-Gf associations across the full P-FIT network.

Coefficients of age increased between the age-only model and the model that incorporated GM, whereas the quadratic term remained stable. However, the age coefficient was not statistically significant in either model, meaning neither GM nor CT mediated the effect of age on fluid intelligence. Taken together, these findings suggest that the GM contributes to Gf independently of age. One interpretation of the relationship is that instead of mediating age-related decline, GM preservation may buffer or compensate for it; individuals with higher GM perform better regardless of age. However, this interpretation remains speculative and future studies should try to use more targeted statistical methods (e.g., formal mediation models) to make clear the role of the GM.

These findings do not directly contradict the frontal aging hypothesis, but suggest that, if cognitive decline is mediated by brain function or anatomy, it is not specifically within the DLPFC area. This is a somewhat unexpected finding given that this is typically a region experiencing the greatest decline in cortical volume. However, it is possible that this arose as a result of using the RMFG (around BA9) as an approximation of the DLPFC (consisting of both BA9 and BA46).

Limitations

A key limitation of this study is that it used a cross-sectional design rather than longitudinal. On one hand this has its benefits such as avoiding confounding factors due to attrition or practice effects. Practice effects are known to inflate estimates of longitudinal decline in Gf (Lövdén et al., 2004; Salthouse, 2010). However, using cross-sectional data may lead to cohort-effects being misinterpreted as age differences as people born in different eras may differ due to factors unrelated to ageing (e.g., education, lifestyle) whereas a longitudinal design captures within-subject changes to isolate true age effects. Furthermore, using a longitudinal design helps assess temporal precedence to see whether changes in brain structure precede changes in cognition or vice versa. Future research should use a longitudinal design to assess the relationship between changes in Gf and brain structure and volume through cross-lagged panel modelling (Kenny, 1975), and applying a “boost factor” (Hoffman et al., 2011) to account for practice effects.

Furthermore, this study only assessed age changes in adults. Further insights could be gained by studying predictors of changes in fluid intelligence throughout the full lifespan (from childhood), to assess whether mechanisms are the same or different (i.e., are the increases in intelligence through adolescence due to increased volume or connectivity in circumscribed brain regions).

Conclusion

This study explored how age-related changes in Gf may be explained by changes in cortical thickness and grey matter volume in the DLPFC. The results revealed that Gf

declined nonlinearly with age. While both CT and GM decreased with age, only GM significantly predicted Gf when age was controlled for. Including GM in the model increased the age coefficient but it remained nonsignificant, suggesting GM contributes independently to cognitive performance, though its role remains unclear. These findings are based on the Baron and Kenny mediation procedure and therefore should be viewed as preliminary. Future work using formal mediation methods are needed to clarify the role of DLPFC grey-matter volume in Gf decline.

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Appendix

```
#import data df <- read.csv(file.choose(), header = TRUE, stringsAsFactors = TRUE)
#loadinf pACKAFWS install.packages("tidyverse") install.packages("dplyr")
install.packages("ggplot2") install.packages("car") install.packages("ggstatplot") #not
available install.packages("ggpubr") install.packages("DemographicTable")
install.packages("lmtest") install.packages("sandwich") library(tidyverse)
library(dplyr) library(ggplot2) library(car) library(ggstatplot)# not available
library(ggpubr) library(DemographicTable) library(lmtest) library(sandwich) #inspect
str(df) summary(df)

summary(df_complete$performance) mean(df_complete$performance)
sd(df_complete$performance)

summary(df_complete$GM_DLPFC) mean(df_complete$GM_DLPFC)
sd(df_complete$GM_DLPFC)

summary(df_complete$CT_DLPFC) mean(df_complete$CT_DLPFC)
sd(df_complete$CT_DLPFC)
```

#clean data #remove NaN df_complete <- df[complete.cases(df[, c("age", "performance", "lh_GM_rostralmiddlefrontal", "rh_GM_rostralmiddlefrontal", "lh_CT_rostralmiddlefrontal", "rh_CT_rostralmiddlefrontal")]),] #making them into whole regions df_complete$GM_DLPFC <- df_complete$lh_GM_rostralmiddlefrontal + df_complete$rh_GM_rostralmiddlefrontal df_complete$CT_DLPFC <- df_complete$lh_CT_rostralmiddlefrontal + df_complete$rh_CT_rostralmiddlefrontal #remove outliers sd_cattell <- sd(df_complete$performance) mean_cattell <- mean(df_complete$performance) par(mfrow=c(2,2)) boxplot(df_complete$performance, ylab= "Cattell score", title = "Distribution of Cattell scores") #there appears to be an outlier at the lower end help(boxplot) #VERDICT: I will not be removing this outlier (below lower bound) #because it represents a value of 12, which multiple particiapnts achieved (and a few also got 13) #therefore it is unlikely to be an anomaly? boxplot(df_complete$GM_DLPFC)

