The Influence of Socioeconomic Status and Gender on Verbal Intelligence

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Abstract

This study examined the influence of socioeconomic status (SES) and gender on the development of verbal intelligence across childhood. After deleting children with missing and implausible values, the sample consisted of 1476 Dutch children (699 boys, 777 girls) aged 4.35 to 21.89 years old (M = 11.22, SD = 4.42). Verbal intelligence was assessed using two subtest from the IDS-2 diagnostic test. SES was based on the educational level of the mother and categorized into low, medium and high. The verbal scores of the children were analyzed using Generalized Additive Models for Location, Scale and Shape (GAMLSS). Results indicated a significant positive relationship between SES and verbal intelligence. Children from medium and high SES backgrounds showed steeper growth trajectories than children from low SES backgrounds. Gender did not significantly influence verbal intelligence once SES was accounted for. Additionally, the variance in verbal intelligence scores was found to increase with age in all SES groups. These findings highlight the importance of early intervention for children from low SES backgrounds.

Keywords: socioeconomic status, verbal intelligence, gender differences, GAMLSS

The Influence of Socioeconomic Status and Gender on Verbal Intelligence

Language development in young children is a key part of cognitive growth and academic performance, because it enhances children's ability to access and learn complex content in subjects such as science, math and literacy (Snow, 2010). A consistent predictor for language development in children is the child's socioeconomic status (SES) (Fernald et al., 2013; Hoff, 2003; Ma et al., 2024; Noble et al., 2012). SES is commonly defined as a measure that reflects an individual's or family's access to economic and social resources, which is typically assessed through factors such as parental education level, household income and occupational status (Bradley & Corwyn, 2002). In particular, the SES of the parents has been shown to affect both the quantity and quality of language input that children receive, which in turn can influence language development (Hoff, 2003; Bornstein and Bradley, 2014). More general, SES has been identified as an influential factor for the ability to learn and correlates with cognitive results consistently (Bradley & Corwyn, 2002; Hoff, 2003; Hackman & Farah, 2009). The difference between children of higher SES parents and lower SES parents can already be observed in children as young as 18 months of age (Fernald et al., 2013).

An additional question is whether the effect of SES on verbal intelligence is the same for boys and girls. Gender differences in verbal intelligence have been studied frequently and there are multiple explanations for this difference in previous studies. While the study by Bornstein et al (2004) does not explicitly mention SES, it does state that girls overall develop verbal skills faster and tend to do better on verbal tasks than boys. A possible reason for this difference between boys and girls could be that mothers tend to speak more frequently and engage in more complex verbal interactions with their daughters compared to their sons, which could contribute to girls' earlier and stronger vocabulary development (Hoff, 2003). However, there are some studies that do mention SES and gender explicitly. This research suggests that the impact of SES on language development may differ by gender, with boys often being more negatively affected by SES than girls. For example, Barbu et al. (2015) found that low SES boys performed significantly worse on a language test than both low SES girls and high SES children, suggesting that boys may be more affected by SES. Similarly, Lankinen et al. (2018) found that SES, in this case fathers education level, was more strongly associated with vocabulary development in boys than in girls at 24 months old. Likewise, a study by Guhn et al. (2016) found that the negative effect of neighborhood SES on development, including language skills, is usually greater for boys than for girls.

This study made use of an already existing dataset collected for norming purposes of the IDS-2. The IDS-2 is a diagnostic test that assesses children's cognitive and developmental capabilities across six domains in 30 subtests (IDS-2 by Hogrefe AG, n.d.). The structure of the IDS-2 is based on the Cattel-Horn-Carrol (CHC) theory of intelligence. The CHC theory is one of the most widely accepted frameworks for understanding cognitive abilities (Flanagan & Dixon, 2014; McGrew, 2005). The CHC model uses a hierarchical organization of intelligence. It has a general factor at the top, multiple broad cognitive abilities at the middle level and specific abilities at the bottom level (McGrew, 2009). In line with the CHC model, the IDS-2 includes two subtests that assess verbal intelligence.

This study used Generalized Additive Models for Location, Scale, and Shape (GAMLSS) to analyze the data. GAMLSS is a flexible statistical framework that allows for not only the mean to change, but also for the variance to change depending on the explanatory variables. This makes GAMLSS useful for working with not normally distributed data (Rigby & Stasinopoulos, 2005).

