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The moderating influence of school achievement on intelligence in young adulthood

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Abstract

Education has been suggested to be possibly the most consistent, robust, and durable method available for raising intelligence, but little is known about the genetic and environmental interplay underlying this association. Therefore, we investigated how school achievement, as measured by grade point average in lower secondary school at 15 years of age, moderated intelligence variation in young adulthood. The sample consisted of all Danish male twin pairs who had left lower secondary school since 2002 and appeared, typically at age 18, before a draft board through 2015 ($N = 2,660$). Shared environmental variance unique to intelligence (10% of total variance) was found to be greater among individuals with poor school achievement. However, school achievement did not moderate the genetic influences or the non-shared environmental influences on intelligence. We discuss the implications of this in light of the constraints imposed by the statistical models we used.

Keywords: intelligence, school achievement, genetic and environmental influences, gene-environment interaction, Denmark

The Moderating Influence of School Achievement on Intelligence in Young Adulthood

Education and intelligence are substantially interrelated. Irrespective of whether education is measured by indicators of achievement (i.e. scores on standardised academic achievement tests and school grades) or indicators of attainment (i.e. time spent in full-time education and school-leaving credentials), its correlations with intelligence test scores are typically around .5 (e.g. Strenze, 2007).

Given that the first successful intelligence test was developed at the beginning of the twentieth century to identify children who, because of intellectual level, would have difficulties benefiting from normal education (Binet & Simon, 1905), this is neither new nor surprising. In fact, the substantial correlations have for a long time been interpreted as suggesting that intelligence is beneficial to educational outcomes. Whether the association is reciprocal has been more controversial, but already three decades ago Ceci (1991) noted eight types of evidence supporting this possibility: positive correlation between educational attainment and intelligence test scores; disadvantageous influences of summer vacation, intermittent school attendance, later school entry, and early school termination on intelligence test scores; associations between achievement test and intelligence test scores; lower intelligence test scores in children who entered school one year later than others of the same chronological age; and secular increases in both educational attainment and intelligence test scores. The influence of education on intelligence was hypothesized to be due to educational institutions using teaching material of direct relevance to intelligence tests, training students' modes of thinking, and inculcating concentration and self-control. However, the evidence was mostly based on observational correlational studies. Both parents and school officials may choose to enter brighter children in school at younger ages and defer entry of children seeming less able (e.g. The Highland Council, 2020). Brighter children are also more likely to remain in school longer (e.g. Deary & Johnson, 2010). Thus, correlational studies cannot isolate education as the causative factor though their consistent observations of positive associations suggest that education may be able to raise intelligence.

Several reviews of stronger studies have continued to suggest that education may raise intelligence (e.g. Deary & Johnson, 2010; Gustafsson, 2001; Snow, 1996). Though the two oldest reviews mainly focused on the previously noted evidence, they also presented evidence from longitudinal studies, which tried to circumvent the selection problem by taking into account childhood intelligence, family background, and other variables likely to influence both level of education and intelligence (see Balke-Aurell, 1982; Husén & Tuijnman, 1991; Winship & Korenman, 1997). Still, it cannot be ruled out that other factors that were not taken into account in these studies might have influenced the association between level of education and intelligence. However, in the third review alternative explanations of the association were more thoroughly discussed (Deary & Johnson, 2010). Thus, this review first presented studies observing lower intelligence test scores in children with postponed school entry and in children who for administrative reasons entered school one year later than others of the same chronological age, acknowledging that these studies might be influenced by the selection problem noted above. Second, the review presented studies investigating genetic and environmental influences underlying the association, suggesting that a major part could be attributed to common genetic influences making gene-environment correlations likely strongly present. However, even when this was taken into account, education still seemed able to raise intelligence.

In fact, a recent meta-analysis building on the above-mentioned reviews and a large number of newer studies observed that education was associated with an increase in intelligence of 1 to 5 IQ points per extra year of education (Ritchie & Tucker-Drob, 2018). This led the authors to suggest that education might be the most consistent, robust, and durable method currently available for raising intelligence. The meta-analysis included 28 studies, which were all designed to circumvent the selection problem inherent in the association between education and intelligence. Seven studies had analysed the association in individuals with various levels of education controlling intelligence test scores taken when they were in the same grade of compulsory education and observed 1.2 IQ points higher intelligence test scores per extra year of education. Eleven studies had compared intelligence test scores of otherwise comparable groups who were either affected or (at time of study) unaffected by policy changes in length of compulsory education and observed 2.1 IQ points higher intelligence test scores per extra year of education. And 10 studies had taken advantage of school entry age cut-offs and compared intelligence test scores of similar-aged children who had entered school in successive school years and observed 5.2 IQ points higher intelligence test scores per extra year of school. The three study designs all had their own strengths and limitations, and none of them circumvented the selection problem completely, but the policy change design came closest. Thus, there seems to be considerable evidence that education may raise intelligence test scores at least by a couple of points.