boxplot(df_complete$CT_DLPFC) #same

#testing assumptions #AGE MODELS: df_complete$age2 <- df_complete$age^2 lmAge <- lm(performance ~ age, data=df_complete) #as the age effects are often nonlinear eg that study saying rapid deline in 1970s? lmAge2 <- lm(performance ~ age + age2, data=df_complete) #checking whether linear or nonlinear looks like a better fit

ggplot(df_complete, aes(x = age, y = performance)) + geom_point(size = 1.2, alpha = 0.4) + geom_smooth(method = "loess", se = TRUE, color = "steelblue", fill = "lightblue") + scale_x_continuous(breaks = seq(20, 80, by = 10), limits = c(15, max(df_complete$age)+1), expand = c(0, 0)) + scale_y_continuous(limits = c(0, max(df_complete$performance)+1), expand = c(0, 0)) + labs(title = "Figure 1", subtitle = "LOESS Smoothed Curve for Age and Cattell Score", x = "Age (years)", y = "Cattell Performance Score") + theme_classic(base_size = 12, base_family = "sans") + theme(panel.border = element_rect(fill = NA, colour = "grey40"), axis.line = element_line(colour = "grey40"), panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor = element_blank(), plot.title = element_text(hjust = 0, face = "bold", size = 14, margin = margin(t=10)), plot.subtitle = element_text(hjust = 0, face = "italic", margin = margin(t=10, b=10))) #is more nonlinear therefore i willl use age2 anova(lmAge,lmAge2) #yes they are significantly different

#MEDIATION MODELS: lmCT <- lm(performance~ age + age2 + CT_DLPFC, data= df_complete) lmGM <- lm(performance~ age + age2 + GM_DLPFC, data= df_complete) #lmGMCT <- lm(performance ~ age + age2 + GM_DLPFC + CT_DLPFC, data=df_complete)

par(mfrow=c(2,2)) plot(lmAge.CT) #minor QQ deviations to be expected in large sample and hsouldnt affect coefficient comparisn greatly plot(lmAge.GM) #pretty good! plot(lmAge2) #yes- normal dist #yes - random residuals (homoscedasticity) plot(lmCT) "' yes - normality of residuals Theres a bit of downward curvature in the

red line, and residual spread narrows slightly with higher fitted values this suggests slight heteroscedasticity however, it is likely not enough to invalidate the model we will test with a statistical test! ''' bptest(lmCT) #shows that it has significant heteroskedasticity #therefore we will use robust standard errors when making comparisons #this doesnt involve permenantly changing the model #only chnage the model when drawing the comparisons (of)

plot(lmGM) #yes-normality #as above, there may be heteroscedasticity... bptest(lmGM)

#homogeneity of variance

#collinearity VIF library(car) vif(lmCT) vif(lmGM) vif(lmAge2) #no multicollinearity for either CT or GM which is good

version #method of baron and kenny with applied robust SEs

summary(lmAge2) summary(lmGM) library(lmtest) library(sandwich) coeftest(lmAge2, vcov = vcovHC(lmAge2, type = "HC3"))

lmAge.CT <- lm(CT_DLPFC ~ age + age2, data = df_complete) summary coeftest(lmAge.CT, vcov = vcovHC(lmAge.CT, type = "HC3"))

coeftest(lmCT, vcov = vcovHC(lmCT, type = "HC3"))

coeftest(lmAge2, vcov = vcovHC(lmAge2, type = "HC3"))

lmAge.GM <- lm(GM_DLPFC ~ age + age2, data=df_complete) coeftest(lmAge.GM, vcov = vcovHC(lmAge.GM, type = "HC3"))

coeftest(lmGM, vcov = vcovHC(lmGM, type = "HC3"))

#AIC comparison AIC(lmAge2, lmCT, lmGM)

par(mfrow=c(1,1)) #regression cattel vs age with quad fit line ggplot(df_complete, aes(x = age, y = performance)) + geom_point(size = 1.2, alpha = 0.4) + geom_smooth(method = "lm", formula = y ~ x + I(x^2), se = TRUE,

color = "steelblue",

fill = "lightblue"