While previous research has consistently shown that both SES and gender are influential for language development and verbal intelligence, much of the existing research has focused on early verbal skills and not on how this effect evolves over age. In addition, existing research tends to look at SES and gender individually and often neglects their interaction and how they could influence verbal intelligence together. Investigating the interaction between SES and gender in verbal intelligence is important because it helps reveal how social inequalities in verbal development evolve across childhood. Understanding this development better can be useful to design more specific interventions to reduce the inequalities between SES groups. Since previous research has often examined SES and gender separately and focused on early childhood, this study fills a gap by exploring how SES influences verbal intelligence over age and if this effect is different for boys and girls.

This study addresses this gap by applying GAMLSS models to a large dataset of IDS-2 scores of children. This way, a more detailed analysis of the development of verbal score across age, SES and gender can be done.

Methods

Participants

The scores on the IDS-2 test of 1663 Dutch children with the target age of 5 to 20 years old were collected on site for norming purposes. Children with an age slightly outside of this range were also included to improve accuracy of the model, especially at the edges. Because the IDS-2 scores were collected for norming purposes, the sample should be representative for the Dutch population accounting for age, gender, educational level of parents, migration background, urbanity, region in the country, education type and possible diagnosis of the child (IDS-2 by Hogrefe Uitgevers, n.d.). The characteristics that were relevant for this research were age, gender, SES of the mother and the verbal score.

A total of 1476 children were included in the analyses after excluding 187 children with missing or impossible values on the key variables for this research. The final sample consisted of 699 boys and 777 girls. The ages ranged from 4.350 to 21.893 years of age (M = 11.217, SD = 4.415).

Materials

This research used artificial IDS-2 data that was designed to mimic how the real data would behave. The variables in the dataset that were used for this research were date of birth (divided in birth year, birth month and birth day), test date (divided in test year, test month and test day), education of mother, gender, and the raw scores in the subtests naming categories (VD) and naming opposites (VV).

Naming categories measures the ability of a child to name the correct category for a group of pictures or concepts. Naming opposites measures a child's ability to name the opposite of an adjective (IDS-2 by Hogrefe Uitgevers, n.d.). In the IDS-2, the verbal score is the composite of the scores from naming categories and naming opposites. The verbal scores ranged from 11 to 66 ($M = 37.00$, $SD = 11.19$).

Education of the mother in the dataset was divided into six categories. The Dutch education system is classified into several levels of education (Rijksoverheid, n.d.; Nuffic, 2021). The categories in the dataset were based on the different levels of the Dutch education system, namely basisonderwijs/lagere school, VMBO/LBO/MBO1, MBO2-4/HAVO/VWO, HBO/Universiteit and lastly two categories pointing to missing values. Basisonderwijs/lagere school is an equivalent to elementary or primary school for children aged 4 to 12 years old. VMBO/LBO/MBO1 includes the lowest level of high school or secondary school(VMBO) and entry-level vocational education (LBO/MBO1). MBO2-4/HAVO/VWO includes the two higher levels of high school or secondary school (HAVO/VWO) and the upper levels of secondary vocational education (MBO2-4). HBO/Universiteit includes university of applied sciences (HBO) and academic university (Universiteit), which is comparable to higher education internationally (Rijksoverheid, n.d.; Nuffic, 2021).

All statistical analyses and data visualizations were conducted using R version 4.4.3 (2025-02-28, ucrt) and RStudio version 2024.12.1 (build 563). The R packages used for this research were gamlss (R Core Team, 2025) version 5.4.22 (including gamlss.dist and gamlss.data), tidyverse (Wickham et al., 2019) version 2.0.0 (including dplyr, ggplot2, readr, tibble, tidyr, stringr, forcats and purr), nlme (Pinheiro et al., 2025) version 3.1.167, haven (Wickham et al., 2023) version 2.5.4 and lubridate (Grolemund & Wickham, 2011) version 1.9.4.

