Socioeconomic Status and Intelligence in Dutch Children

Lan Gui van der Logt

S5170532

Department of Psychology, University of Groningen

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Group: 2425_2a_08 EN

Supervisor: H.M. Heister

Second evaluator: S. E. Dalley

In collaboration with: G. Bayerl, L. Ernst, C. Koobs, and T. Wollesen

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Abstract

This study examined how socioeconomic status (SES) relates to intelligence across childhood and adolescence, using data modeled after the Dutch norming sample for the Intelligence and Development Scales–2 (IDS-2). A total of 1,372 participants aged 5 to 20 were included in the analysis. Generalized Additive Models for Location, Scale, and Shape (GAMLSS) were used to investigate developmental trajectories and distributional differences in general intelligence (G), fluid intelligence (Gf), and crystallized intelligence (Gc). Results showed that children from higher SES backgrounds consistently scored higher in all intelligence domains. SES tended to widen with age, particularly for the lower-performing children. In contrast, SES gaps narrowed at higher performance levels, suggesting that high-performing children may be less affected by SES constraints. Due to methodological limitations, differences in SES effects between Gf and Gc could not be directly compared. These findings underscore the need to consider SES when interpreting intelligence test scores and raise concerns about the fairness of cognitive assessments in socioeconomically diverse populations.

Socioeconomic Status and Intelligence in Dutch Children

Intelligence testing has played a central role in psychology and society for over a century. The first widely recognized intelligence test, the Binet-Simon Intelligence Scale, was developed by Alfred Binet and Theodore Simon (1905) to identify children with cognitive impairments. Since then, intelligence tests have evolved significantly. During World War I intelligence tests gained traction as they were used to assess military recruits (Boake, 2002; Wasserman, 2018). Today, intelligence tests are widely used in various domains, including personnel selection (Ghiselli & Brown, 1948; Ree & Earles, 1992; Salgado, 2017), healthcare (Decker et al., 2012), and education. In educational settings, intelligence tests serve multiple purposes: they aid in diagnostic classification (e.g., identifying intellectual impairment or learning disabilities), assessing giftedness, and informing appropriate interventions for children (Farmer & Floyd, 2018; Flanagan et al., 2018; McIntosh et al., 2018). They are also used in school career decisions. Standardized aptitude assessments such as the Centraal Instituut voor Toetsontwikkeling (CITO) in the Netherlands (Cito, n.d.), and the Scholastic Assessment Test (SAT) in the United States (College Board, n.d.) are routinely used for college and university admissions. In the Netherlands, IQ scores are also used to assess whether a person with an intellectual disability qualifies to receive permanent care under Dutch legislation (van Hoogdalem & Bosman, 2024). Importantly, intelligence test scores obtained in childhood have been shown to predict various important life outcomes, such as educational achievement, occupational status, income, and health (Batty et al., 2007; Deary et al., 2007; Gottfredson & Deary, 2004; Strenze, 2007). As a result, intelligence is one of the most frequently measured constructs in psychology (Goldstein et al., 2015) and test outcomes can have lasting impact on an individual's life opportunities and life outcomes.

Many modern intelligence tests are based on the concept of general intelligence, or *g*, a single underlying cognitive ability that influences performance across a wide variety of mental tasks (Spearman, 1904). According to Spearman's theory, individuals who perform well in one cognitive domain (e.g. verbal reasoning), tend to perform well in others (e.g. spatial reasoning), suggesting the existence of a general cognitive factor. The Cattel-Horn-Carroll (CHC) model of intelligence builds on this idea of general intelligence (G). It integrates two earlier theoretical frameworks: Cattell and Horn's theory of fluid and crystallized intelligence and Carroll's three-stratum theory of cognitive abilities. (Cattell, 1971; Euler et al., 2023; Flanagan & Dixon, 2014; Horn & Blankson, 2012). The CHC model proposes that general intelligence (G) consists of multiple cognitive abilities: fluid intelligence (Gf) which involves inductive and deductive reasoning and is shaped by both biological and environmental factors, and crystallized intelligence (Gc) which includes acquired skills and knowledge, visual processing (Gv), short-term memory (Gsm), long-term memory (Glm), processing speed (Gs), auditory processing (Ga), and quantitative knowledge (Gn) (Cattell, 1971; Euler et al., 2023; Flanagan & Dixon, 2014; Horn & Blankson, 2012). The Three-Stratum Theory is based on an analysis of over 460 cognitive abilities and states that factors and abilities can be grouped into three strata: narrow (stratum I), broad (stratum II), and general (stratum III). The different cognitive abilities identified by Cattell and Horn can be translated into the broad stratum (Carroll, 1997; Cattell, 1971; Euler et al., 2023; Flanagan & Dixon, 2014; Horn & Blankson, 2012). This model forms the theoretical foundation for many widely used intelligence tests today (Sternberg, 2022).

Historically and in contemporary practice, intelligence tests are often interpreted as measures of a person's potential (Kamphaus, 2005). In this context, potential refers to a person's capacity to acquire knowledge, solve problems, and adapt to new situations in the future rather than simply reflecting their current abilities or learned skills. However, despite advances in theory and measurement, concerns about the fairness of intelligence tests remain, in particular in relation to socioeconomic status (SES). Binet himself acknowledged early on that environmental factors like SES could affect test performance (Binet & Simon, 1916). Contemporary research supports these concerns. It has shown that children from lower-SES backgrounds tend to score lower on intelligence tests than children from a higher-SES household (Molfese et al., 1997; Strenze, 2007; von Stumm & Plomin, 2015). Von Stumm and Plomin (2015) not only report lower intelligence test performance in early childhood among low SES children, but also suggest that SES has a cumulative impact on cognitive development over time. These differences may reflect differences in access to enriching educational environments, language exposure, and cognitive stimulation (Hackman et al., 2010). Additional research shows that both Gf and Gc are influenced by SES but Gc tends to be more strongly affected due to its reliance on environmental exposure and educational access (Anum, 2022; Rinderman et al., 2010).