) + scale_x_continuous(breaks = seq(20, 80, by = 10), limits = c(15, max(df_complete$age)+1), expand = c(0, 0)) + scale_y_continuous(limits = c(0, max(df_complete$performance)+1), expand = c(0, 0)) + labs(title = "Figure 2", subtitle = "Quadratic Fit of Cattell Score on Age", x = "Age (years)", y = "Cattell Performance Score") + theme_classic(base_size = 12, base_family = "sans") + theme(panel.border = element_rect(fill = NA, colour = "grey40"), axis.line =

```
element_line(colour = "grey40"), panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor = element_blank(), plot.title = element_text(hjust = 0, face = "bold", size= 14, margin = margin(t=10)), plot.subtitle = element_text(hjust = 0, face = "italic", margin = margin(t=10,b=10)) )

ggplot(df_complete, aes(x = age, y = GM_DLPFC)) + geom_point(size = 1.2, alpha = 0.4) + geom_smooth( method = "lm", formula = y ~ x + I(x^2), se = TRUE,

 color = "hotpink4",

 fill = "hotpink"

 ) + scale_x_continuous( breaks = seq(20,80,10), limits = c(min(df_complete$age)-1, max(df_complete$age)+1), expand = c(0, 0) ) + scale_y_continuous( limits = c(min(df_complete$GM_DLPFC)-5000, max(df_complete$GM_DLPFC)+1000), expand = c(0, 0) ) + labs( title = "Figure 5", subtitle = "DLPFC Grey Matter Volume vs. Age", x = "Age (years)", y = expression("Grey Matter Volume in the DLPFC"* (mm^3)), caption = substitute(paste(italic("Note:"), " DLPFC: dorsolateral prefrontal cortex")) ) + theme_classic(base_size = 12, base_family = "sans") + theme( panel.border = element_rect(fill = NA, colour = "grey40"), axis.line = element_line(colour = "grey40"), panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor = element_blank(), plot.title = element_text(hjust = 0, face = "bold", size=14, margin = margin(t=10)), plot.subtitle = element_text(hjust = 0, face = "italic", margin = margin(t=10, b=10)), plot.caption = element_text(hjust = 0, size = 12) )

ggplot(df_complete, aes(x = age, y = CT_DLPFC)) + geom_point(size = 1.2, alpha = 0.4) + geom_smooth( method = "lm", formula = y ~ x + I(x^2), se = TRUE,

 color = "palegreen4",

 fill = "palegreen"

 ) + scale_x_continuous( breaks = seq(20,80,10), limits = c(min(df_complete$age)-1, max(df_complete$age)+1), expand = c(0, 0) ) + scale_y_continuous( limits = c(min(df_complete$CT_DLPFC)-0.1, max(df_complete$CT_DLPFC)+0.1), expand = c(0, 0) ) + labs( title = "Figure 3", subtitle = "DLPFC Cortical Thickness vs. Age", x = "Age (years)", y = "Cortical Thickness in the DLPFC (mm)", caption = substitute(paste(italic("Note"), ": DLPFC: dorsolateral prefrontal cortex")) ) +

 theme_classic(base_size = 12, base_family = "sans") + theme( panel.border = element_rect(fill = NA, colour = "grey40"), axis.line = element_line(colour = "grey40"), panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor = element_blank(), plot.title = element_text(hjust = 0, face = "bold", size = 14, margin = margin(t=10)), plot.subtitle = element_text(hjust = 0, face = "italic", margin = margin(t=10,b=10)), plot.caption = element_text(hjust = 0, size = 12) )
```

```
ggplot(df_complete, aes(x = GM_DLPFC, y = performance)) + geom_point(size =
1.2, alpha = 0.4) + geom_smooth( method = "lm", se = TRUE,

 color = "steelblue",

 fill = "lightblue"

 ) + scale_x_continuous( breaks = seq(10000, 50000, 10000), limits =
c(min(df_complete$GM_DLPFC)-1000, max(df_complete$GM_DLPFC)+1000),
expand = c(0, 0) ) + scale_y_continuous( breaks = seq(10,40,10), limits = c(10,
max(df_complete$performance)+1), expand = c(0, 0) ) + labs( subtitle = "Cattell
Score vs. DLPFC Grey Matter Volume", title = "Figure 6", x = expression("DLPFC
Grey Matter Volume"* (mm^3)), y = "Cattell Performance Score" ) +
theme_classic(base_size = 12, base_family = "sans") + theme( panel.border =
element_rect(fill = NA, colour = "grey40"), axis.line = element_line(colour = "grey40"),
panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor =
element_blank(), plot.title = element_text(hjust = 0, face = "bold", size = 14, margin =