Procedure

To examine the distribution of age and SES, tables showing a summary of the data (minimum, first quartile, median, third quartile and maximum) were computed. To examine the distribution of gender, a table showing the amount of girls and boys was computed. Individuals with missing values were excluded from the analysis. In addition, one individual was excluded due to an implausible age value where the test date was before the date of birth. In total, 187 children with missing or implausible values were removed from the analysis.

In the original data, SES was administered with six different categories. These categories were recoded into the categories low, medium and high SES. Basisonderwijs/lagere school and VMBO/LBO/MBO1 were recategorized into low SES, MBO2-4/HAVO/VWO was recategorized into medium SES and HBO/Universiteit was recategorized into high SES. This categorization was based on the categories used by the Dutch government organization CBS (*CBS Statline*, 2025). The low SES group consisted of 183 children, the medium SES group of 553 children and the high SES group of 740 children. Low SES was set as the reference group, which allowed for comparisons to be made between low, medium and high SES.

By subtracting the date of birth from the test date, the variable 'age' was created. Due to the information on test date and date of birth, age could be specified up to the day and was therefore seen as a pseudo continuous variable. The variable verbal score was created by adding up the raw scores from naming categories and naming opposites, two subtests that were on the same scale. Gender was treated and administered as a binary factor with the labels 'boy' and 'girl'.

To examine the effect of age, SES and gender on verbal intelligence scores, four nested GAMLSS models were fitted using the Box-Cox Power Exponential (BCPE) distribution. This distribution was chosen because it is well suited for modeling skewed and heavy-tailed distributions and is known to be useful in modeling growth charts (Rigby & Stasinopoulos, 2005). All models only model the first moment (μ) of the verbal score distribution, all other moments (σ, ν and τ) are modeled with an intercept only. The first model predicted the verbal score based on only age (linear, quadratic and cubic) and SES. In Model 1, the first moment of the verbal score distribution is:

$$\mu = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{age}^2 + \beta_3 \cdot \text{age}^3 + \beta_4 \cdot \text{SES\_medium} + \beta_5 \cdot \text{SES\_high} + \text{error}.$$

The next model added gender onto the first model. In Model 2, the first moment of the verbal score distribution is:

$$\mu = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{age}^2 + \beta_3 \cdot \text{age}^3 + \beta_4 \cdot \text{SES\_medium} + \beta_5 \cdot \text{SES\_high} + \beta_6 \cdot \text{boy} + \text{error}.$$

The next model added the interaction effect between age (linear and quadratic) and SES onto the second model. In Model 3, the first moment of the verbal score distribution is:

$$\mu = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{age}^2 + \beta_3 \cdot \text{age}^3 + \beta_4 \cdot \text{age} \cdot \text{SES\_medium} + \beta_5 \cdot \text{age} \cdot \text{SES\_high} + \beta_6 \cdot \text{age}^2 \cdot \text{SES\_medium} + \beta_7 \cdot \text{age}^2 \cdot \text{SES\_high} + \beta_8 \cdot \text{boy} + \text{error}.$$

The last model added the interaction effect between age (linear and quadratic) and gender onto the third model. In Model 4, the first moment of the verbal score distribution is:

$$\mu = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{age}^2 + \beta_3 \cdot \text{age}^3 + \beta_4 \cdot \text{SES\_medium} + \beta_5 \cdot \text{SES\_high} + \beta_6 \cdot \text{boy} + \beta_7 \cdot \text{age} \cdot \text{SES\_medium} + \beta_8 \cdot \text{age} \cdot \text{SES\_high} + \beta_9 \cdot \text{age}^2 \cdot \text{SES\_medium} + \beta_{10} \cdot \text{age}^2 \cdot \text{SES\_high} + \beta_{11} \cdot \text{age} \cdot \text{boy} + \beta_{12} \cdot \text{age}^2 \cdot \text{boy} + \text{error}.$$

For the two models with the best fit, a visualization of the effect was made. For these models, the resulting age-dependent quantile curves were visually inspected. For each model, two plots were made. The first one was a plot where boys and girls were plotted separately and the quartiles were included. For more clarity on the differences between boys and girls, another plot was made with boys and girls in the same figure. The quartiles were not included in these plots for the sake of clarity.