These findings suggest that intelligence tests do not simply measure cognitive potential; they also reflect environmental influences like SES. This raises important questions about fairness, especially in situations where test results are used to make life-changing decisions and can influence an individual's life outcomes. If performance on these tests is shaped by differences in access to quality education, learning materials, or stimulating home environments, then children from lower SES backgrounds may be placed at a disadvantage through no fault of their own.

Given how widely intelligence tests are used, and the weight they carry in educational and social decision-making, it's crucial to better understand how SES affects test outcomes. This study aims to investigate the relationship between SES and intelligence test scores in greater detail by applying generalized additive models for location, scale, and shape (GAMLSS). These models allow for more flexible estimation of not just average differences, but also variability and distributional changes across SES groups. Notably, GAMLSS is also used in the norming procedure of the intelligence test used in this study, which makes it especially suitable. We specifically examine general intelligence (G), fluid intelligence (Gf), and crystallized intelligence (Gc). This distinction allows for a more nuanced understanding of how different components of intelligence are influenced by socioeconomic factors. First, we expect that children from higher SES backgrounds will score higher on intelligence tests than those from lower SES backgrounds. Second, we hypothesize that the gap in intelligence scores between SES levels will increase with age, reflecting cumulative effects. Lastly, we hypothesize that both fluid (Gf) and crystallized (Gc) intelligence will increase with SES, but Gc will show a stronger association.

Method

All statistical analyses were conducted using RStudio (Version 2024.12.1, Build 563) and IBM SPSS Statistics (Version 29.0.1.0, Build 171). In R, analyses and data cleaning were performed using the following packages: dplyr (Wickham et al., 2023), tidyr (Wickham et al., 2023), lubridate (Spinu et al., 2023), gamlss (Stasinopoulos et al., 2017), haven (Wickham & Miller, 2023), and ggplot2 (Wickham, 2016) for data visualization.

Participants

The data used in this study are from a Dutch sample which was initially collected to norm the Intelligence and Development Scales 2 (IDS-2; Grob et al., 2018). For the current study mock data were used which behaves like real data. A total of 1,663 participants completed the IDS-2 on site in a controlled environment. Of these, 51.3% (*n* = 853) were female, 47.6% (*n* = 791) were male, and 1.1% (n = 19) did not report their gender. The sample had an average age of 12.1 years (*SD* = 4.5) and ranged from 4.4 to 21.9 years, except for one outlier with a negative age (-0.82).

From the initial sample, 187 were excluded due to missing values for either the education of their mother, or one or more of the IDS-2 subtest scores. An additional 23 participants were excluded because their mother’s education was classified as ‘other’. Given that the IDS-2 is designed for children with ages 5-20 years (Grieder et al., 2023), 42 participants whose ages fell outside this range were excluded. Lastly, 30 participants were removed for having subtest scores that exceeded the maximum values specified by the IDS-2. After removing these participants, the final sample consisted of 1,372 participants.

Measures

Intelligence

Intelligence was assessed using the IDS-2 intelligence domain which consists of seven broad abilities: visual processing, long-term memory, processing speed, auditory short-term memory, visual short-term memory, abstract reasoning, and verbal reasoning. Composite scores were calculated for overall intelligence (*G*), fluid intelligence (*Gf*), and crystallized intelligence (*Gc*). The results from the IDS-2 can be found in Table 1.

Although IDS-2 primarily assesses Gf through abstract reasoning and Gc through verbal reasoning, additional subtests also contribute to these constructs. In the subtests for the visual processing domain, participants were asked to reconstruct geometric figures using squares, triangles, and circles, which requires working memory. Working memory is considered a predictor for Gf (Colom et al., 2015; Martinez, 2019; Salthouse & Pink, 2008). Furthermore, in a subtest of the short-term memory domain, participants have to memorize figures and rotated versions of these figures, which also involves working memory. Because of this, along with the abstract thinking subtest, we included the visual processing subtests and the rotated figures subtest in the measurement of Gf. Similarly, long-term memory directly influences Gc (Martinez, 2019) and therefore, in addition to verbal reasoning, we have also included the long-term memory subtests in the measurement of Gc. Scores from each subtest were scaled from 0 to 100, taking into account age-dependent maximum values, to ensure equal contribution of the subtests to the composite scores.

To assess robustness, we compared results based on alternative subtest groupings for Gf and Gc. This allowed us to examine whether the findings were sensitive to the specific subtests selected to represent each construct.

Table 1

IDS-2 Test scores (N=1372)

Scores per subdomain scaled, *M* (SD)		
Visual processing[1]	52.38	(12.92)
Copy figure	50.53	(16.11)
Copy circles	54.21	(16.83)
Long-term memory[2]	56.41	(15.85)
Story retelling	54.72	(18.19)
Describing picture	58.10	(18.30)
Processing speed	51.91	(13.24)
Cross out two features	44.64	(13.76)
Cross out figure	59.20	(14.67)
Auditory short-term memory		
Repeating number- and letter sequences	50.71	(12.53)
Visual spatial short-term memory	32.98	(11.13)
Recognizing figures	34.36	(12.47)

Recognizing rotated figures[1]	31.60	(11.96)
Abstract reasoning[1]	44.28	(15.00)
Reasoning matrices	39.14	(16.69)
Recognizing different pictures	49.43	(16.90)
Verbal reasoning[2]	54.69	(16.24)
Naming categories	55.67	(18.43)
Naming contradictions	53.71	(15.44)
Total scores scaled, *M* (*SD*)		
G	49.05	(11.31)
Gf	46.97	(11.28)
Gc	55.55	(14.57)

Note. Superscript numbers indicate the domains used to compute the composite scores: ¹ Included in the Gf composite (fluid intelligence); ² Included in the Gc composite (crystallized intelligence). Names of subtests were translated from Dutch to English.