margin(t=10)), plot.subtitle = element_text(hjust = 0, face = "italic", margin =
margin(t=10,b=10)) )

ggplot(df_complete, aes(x = CT_DLPFC, y = performance)) + geom_point(size = 1.2,
alpha = 0.4) + geom_smooth( method = "lm", se = TRUE,

 color = "steelblue",

 fill = "lightblue"

 ) + scale_x_continuous(, limits = c(min(df_complete$CT_DLPFC)-0.1,
max(df_complete$CT_DLPFC)+0.1), expand = c(0, 0) ) + scale_y_continuous(
breaks = seq(10,40,10), limits = c(10, max(df_complete$performance)+1), expand =
c(0, 0) ) + labs( subtitle = "Cattell Score vs. DLPFC Cortical Thickness", title =
"Figure 4", x = "DLPFC Cortical Thickness (mm)", y = "Cattell Performance Score",
caption = substitute(paste(italic("Note"), ": DLPFC: dorsolateral prefrontal cortex")) )
+ theme_classic(base_size = 12, base_family = "sans") + theme( panel.border =
element_rect(fill = NA, colour = "grey40"), axis.line = element_line(colour = "grey40"),
panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor =
element_blank(), plot.title = element_text(hjust = 0, face = "bold", size = 14, margin =
margin(t=10)), plot.subtitle = element_text(hjust = 0, face = "italic", margin =
margin(t=10,b=10)), plot.caption = element_text(hjust = 0, size = 12) )

#graph for the moderation (likw cattell~ DLPFC by age) df_complete <- df_complete
%>% mutate(GM_tertile = ntile(GM_DLPFC, 3),

 GM_group = factor(GM_tertile, labels = c("Low GM", "Medium GM", "High GM")))
VIF(lmAge2)
```

```
ggplot(df_complete, aes(x = age, y = performance, color = GM_group)) +
geom_point(size = 1.2, alpha = 0.4) + geom_smooth(method = "lm", formula = y ~ x
+ I(x^2), se = FALSE) + scale_x_continuous( breaks= seq(20,90,10), limits =
c(15,90), expand = c(0, 0) ) + scale_y_continuous( breaks = seq(10,40,10), limits =
c(10, max(df_complete$performance)+1), expand = c(0, 0) ) + labs( title = "Cattell
Performance by Age and GM DLPFC Tertiles", x = "Age (years)", y = "Cattell
Performance Score", subtitle = "Model: cattell ~ age + age^2", color = "GM Volume" )
+ theme_minimal() + theme_classic(base_size = 11) + theme( panel.border =
element_rect(fill = NA, colour = "grey40"), axis.line = element_line(colour = "grey40"),
panel.grid.major = element_line(colour = "grey90", size = 0.3), panel.grid.minor =
element_blank(), plot.title = element_text(hjust = 0.5, face = "bold"), plot.subtitle =
element_text(hjust = 0.5), legend.position = c(0.098, 0.2), legend.background =
element_rect(fill="transparent", colour="black", size = 0.3) )

#repeat with CT just for the sake of comparison

df_complete <- df_complete %>% mutate(CT_tertile = ntile(CT_DLPFC, 3),

 CT_group = factor(CT_tertile, labels = c("Low CT", "Medium CT", "High CT")))

ggplot(df_complete, aes(x = age, y = performance, color = CT_group)) +
geom_point(size = 1.2, alpha = 0.4) + geom_smooth(method = "lm", formula = y ~ x
+ I(x^2), se = FALSE) + scale_x_continuous( breaks= seq(20,90,10), limits =
c(15,90), expand = c(0, 0) ) + scale_y_continuous( breaks = seq(10,40,10), limits =
c(10, max(df_complete$performance)+1), expand = c(0, 0) ) + labs( title = "Cattell
Performance by Age and CT DLPFC Tertiles", x = "Age (years)", y = "Cattell
Performance Score", subtitle = "Model: cattell ~ age + age^2", color = "Cortical
Thickness" ) + theme_minimal() + theme_classic(base_size = 11) + theme(
panel.border = element_rect(fill = NA, colour = "grey40"), axis.line =
element_line(colour = "grey40"), panel.grid.major = element_line(colour = "grey90",
size = 0.3), panel.grid.minor = element_blank(), plot.title = element_text(hjust = 0.5,
face = "bold"), plot.subtitle = element_text(hjust = 0.5), legend.position = c(0.098,
0.2), legend.background = element_rect(fill="transparent", colour="black", size = 0.3)
) summary(df$sex) max(df$age)

AIC(lmAge2, lmCT, lmGM)

#making summary tables in APA format install.packages("gt") library(gt)

install.packages("tibble") library(tibble)

data <- tibble( Variable = c( "Cattell Performance Score", "RMFG Grey Matter
Volume [mm³]", "RMFG Cortical Thickness [mm]" ), Mean (SD) = c("32.2 (6.6)",
```