Model comparisons were conducted using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These model comparisons were done to determine for each model whether the added variables improved the fit. The two models with the best fit according to the AIC and BIC were included in the results section.

A robustness check was done by categorizing the SES into four groups instead of three and seeing if the results were different with this categorization. Instead of combining basisonderwijs/lagere school and VMBO/LBO/MBO1 into one category, each of the education levels were a category on their own. The new categories were very low, low, medium and high. Another robustness check was done by excluding one of the two subtests making up the verbal score variable and checking if the results were different because of this. This was done for both subtests making up the verbal score.

Results

To investigate the relationship between age, SES, verbal score and gender, four GAMLSS models were evaluated. The complexity increased with each model, with the first model only including age and SES and the fourth model including gender and interaction effects between age, SES and gender.

Table 1 shows the model fit of the models. AIC and BIC were used to compare the models. The lower the numbers are, the better the model fit for the specific model is. Model 3 has the best fit according to the BIC. This suggests that including the interaction between age and SES improves the performance of the model. Model 4 has the best fit according to the AIC, which better accounts for the model complexity. This suggests that including both the interaction between SES and age and the interaction between gender and age improves the performance of the model.

Table 1

The Fit of the Models Using AIC and BIC

	df	AIC	BIC
Model 1	9	9088.914	9136.371
Model 2	10	9089.768	9142.499
Model 3	12	9061.056	9124.333
Model 4	16	9054.886	9139.255

The third model predicts verbal score based on SES, age and gender, but also focusses on interaction effects between age and SES. See the methods section for the formula of Model 3. Figure 1 shows the quantile curves of the fitted model for boys and girls separately.

Because the difference between girls and boys is hard to see in Figure 1, another figure was added. Figure 2 clearly shows the difference between boys and girls.

Figure 1

Median and Quantile Curves of Model 3

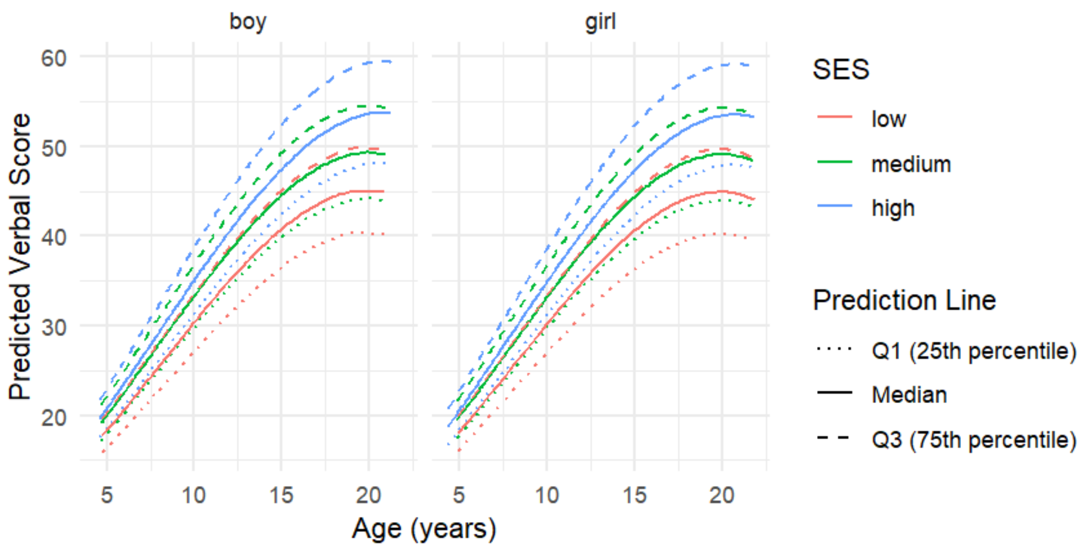
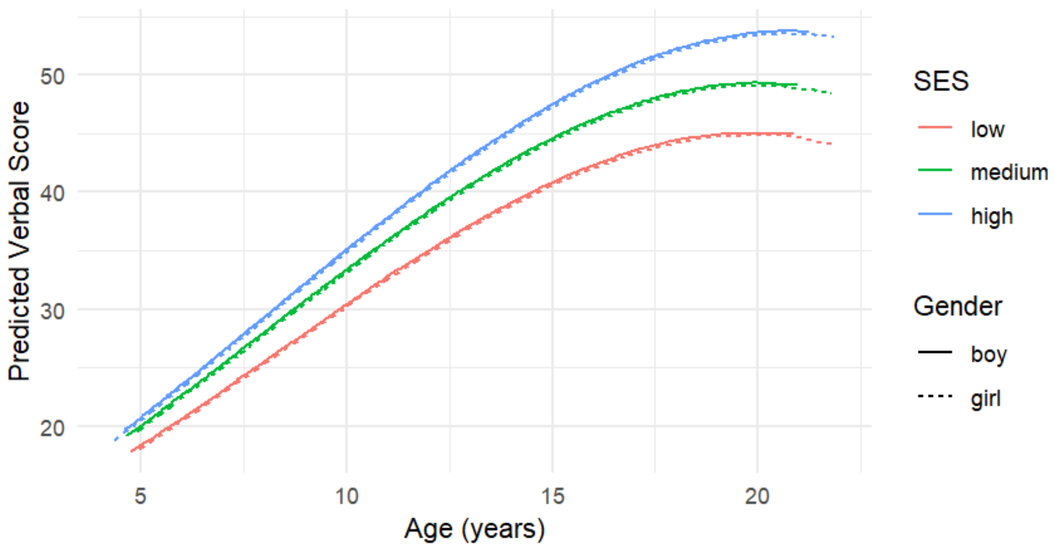