Socioeconomic Status

In this study, socioeconomic status (SES) was determined based on the highest level of education attained by participants' mothers, a commonly used indicator for SES in psychological and educational research (Cowan et al., 2012; Long & Rengbarger, 2023). Classification of SES followed the international Eurostat framework, dividing participants into three groups: low (basisschool, lagere school, VMBO, LBO & MBO1), middle (MBO2tm4, HAVO & VWO), and high (HBO & Universiteit) (Eurostat, 2022; Table 2).

Table 2

Socioeconomic status based on the level of education mother (N=1302)

Socioeconomic status, *n* (*%*)		
Low	176	(12.6)
Basisschool/lagere school	32	(2.3)
VMBO/LBO/MBO1	144	(10.3)
Middle		
MBO2tm4/HAVO/VWO	526	(37.5)
High		
HBO/Universiteit	700	(49.9)

Generalized Additive Models for Location, Scale, and Shape

To analyze and compare the data across different levels of SES, and their relationship with total, fluid, and crystallized intelligence, we use Generalized Additive Models for Location, Scale, and Shape (GAMLSS; Rigby & Stasinopoulos, 2005). GAMLSS is a flexible framework for modeling the distribution of an outcome variable by allowing the mean (location; μ), variance (scale; σ), and shape (skewness; ν; kurtosis; τ) to be modeled as smooth functions of covariates, such as age and SES (Stasinopoulos et al., 2024; Timmerman et al., 2021). This flexibility is especially beneficial in the current study, as it allows for modeling complex, non-linear associations between SES and different aspects of intelligence. For example, the relationship between SES and intelligence test performance may vary across SES groups or across age, which traditional linear models might not capture accurately.

Intelligence tests are typically normed based on age to adjust for systematic differences in intelligence scores across age (Grieder et al., 2023; Roid, 2003; Wechsler, 2014). Traditional norming methods divide age into discrete intervals, assuming that the distribution remains consistent within each interval. This assumption can be problematic, as it implies that a uniform distribution of scores across all age groups. In practice, depending on the size of the intervals, this assumption is frequently unrealistic, leading to potential distortions in the data creating 'jumps' between the intervals (Timmerman et al., 2021). In contrast, GAMLSS uses continuous norming which allows for smooth modeling of intelligence scores without these discontinuities. This approach not only avoids the 'jumps' that can occur with discrete intervals but also enables more nuanced modeling of the variance and standard deviation of scores. By incorporating both the mean and the variance, GAMLSS provides a more comprehensive view of how intelligence scores change across age. It accounts for variability in the data, allowing for more precise understanding of the spread of scores within each age group, as well as across different SES levels (Stasinopoulos et al., 2024; Timmerman et al., 2021). Ultimately, the use of GAMLSS allows us to better assess the relationship between intelligence test scores and SES by accounting for both central tendencies and variability in a way traditional methods cannot.

Distribution and Model Selection

Given the diverse ways in which data can behave, a variety of statistical distributions are available to model different data characteristics. The choice of distribution depends on specific properties of the data including its location, scale, and shape. Some distributions may provide a better fit to the data than others, depending on these characteristics. In this study, we fitted separate models for each intelligence domain using age (fourth-degree polynomial determined by forward selection) and SES as predictors (Equation 1). SES was dummy coded, with the lowest SES group serving as the reference category. We compared four candidate distributions using the Akaike Information Criterion (AIC): Box-Cox Cole and Green (BCCG), Gamma, Box-Cox t (BCT), and Box-Cox Power Exponential (BCPE). As a robustness check, we also estimated models using an alternative distribution to ensure that the main findings were not dependent on the initial distributional choice. In the final model, the location parameter (μ) was modeled as a fourth-degree polynomial function of age and SES level for all intelligence types (*G*, *Gf*, *Gc*; Equation 1). The scale parameter (σ) was modeled as a thirddegree polynomial function of age and SES. Both skewness (ν) and kurtosis (τ) were modeled as intercept-only, held constant across age and SES.

$$g(\mu_{G/Gf/Gc}) = \beta_0 + \beta_1 age + \beta_2 age^2 + \beta_3 age^3 + \beta_4 age^4 + \beta_5 SES_{middle} + \beta_6 SES_{high} \quad (1)$$

Results

Prior to analysis, all subtest scores were rescaled so that the maximum score for each subtest equaled 100. This rescaling allowed for comparability across different cognitive subdomains ensuring that scores across different subtests are placed on a common scale. However, this rescaling might have unintentionally inflated the relative scores for *Gc*, which consistently shows higher predicted scores than other domains (Figure 1). While this does not affect the interpretation of developmental trends or SES-related differences within each domain, it limits direct comparisons of absolute score levels of Gc.

We had originally intended to test whether SES was more strongly associated with Gc than with Gf, as outlined in Hypothesis 3. However, because we could not directly compare the absolute score levels of *Gf* and *Gc*, Hypothesis 3 could not be tested as intended.

Model Selection

To select the most appropriate model for each domain, we compared four candidate distributions: Box-Cox Cole and Green (BCCG), Gamma, Box-Cox t (BCT), and Box-Cox Power Exponential (BCPE). The comparison was based on Akaike Information Criterion (AIC) values. The BCT distribution yielded the lowest AIC values for all domains except for Gc where BCCG had a lower AIC (9841.15) than BCT (AIC = 9843.15) (Table 3). Because BCT had the lowest AIC value for G and Gc and the difference in AIC values for Gc between BCT and BCCG is relatively small, BCT was therefore selected for final modeling for consistency and interpretability.