"34767.2 (5178.6)", "5.7 (0.3)"), Min / Max = c("12 / 44", "23522 / 53345", "4.8 / 6.6"))

gt(data) %>% cols_label(Mean (SD) = html("Mean (*SD*)")) %>% tab_header(title = html("

Table 1
"), subtitle = html("

Descriptive Statistics
")) %>% cols_align(columns = c(1), align = "left") %>% cols_align(columns = c(-1), align = "center") %>% tab_options(table.font.names = "Arial",

table.font.size = 14, heading.title.font.size = 14, column_labels.font.size = 14, #title.font.size = 12, source_notes.font.size = 14, data_row.padding = px(5), table.align = "left"

) %>% tab_source_note(source_note = html("

Note. SD = standard deviation; RMFG = rostral middle frontal gyrus.
"))

summary(lmAge2) #r2 is .4671 summary(lmAge.CT) #r2 is .3684 summary(lmCT) # r2 is .4661 #table for the coefficients and p-values #fix age^2 (maybe using expression(""*mm^2)) data2 <- tibble(Model = c("Path A: Cattell ~ age + age²", "Path B: CT ~ age + age²", "Path C: Cattell ~ age + age² + CT"), Age; b,p = c("0.046, .502", "-0.017, *", "0.049, .072"), Age^2; b,p = c("-0.003, *", " †, .188", "-0.003, *"), CT; b, p = c("N/A", "N/A", "0.152, .857"), Adjusted R2 = c(".467", ".368", ".466"))

gt(data2) %>% cols_label(Age; b,p = html("Age; *b*, *p*"), Age^2; b,p = html("Age^2; *b*, *p*"), CT; b, p = html("CT; *b*, *p*"), Adjusted R2 = html("Adjusted R^2")) %>% tab_header(title = html("

Table 2a
"), subtitle = html("

Regression Coefficients for Cortical Thickness Models
")) %>% cols_align(columns = c(1), align = "left") %>% cols_align(columns = c(-1), align = "center") %>% tab_options(table.font.names = "Arial",

table.font.size = 14, heading.title.font.size = 14, column_labels.font.size = 14, #title.font.size = 12, source_notes.font.size = 14, data_row.padding = px(5), table.align = "left"

) %>% tab_source_note(html("

Note. Values are given to three decimal places to provide greater precision and facilitate comparison.

CT = cortical thickness in the rostral middle frontal gyrus;
† *b* < 0.001, * *p* < .001.
")) #find how to make b and p italics and get superscript

summary(lmAge2) #r2 is .4671 summary(lmAge.GM) #r2 is .3699 summary(lmGM) # r2 is .4877 #table for the coefficients and p-values #fix age^2 (maybe using expression(""*mm^2)) data2b <- tibble(Model = c("Path A: Cattell ~ age + age²", "Path B: GM ~ age + age²", "Path C: Cattell ~ age + age² + GM"), `Age; b,p` = c("0.046, .502", "-357.196, *", "0.131, .068"), `Age^2; b,p` = c("-0.003, *", " 1.733, .011", "-0.003, *"), `GM; b, p` = c("N/A", "N/A", "†, *"), `Adjusted R2` = c(".467", ".370", ".488"))

gt(data2b) %>% cols_label(`Age; b,p` = html("Age; *b*, *p*"), `Age^2; b,p` = html("Age^2; *b*, *p*"), `GM; b, p` = html("GM; *b*, *p*"), `Adjusted R2` = html("Adjusted R^2")) %>% tab_header(title = html("

Table 2b
"), subtitle = html("

Regression Coefficients for Grey Matter Volume Models
")) %>% cols_align(columns = c(1), align = "left") %>% cols_align(columns = c(-1), align = "center") %>% tab_options(table.font.names = "Arial",

table.font.size = 14, heading.title.font.size = 14, column_labels.font.size = 14, #title.font.size = 12, source_notes.font.size = 14, data_row.padding = px(5), table.align = "left"

) %>% tab_source_note(html("

Note. Values are given to three decimal places to provide greater precision and facilitate comparison.
GM = grey matter volume in the rostral middle frontal gyrus;
† *b* < 0.001, * *p* < .001.
Path A is identical in Tables 2a and 2b.
"))