Figure 2

The Difference Between Boys and Girls of Model 3



In Model 3, several variables showed significant effects on verbal intelligence (see Appendix A). A significant cubic age trend was found, with a positive quadratic term (t = 2.38, p = .018) and a negative cubic term (t = -3.38, p < .001. Interactions between age and SES were also significant: compared to the low SES group, children from the medium SES group (t = 3.34, p < .001) and the high SES group (t = 4.56, p < .001) showed a steeper increase in scores with age. Gender was not a significant factor predicting verbal intelligence (p = .50). Full parameter estimates, including for scale (σ), skewness (ν) and kurtosis (τ), are provided in Appendix A.

The fourth model is the most complex and predicts verbal score based on age, SES, gender and also takes interaction effects between age and SES, and between age and gender into account. See the methods section for the formula of Model 4. Figure 3 shows the quantiles of the fitted model for boys and girls separately. Figure 4 shows the difference between boys and girls.

Figure 3

Median and Quantile Curves of Model 4

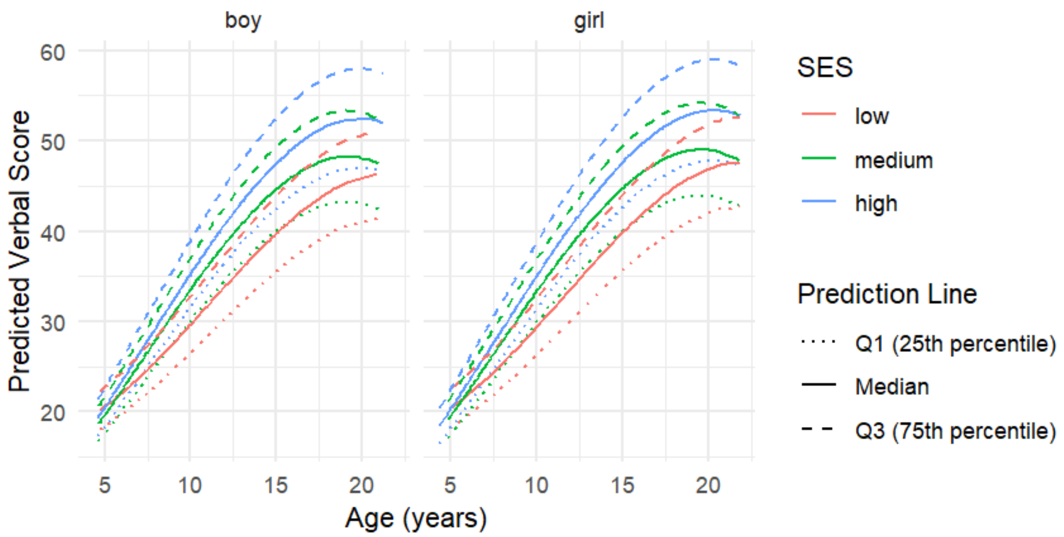
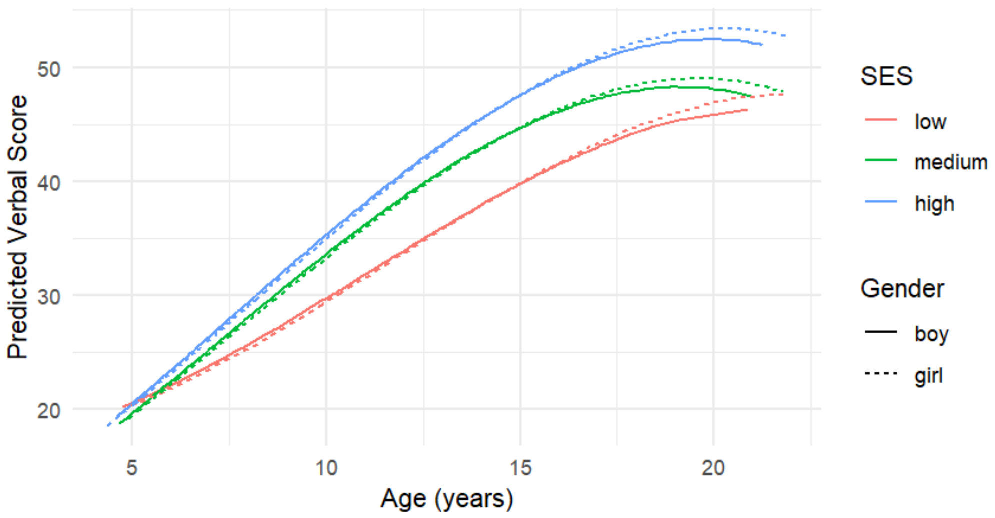


Figure 4

The Difference Between Boys and Girls of Model 4



In Model 4, several variables showed significant effects on verbal intelligence (see Appendix B). A significant non-linear age effect was found, with a positive quadratic term (t = 4.98, p < .001) and a negative cubic term (t = -5.26, p < .001). Children from the medium SES group (t = -3.56, p < .001) and the high SES group (t = 3.44, p < .001) had lower intercept scores compared to the low SES group. However, interactions between age and SES showed that children from the medium SES group (t = 4.26, p < .001) and from the high SES group (t = 4.42, p < .001) experienced steeper increases in scores over time. These interactions were moderated by a significant negative interaction effect between age^2 and SES (p < .001). Gender and its interactions with age were not significant factors in predicting verbal intelligence. Full parameter estimates, including for scale (σ), skewness (ν) and kurtosis (τ), are provided in Appendix B.

Robustness checks were done to test whether the results and therefore conclusions change based on the assumptions made during the research. The first robustness check gave similar results as the main results. While Model 4 remained the best-fitting model based on the AIC, the BIC preferred the more simple Model 1 with the alternative SES coding (see Appendix C). The second robustness check was conducted by analyzing the two subtest making up the verbal score separately. The results from this showed that Model 4 remained the model with the best fit according to the AIC, while the BIC preferred the simpler Models 1 and 2 for both subtests (see Appendix D).

Discussion

The results of this study indicate that SES is correlated with higher scores on verbal intelligence across all ages included in this research (5 to 20 years old). The observed positive correlation between SES and verbal intelligence aligns with previous research by Bornstein and Bradley (2014). This article states that children from higher SES parents typically have more exposure to difficult language and access to better educational resources, resulting in stronger verbal skills and thus a higher verbal intelligence.

The analyses of this research reveal that children in the medium SES and high SES groups show a steeper growth over time compared to those from the low SES group. Although the initial scores of all the SES groups were approximately the same, over time the high SES group outperformed both of the other groups and the medium SES group outperformed the low SES group. The difference between the groups grew bigger with age. These findings suggest that SES not only influences early verbal ability, but also shapes the pace and trajectory of language development across childhood.