Table 3

Akaike Information Criterion (AIC) comparison table for each candidate distribution across intelligence domains

Model type	BCCG	Gamma	BCT	BCPE
G	8943.88	9021.68	8936.66	8939.60
Gf	9841.15	9908.37	9843.15	9842.75
Gc	9377.54	9450.95	9374.21	9377.25

While the initial model selection suggested that the skewness parameter (ν) should be modeled with only an intercept, we explored whether including SES would improve model fit. Adding SES to the ν sub model did result in some significant effects (Table A1). For example, the high SES group in the fluid intelligence model ($p = .005$). However, these effects were not consistent across domains and didn't meaningfully improve the overall model fit or change our conclusions. To keep the models as straightforward and interpretable as possible, we decided to only use the intercept to model ν in the final analyses.

Robustness Checks

To evaluate the robustness of our findings, we re-estimated the GAMLSS models using the Box-Cox Power Exponential (BCPE) distribution instead of the Box-Cox t (BCT) distribution. This alternative distribution was chosen because after the BCT distribution it had the next-lowest AIC scores after BCT (Table 3). The models produced highly similar predicted trajectories, with no notable changes in SES effects or developmental trends (Figure A1), suggesting that our findings are robust to the choice of distribution.

We also tested whether our results were influenced by how we defined Gf and Gc. In the main analyses, Gf and Gc were based on multiple subdomains (Table 1). As a robustness check, we re-estimated the models using narrower definitions as they were also intended by the IDS-2: using only the abstract thinking subtests for Gf, and only the verbal reasoning subtests for Gc. While overall patterns remained consistent, these alternative models showed slightly greater variation in curve shapes over age and more pronounced differences between quantiles, especially for Gf (Figure A2). This suggests that more narrowly defined subdomains may increase observed variability but do not substantially alter the interpretation of SES effects.

SES Effects and Developmental Patterns

SES was a significant predictor of both the location (μ) and scale (σ) parameter in all models. Table 4 summarizes these fixed effects across domains. Higher SES was associated with higher average scores and reduced variability in scores, indicating more consistent cognitive performance among higher SES groups. These results provide support for Hypothesis 1, confirming that children from higher-SES background consistently score higher than those from lower SES groups across all intelligence domains.

Table 4

Estimated Effects of SES on the Location (μ) and Scale (σ) Parameters by Intelligence Domain

Domain	SES Level	μ Estimate (b)	μ p-value	σ Estimate (b)	σ p-value
G	Middle SES	3.51	< .001*	-0.15	.041*
	High SES	6.03	< .001*	-0.27	< .001*
Gf	Middle SES	4.25	< .001*	-0.21	< .001*
	High SES	7.20	< .001*	-0.34	< .001*

Gc	Middle SES	3.64	< .001*	-0.13	.070
	High SES	6.20	< .001*	-0.23	< .001*

Note. * indicates $p < .05$

Visual Interpretation of Predicted Trajectories

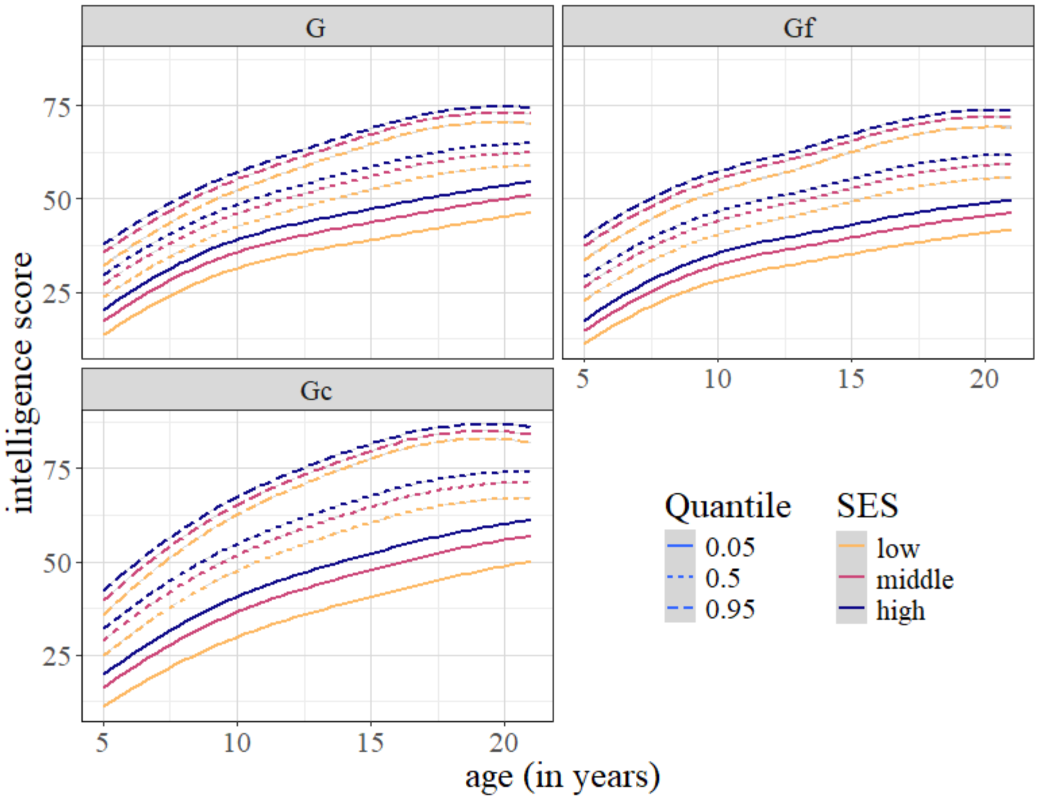
Plots of predicted intelligence scores by age, SES group, and quantile revealed clear and consistent developmental trends. Scores increased with age across all domains, with rapid growth in early childhood that gradually tapered in later adolescence. For all SES groups, the pattern was similar in shape, but higher SES groups consistently showed higher predicted scores across quantiles and age. Differences between SES groups were visible at all quantiles, but the gaps were most pronounced at the lower quantiles (Figure 1, Table A2, A3, and A4) suggesting that SES-related disparities are especially prominent in lower-performing children.

Additionally, SES gaps tended to widen with age at the lower quantiles (Figure 1, Table A2, A3, and A4). For instance, in *Gc*, the difference between high and low SES groups at the 5th percentile grew from approximately 8 points at age 5 to nearly 12 points by age 17. Similar trends were found in *G* and *Gf*. In contrast, the SES-gaps at the higher quantiles seemed to decrease over time. These findings mostly support Hypothesis 2, which proposed that SES-related differences would accumulate over time, indicating a compounding effect of SES on intelligence development across childhood and adolescence.

Taken together, these results indicate that SES is a strong and consistent predictor of both average performance and variability in intelligence across domains. Despite the limitations introduced by domain-specific scaling, the findings were stable across multiple model specifications and robust to alternative domain definitions.

Figure 1

GAMLSS Model of Intelligence Score (G, Gf & Gc) by SES level across age



Discussion

This study investigated the relationship between socioeconomic status (SES) and intelligence test performance in a Dutch sample of children and adolescents using the Intelligence and Development Scales 2 and analyzed with Generalized Additive Models for Location, Scale, and Shape (GAMLSS). In line with our first hypothesis, we found that higher SES was significantly associated with higher scores in general intelligence (G), fluid intelligence (Gf), and crystallized intelligence (Gc). These results are consistent with previous research showing that children from higher SES backgrounds tend to perform better on intelligence tests than their lower SES peers (Molfese et al., 1997; Strenze, 2007; von Stumm & Plomin, 2015).

Importantly, score variability was also lower among high-SES children, suggesting more uniform cognitive development in this group. This pattern may reflect more consistent access to educational resources, enriched home environments, and greater exposure to language and problem-solving activities, factors frequently associated with higher SES (Bradley & Corwyn, 2002; Hackman et al., 2010). Additionally, parents from higher SES backgrounds are often more engaged in their children's learning, which has been shown to significantly influence educational outcomes (Harris & Goodall, 2008). In contrast, children from lower SES backgrounds may experience more variability in support and stimulation, leading to greater within-group variability in intelligence test performance.

We also found that SES-related differences were most pronounced at the lower percentiles of the intelligence score distribution. This indicates that SES has the greatest impact on children with lower cognitive performance, who may be most vulnerable to environmental disadvantages. Early exposure to stereotype threat, whereby children from lower SES backgrounds underperform due to negative societal expectations, may also contribute to this disparity (Désert et al., 2009)

Additionally, SES gaps tended to widen with age, especially at the lower end of the distribution. This supports our second hypothesis and suggest a cumulative SES effect on cognitive development over time (von Stumm & Plomin, 2015). Interestingly, at higher percentiles, SES gaps decreased over age, suggesting that high-performing children may be less affected by SES-related constraints. One possibility is that high performers, regardless of their SES background, are more likely to access or capitalize on enriching opportunities, either through intrinsic motivation, school support, or compensatory mechanisms (Duncan & Magnuson, 2012; Jacobs & Wolbers, 2018; Sirin, 2005).

Although we intended to test whether SES was more strongly associated with Gc than Gf (Hypothesis 3), limitations related to domain-specific scaling prevented us from comparing effect sizes directly. As a result, we were unable to determine whether Gc is more sensitive to SES than Gf. This hypothesis was based on prior research suggesting that crystallized abilities are more dependent on environmental input and therefore more susceptible to SES influences (Anum, 2022; Rindermann et al., 2010). Future research using standardized scores or structural models could help clarify domain-specific SES effects more reliably.

Limitations and Future Directions

This study has several limitations. First, the data used were synthetic mock data based on a real Dutch norming sample, which, while designed to closely mimic real responses, may not capture the full nuance and variability of live testing conditions. As a result, the generalizability of the results is limited and while patterns may be indicative, they should be interpreted with caution.

Second, SES was measured solely through maternal education, which, while widely used, may not fully capture the multifaceted nature of socioeconomic background. Including additional indicators like income or occupational status could improve measurement validity.

Third, the relatively small number of participants in the low SES group (n = 176) compared to the middle (n = 526) and high SES (n = 700) groups, might reduce the statistical power to detect differences involving the low SES group and may have resulted in less precise estimates of cognitive performance within this group. As a result, findings related to SES effects, particularly at the lower end of the socioeconomic spectrum, should be interpreted with caution.

Moreover, the cross-sectional design limits the ability to infer causality. Although we observed developmental patterns, we cannot conclusively determine whether SES causes the observed differences in cognitive development. Longitudinal designs would be better suited to test the cumulative effects over time. Additionally, while GAMLSS offers detailed modeling of distributional change, it remains descriptive in nature and cannot account for underlying causal mechanisms.

Finally, because findings are based on a Dutch sample, they may not generalize to populations with different educational systems, cultural norms, or socioeconomic structures.

Conclusion

This study offers a detailed examination of how SES relates to different components of intelligence across development. Using GAMLSS, we demonstrated that SES is linked not only to average intelligence scores, but also variability and developmental trajectories, particularly among lower performing children. These findings reinforce the need for careful interpretation of intelligence test results in socioeconomically diverse populations. They also highlight the importance of early intervention and policy efforts to reduce SES-related disparities in cognitive development.