GAMLSS modeling revealed that SES not only influences the mean of the verbal scores, but also the variance of the verbal scores. The models indicate that the variance of verbal scores gets bigger with age. This increase in variance with age could be caused by growing differences in different social factors like education level, friend groups or motivation for school. These findings suggest that SES, as shown in previous research, remains a strong predictor of verbal intelligence across childhood (Fernald et al., 2013; Hoff, 2003; Ma et al., 2024; Noble et al., 2012).

Although some small gender differences were found in the most complex model including age, SES, gender, interaction effects between age and SES and interactions effects between age and gender, neither gender itself or any interactions with gender were found to be significant. This suggests that, once SES is accounted for, gender differences in verbal development are minimal. This is contradictory to previous research that suggested that boys might be more negatively affected by SES than girls (Barbu et al., 2015; Lankinen et al., 2018; Guhn et al., 2016).

The results of the robustness check using an alternative SES categorization indicate that the conclusions regarding the model fit are stable. Although the BIC favored a simpler model under the alternative SES coding, the AIC preferred the same model. The goal of this research is to best model the development of verbal intelligence. Given this, the AIC might be a better criterion than the BIC as it places more emphasis on accuracy and model fit instead of on simplicity. These findings suggest that while the exact model ranking can shift depending on the information criterion used, the overall results remain stable. This supports the robustness of the main conclusions. The results of the robustness check analyzing the subtest making up the verbal score, indicate that the main conclusions about the model fit are stable. Although the BIC preferred a simpler model, the AIC preferred the same model. These results support the robustness of the main conclusions once more.

The findings of this study emphasize the importance of early support for children of lower SES parents to improve their verbal development. Previous research shows that inequalities related to SES begin early in life and can be of great influence throughout the childhood (Hoff, 2003). Several interventions, such as early childhood education of high quality, family language enrichment programs and support of parents have been found to improve the development of verbal skills. This improvement is especially noticeable in lower

SES populations (Barnett, 2011). Furthermore, policies aimed at reducing structural inequalities are important both to bring the differences between groups in performances closer together and to decrease the variance in verbal intelligence observed with age (Sirin, 2005).

One of the strengths of this research is the use of GAMLSS, which allows for the modeling of not only the mean, but also the variance of verbal intelligence. Another strength is the broad age range that was used for this research, which enables the effect of SES and gender on verbal intelligence to be studied across a long time and to study the development of it.

However, several limitations of this study must be acknowledged. One of the biggest limitations is that SES was only measured by the educational level of the mother. This excludes other factors that could possibly influence SES, like educational level of the other parent, income and current occupation. It also does not account for children that grow up without their mother present in their life. Another limitation was that multiple contextual factors were not added into the research. Factors such as education quality, the language use of parents, parenting style or cultural background were not accounted for, but could be of great influence to the verbal skills of children.

Future research should consider a more complete measurement of SES that is not only based on the education level of one parent, but also the education level of the other parent or caregiver, as well as household income and occupational status. In addition to SES, other factors that could be influential to verbal development, such as parental style and educational resources, should also be examined. Although this research did not find significant gender differences, in contrast to previous research that did find gender differences, more research would be needed on this topic. Finally, research should aim to identify effective interventions that can help decrease this difference and therefore decrease the inequality between children from different SES backgrounds.

Conclusion

This study aimed to investigate how SES influences verbal intelligence across childhood and adolescence and whether boys and girls are affected differently. The findings show that SES is consistently positively correlated with verbal scores across the ages 5 to 20 years. Children from medium and high SES backgrounds scored higher on verbal intelligence than children from low SES backgrounds. They also demonstrated steeper developmental trajectories than low SES over time, which resulted in increasing differences in verbal intelligence with age. These results show that SES does not only affect early verbal skills, but it continues to shape verbal development into later childhood and adolescence.

Although gender differences have been found in earlier research, this study did not find significant main effects or interaction effects of gender once SES was accounted for. This suggest that SES may be a more important determinant of verbal development than gender.

The analysis with GAMLSS enabled a more nuanced understanding of the verbal intelligence development by not only modeling the mean but also the variance of the verbal scores. The findings revealed that the variance of verbal intelligence increased with age. This means that the inequality between the different SES groups increases over childhood. These finding show the importance to investigate not only the mean of verbal intelligence, but also the variance. They also highlight the added value of statistical models like GAMLSS to use for analyses in developmental research.