These results reinforce longstanding concerns about the fairness of intelligence testing in socioeconomically diverse populations. As Binet and later researchers have emphasized, intelligence test outcomes reflect not only innate ability, but also environmental access to learning opportunities and cognitive stimulation. Our findings highlight the risk that children from lower SES backgrounds may be systematically disadvantaged by assessments that do not account for these contextual factors, underscoring the importance of equitable educational policy and test interpretation.

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Appendix A

Artificial Intelligence Acknowledgement and Supplementary Analyses

Artificial Intelligence Acknowledgement

I used OpenAi’s ChatGPT to support my work with coding in R. Specifically, I used it to help troubleshoot errors, understand R functions, and generate initial versions of code snippets. All AI-generated code was carefully reviewed, tested, and adapted by me, and I remain responsible for all analyses and interpretations.

Table A1

Effects of SES on the Skewness (v) Parameter

Model type	Predictor	Estimate	SE	t	p
G	SES_{middle}	1.038	0.545	1.91	.57
	SES_{high}	1.840	0.581	3.17	.002
Gf	SES_{middle}	0.432	0.348	1.24	.215
	SES_{high}	0.598	0.345	1.73	.083
Gc	SES_{middle}	0.648	0.431	1.50	.133
	SES_{high}	1.299	0.465	2.80	.005

Figure A1

GAMLSS Model of Intelligence Score (G, Gf & Gc) by SES level using the BCPE distribution

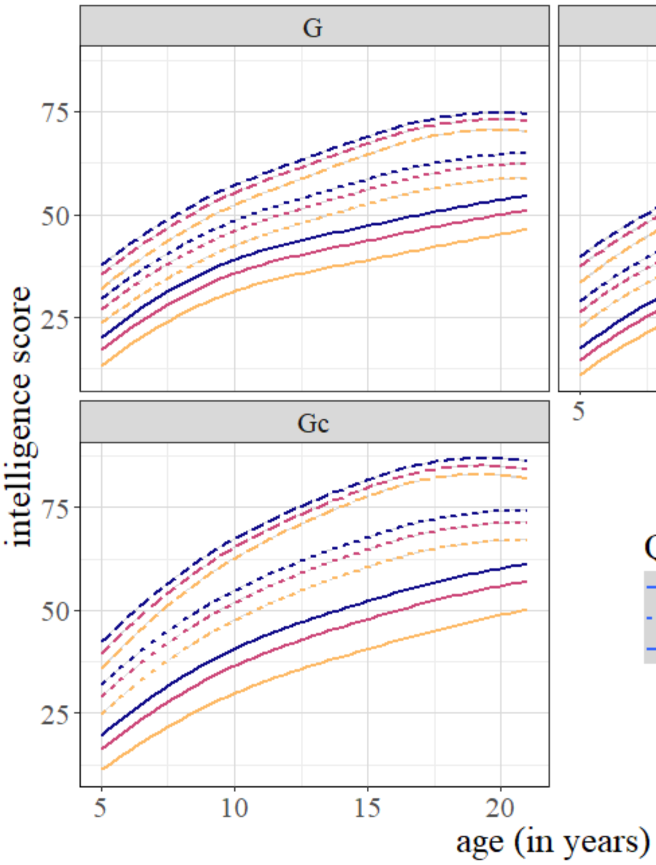

Figure A2

GAMLSS Model of Intelligence Score (G, Gf & Gc) by SES level using the BCT distribution and an alternative composition for Gf and Gc

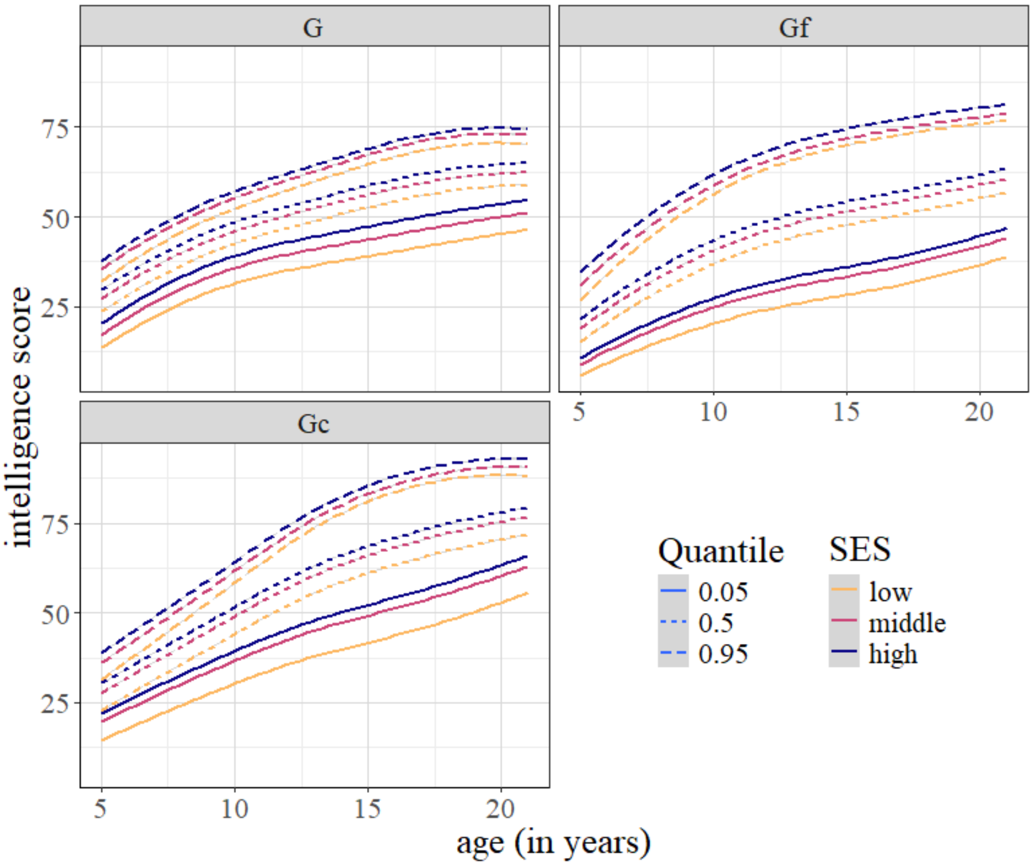

Table A2

Difference in G scores between SES levels across ages and quantiles

Age	Quantile	Low	Middle	High	High-Low	Middle-Low	High-Middle
5	.05	12.76	16.30	19.23	6.47	3.54	2.93
6	.05	18.07	21.98	25.11	7.03	3.91	3.12
7	.05	22.59	26.68	29.89	7.30	4.09	3.21
8	.05	26.25	30.44	33.70	7.45	4.19	3.26
9	.05	29.16	33.42	36.71	7.56	4.26	3.30
10	.05	31.47	35.80	39.14	7.66	4.33	3.34
11	.05	33.36	37.75	41.13	7.77	4.39	3.38
12	.05	34.94	39.40	42.83	7.89	4.46	3.43
13	.05	36.34	40.87	44.36	8.03	4.54	3.49
14	.05	37.63	42.25	45.80	8.17	4.62	3.55
15	.05	38.89	43.59	47.21	8.32	4.70	3.62
16	.05	40.16	44.94	48.61	8.45	4.77	3.68
17	.05	41.48	46.30	50.02	8.54	4.83	3.71
18	.05	42.82	47.67	51.39	8.57	4.85	3.72
19	.05	44.14	48.96	52.66	8.52	4.82	3.70

20	.05	45.31	50.04	53.66	8.36	4.73	3.62
5	.5	22.42	25.92	28.43	6.00	3.49	2.51
6	.5	28.44	31.94	34.46	6.02	3.50	2.52
7	.5	33.18	36.69	39.20	6.02	3.51	2.52
8	.5	36.94	40.45	42.96	6.03	3.51	2.52
9	.5	39.98	43.49	46.01	6.03	3.51	2.52
10	.5	42.52	46.03	48.55	6.03	3.51	2.52
11	.5	44.75	48.26	50.78	6.03	3.51	2.52
12	.5	46.79	50.30	52.82	6.03	3.51	2.52
13	.5	48.74	52.25	54.77	6.03	3.51	2.52
14	.5	50.65	54.16	56.68	6.03	3.51	2.52
15	.5	52.53	56.04	58.56	6.03	3.51	2.52
16	.5	54.33	57.84	60.36	6.03	3.51	2.52
17	.5	55.99	59.50	62.01	6.03	3.51	2.52
18	.5	57.37	60.88	63.39	6.03	3.51	2.52
19	.5	58.32	61.82	64.34	6.03	3.51	2.52
20	.5	58.61	62.12	64.64	6.03	3.51	2.52
5	.95	30.47	34.05	36.34	5.87	3.58	2.29
6	.95	37.23	40.56	42.69	5.45	3.33	2.13
7	.95	42.31	45.49	47.52	5.21	3.17	2.04
8	.95	46.27	49.35	51.32	5.05	3.07	1.98
9	.95	49.51	52.51	54.44	4.94	3.00	1.93
10	.95	52.30	55.24	57.13	4.84	2.94	1.89
11	.95	54.85	57.74	59.59	4.74	2.89	1.85
12	.95	57.31	60.14	61.94	4.64	2.83	1.81
13	.95	59.74	62.51	64.27	4.53	2.77	1.76
14	.95	62.18	64.89	66.60	4.42	2.71	1.71
15	.95	64.59	67.24	68.90	4.31	2.65	1.66
16	.95	66.86	69.45	71.06	4.20	2.59	1.62
17	.95	68.82	71.37	72.95	4.13	2.54	1.58
18	.95	70.27	72.79	74.36	4.09	2.52	1.57
19	.95	70.94	73.47	75.05	4.11	2.53	1.58
20	.95	70.56	73.13	74.76	4.20	2.58	1.63

Table A3

Difference in Gf scores between SES levels across ages and quantiles

Age	Quantile	Low	Middle	High	High-Low	Middle-Low	High-Middle
5	.05	10.42	13.64	16.31	5.89	3.22	2.67
6	.05	15.54	19.22	22.16	6.62	3.68	2.94
7	.05	19.90	23.82	26.88	6.98	3.92	3.06
8	.05	23.37	27.41	30.54	7.17	4.04	3.13
9	.05	26.06	30.17	33.33	7.28	4.12	3.16
10	.05	28.15	32.32	35.50	7.36	4.17	3.19
11	.05	29.83	34.04	37.25	7.43	4.21	3.21
12	.05	31.26	35.52	38.76	7.50	4.26	3.24
13	.05	32.57	36.88	40.16	7.59	4.31	3.28