The results found in this research underscore the importance of support for children from lower SES backgrounds. Interventions such as high quality early childhood education, family language enrichment programs and the support of parents have been shown to improve verbal development, especially in children from low SES backgrounds. These interventions may improve average verbal intelligence in low SES groups and will therefore help reduce the inequality between the difference SES groups.

Future research should use a more complete measure of SES instead of only the education level of one parent. Additionally, further research should explore what other factors influence the mean and variance of verbal scores and what can be done to decrease the inequality between different SES populations.

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Appendix A

Parameter Estimates for Model 3

	Estimate	Std. Error	t value	Pr(>|t|)	Moment
Intercept	10.191475	2.813786	3.622	0.000303***	μ
Age	0.912061	0.841152	1.084	0.278415	μ
Age^2	0.176764	0.074378	2.377	0.017606*	μ
Age^3	-0.006769	0.002003	-3.378	0.000749***	μ
Gender: girl	-0.181641	0.268135	-0.677	0.498247	μ
Age : SES medium	0.394275	0.118182	3.336	0.000871***	μ
Age : SES high	0.515923	0.113188	4.558	5.6e-06***	μ
Age^2 : SES medium	-0.008993	0.007957	-1.130	0.258577	μ
Age^2 : SES high	-0.003685	0.007696	-0.479	0.632145	μ
Intercept	-1.85811	0.02038	-91.16	<2e-16***	Log(σ)
Intercept	0.8868	0.1419	6.248	5.46e-10***	ν
Intercept	0.57358	0.05634	10.18	<2e-16***	Log(τ)

Note. Significance codes: *** $p < .001$, ** $p < .01$, * $p < .05$, . $p < .1$. Non-significant results are unmarked.

Appendix B

Parameter Estimates for Model 4

	Estimate	Std. Error	t value	Pr(>|t|)	Moment
Intercept	19.002350	3.029542	6.272	4.71e-10***	μ
Age	-0.734107	0.678221	-1.082	0.279258	μ
Age^2	0.250355	0.050303	4.977	7.25e-07***	μ
Age^3	-0.007289	0.001387	-5.257	1.69e-07***	μ
SES medium	-10.452829	2.932573	-3.564	0.000377***	μ
SES high	-9.614904	2.797455	-3.437	0.000605***	μ
Gender	0.476937	2.212115	0.216	0.829329	μ
Age : SES medium	2.286776	0.537099	4.258	2.20e-05***	μ
Age : SES high	2.256421	0.510922	4.416	1.08e-05***	μ
Age^2 : SES medium	-0.083259	0.022142	-3.760	0.000177***	μ
Age^2 : SES high	-0.071992	0.021198	-3.396	0.000702***	μ
Age : Gender	-0.158380	0.422237	-0.375	0.707644	μ
Age^2 : Gender	0.008595	0.017923	0.480	0.631599	μ
Intercept	-1.86296	0.02049	-90.94	<2e-16***	Log(σ)
Intercept	0.8993	0.1426	6.308	3.78e-10***	ν
Intercept	0.5644	0.0565	9.99	<2e-16***	Log(τ)

Note. Significance codes: *** $p < .001$, ** $p < .01$, * $p < .05$, . $p < .1$. Non-significant results are unmarked.

Appendix C

The Fit of the Models Using AIC and BIC (Different SES Categorization)

	df	AIC	BIC
Model 1	10	9087.912	9140.649
Model 2	11	9088.763	9146.775
Model 3	14	9067.136	9140.969
Model 4	19	9064.739	9164.941

Appendix D

The Fit of the Models Using AIC and BIC (Only Including Naming Opposites)

	df	AIC	BIC
Model 1	10	7296.830	7349.568
Model 2	10	7296.830	7349.568
Model 3	12	7287.609	7350.894
Model 4	16	7284.020	7368.400

The Fit of the Models Using AIC and BIC (Only Including Naming Categories)

	df	AIC	BIC
Model 1	10	7714.020	7766.758
Model 2	10	7714.020	7766.758
Model 3	12	7679.703	7742.988
Model 4	16	7675.411	7759.792