14	.05	33.85	38.22	41.54	7.70	4.37	3.33
15	.05	35.14	39.58	42.95	7.81	4.44	3.37
16	.05	36.46	40.96	44.38	7.92	4.50	3.42
17	.05	37.78	42.34	45.80	8.02	4.56	3.46
18	.05	39.05	43.64	47.13	8.08	4.59	3.49
19	.05	40.15	44.75	48.24	8.09	4.60	3.49
20	.05	40.90	45.47	48.92	8.02	4.57	3.46
5	.5	21.19	24.81	27.37	6.18	3.62	2.56
6	.5	27.54	31.17	33.73	6.19	3.63	2.56
7	.5	32.25	35.89	38.45	6.20	3.63	2.56
8	.5	35.75	39.38	41.95	6.20	3.64	2.56
9	.5	38.39	42.03	44.59	6.20	3.64	2.56
10	.5	40.48	44.12	46.69	6.20	3.64	2.56
11	.5	42.27	45.91	48.47	6.20	3.64	2.56
12	.5	43.94	47.58	50.14	6.20	3.64	2.56
13	.5	45.62	49.26	51.82	6.20	3.64	2.56
14	.5	47.37	51.00	53.57	6.20	3.64	2.56
15	.5	49.19	52.83	55.39	6.20	3.64	2.56
16	.5	51.04	54.67	57.24	6.20	3.64	2.56
17	.5	52.79	56.43	58.99	6.20	3.64	2.56
18	.5	54.27	57.91	60.47	6.20	3.64	2.56
19	.5	55.26	58.90	61.46	6.20	3.64	2.56
20	.5	55.45	59.08	61.65	6.20	3.64	2.56
5	.95	31.10	35.10	37.60	6.51	4.01	2.50
6	.95	38.60	42.26	44.54	5.94	3.66	2.28
7	.95	43.72	47.18	49.35	5.63	3.46	2.17
8	.95	47.32	50.66	52.76	5.44	3.34	2.10
9	.95	49.97	53.24	55.30	5.33	3.27	2.06
10	.95	52.10	55.32	57.35	5.25	3.22	2.03
11	.95	54.02	57.19	59.20	5.18	3.17	2.00
12	.95	55.93	59.05	61.03	5.10	3.13	1.97
13	.95	57.95	61.03	62.97	5.02	3.08	1.94
14	.95	60.14	63.17	65.07	4.92	3.03	1.90
15	.95	62.47	65.44	67.29	4.82	2.97	1.85
16	.95	64.81	67.72	69.53	4.72	2.91	1.81
17	.95	66.97	69.83	71.61	4.63	2.86	1.77
18	.95	68.68	71.50	73.25	4.57	2.82	1.75
19	.95	69.58	72.39	74.13	4.55	2.81	1.74
20	.95	69.26	72.09	73.86	4.61	2.84	1.77

Table A4

Difference in Gc scores between SES levels across ages and quantiles

Age	Quantile	Low	Middle	High	High-Low	Middle-Low	High-Middle
5	.05	11.11	15.79	19.14	8.03	4.68	3.35
6	.05	15.69	21.17	24.84	9.15	5.48	3.67
7	.05	19.94	25.93	29.79	9.85	5.99	3.86

8	.05	23.73	30.03	34.01	10.28	6.30	3.98
9	.05	27.03	33.54	37.60	10.57	6.51	4.06
10	.05	29.89	36.57	40.69	10.80	6.68	4.13
11	.05	32.40	39.21	43.40	11.00	6.81	4.19
12	.05	34.65	41.59	45.83	11.19	6.94	4.25
13	.05	36.71	43.77	48.07	11.36	7.06	4.30
14	.05	38.66	45.83	50.18	11.52	7.17	4.36
15	.05	40.54	47.80	52.20	11.66	7.26	4.40
16	.05	42.39	49.71	54.14	11.75	7.32	4.43
17	.05	44.21	51.55	55.99	11.78	7.34	4.44
18	.05	45.97	53.27	57.69	11.72	7.30	4.42
19	.05	47.59	54.77	59.14	11.55	7.19	4.37
20	.05	48.93	55.93	60.20	11.27	6.99	4.28
5	.5	23.89	28.06	30.99	7.10	4.18	2.93
6	.5	30.48	34.69	37.62	7.14	4.21	2.94
7	.5	35.92	40.14	43.08	7.17	4.23	2.94
8	.5	40.45	44.69	47.63	7.18	4.24	2.94
9	.5	44.30	48.54	51.49	7.19	4.24	2.94
10	.5	47.64	51.89	54.83	7.19	4.25	2.94
11	.5	50.62	54.87	57.81	7.19	4.25	2.94
12	.5	53.34	57.59	60.53	7.19	4.25	2.94
13	.5	55.88	60.13	63.07	7.19	4.25	2.94
14	.5	58.27	62.52	65.46	7.19	4.25	2.94
15	.5	60.52	64.77	67.71	7.19	4.25	2.94
16	.5	62.58	66.83	69.77	7.19	4.25	2.94
17	.5	64.38	68.63	71.57	7.19	4.25	2.94
18	.5	65.80	70.056	73.00	7.19	4.25	2.94
19	.5	66.72	70.96	73.90	7.20	4.25	2.94
20	.5	66.92	71.16	74.10	7.20	4.25	2.94
5	.95	34.28	38.18	40.95	6.67	3.90	2.77
6	.95	42.55	46.01	48.55	6.00	3.46	2.54
7	.95	49.06	52.22	54.60	5.54	3.16	2.38
8	.95	54.34	57.28	59.56	5.21	2.94	2.27
9	.95	58.77	61.54	63.73	4.96	2.77	2.19
10	.95	62.61	65.24	67.36	4.76	2.64	2.12
11	.95	66.05	68.57	70.63	4.57	2.52	2.06
12	.95	69.24	71.65	73.65	4.41	2.41	2.00
13	.95	72.24	74.54	76.49	4.25	2.30	1.95
14	.95	75.06	77.26	79.16	4.11	2.21	1.90
15	.95	77.66	79.78	81.64	3.98	2.12	1.86
16	.95	79.96	82.02	83.84	3.88	2.06	1.83
17	.95	81.81	83.83	85.64	3.83	2.02	1.81
18	.95	83.05	85.07	86.87	3.83	2.02	1.81
19	.95	83.44	85.51	87.35	3.90	2.07	1.83
20	.95	82.77	84.94	86.83	4.06	2.17	1.89