However, in spite of the well-established association between education and intelligence, little is known about whether it applies to measures of both achievement and attainment given that previous studies mainly have focused on the last-mentioned, and little is known about the genetic and environmental interplay underlying this association. Since achievement and attainment both measure aspects of educational processes, the two are strongly related, though not the same (e.g. Novo & Calixto, 2009). More specifically, achievement measures progress in ongoing education, which influences later attainment both indirectly by shaping individuals' attainment ambitions and directly by determining their access to further education (e.g. Ministry of Higher Education and Science et al., 2016; OECD, 2012). Both rely on the same intra-individual factors, such as intelligence, values and aspirations, and hard work (e.g. Deary & Johnson, 2010). Their genetic and environmental links to intelligence are, however, not necessarily the same since attainment also relies on extra-individual factors, such as admission requirements and financial wherewithal (e.g. Ministry of Higher Education and Science et al., 2016). They also reflect different aspects of life-span development. Achievement reflects active performance in educational settings at the time it occurred, which could be at any stage of educational progress. It is relevant to individuals' lives primarily only within educational settings, which means, for the majority, only until young adulthood. In contrast, attainment reflects highest level of educational performance and is often relevant to individuals' lives long after it is awarded. Thus, it is possible that their genetic and environmental links with intelligence may be different in young and older adulthood.

One way to gain some insight into the genetic and environmental links is to apply a dynamic quantitative genetic-environmental model, which is an extension of a standard bivariate variance decomposition measuring the extent to which genetic and environmental influences are correlated across two variables. However, the extended model allows for quantification of both gene-environment correlations and gene-environment interactions. To our knowledge, only three studies have so far applied this statistical method to look into the genetic and environmental interplay involved in the association between education and intelligence (Johnson, Deary, & Iacono, 2009; Johnson, Deary, McGue, et al., 2009; Johnson et al., 2010). However, one study has also applied this method to look into the genetic and environmental interplay involved in the association between occupational status and specific cognitive abilities, but due to its somewhat different focus, this study is of less relevance to our current study (Zavala et al., 2018).

Johnson, Deary, and Iacono (2009) investigated how intelligence moderated genetic and environmental influences on grade point average (GPA) and educational attainment in young adulthood. Based on a population-representative sample of the U.S. state of Minnesota, they observed that non-shared environmental influences on school grades were strong among individuals with low intelligence but less among those with higher intelligence. Johnson and colleagues suggested that this might be because individuals with low intelligence provide less reliable information on school grades and because individuals with high intelligence can often obtain high grades with minimal effort in typical school curricula, while those with low intelligence cannot. Shared environmental influences common to intelligence and educational attainment were also strong among individuals with low intelligence, whereas genetic influences common to intelligence and educational attainment were strong among individuals with high intelligence. They suggested that this might be because family environmental background, such as parental emphasis on education and financial resources, is particularly important to educational attainment among individuals with low intelligence and because genetic influences on characteristics other than intelligence are primarily important to educational attainment among individuals with high intelligence.

Johnson et al. (2010) compared how intelligence moderated genetic and environmental influences on educational attainment in young adulthood in two different contexts. Based on population-representative samples in Sweden and the U.S. state of Minnesota, they observed that patterns of genetic influences on educational attainment were similar in the two contexts, but patterns of shared environmental influences differed. In Sweden, shared environmental influences on educational attainment were strong among individuals with high intelligence, whereas in Minnesota, shared environmental influences on educational attainment were strong among individuals with low intelligence. Johnson and colleagues suggested that this might be because Sweden is characterised by state-supported access (based on ability) to a uniform higher education system, whereas the United States is characterised more by family-supported access to a diverse higher education system within which family background might help individuals with low intelligence obtain educational credentials despite limitations in ability.

Johnson et al. (2009) investigated how educational attainment moderated genetic and environmental influences on intelligence in late life. Interestingly, this study suggested that the moderating influence of educational attainment on intelligence among older people in Denmark was very similar to the moderating influence of intelligence on educational attainment among young adults in the United States. Johnson and colleagues speculated that this might be because similar personality characteristics are involved in using one's intelligence to maximize educational attainment in young adulthood and using one's education to preserve cognitive function in late life.

Given these previous studies' observations, it is clear that there is more to the association between education and intelligence than what is captured by looking at main effects on the mean. Furthermore, it seems that the genetic and environmental interplay underlying the association includes both passive and active gene-environment correlations and gene-environment interactions. However, most of the previous studies have focused on how intelligence moderates genetic and environmental influences on educational outcomes and not on how education moderates genetic and environmental influences on intelligence (Johnson, Deary, & Iacono, 2009; Johnson et al., 2010). The one study, which did, in fact, focus on how education moderated intelligence, looked at the genetic and environmental interplay underlying the association between educational attainment and intelligence in old age (Johnson, Deary, McGue, et al., 2009), but whether this study's findings also apply to measures of achievement and younger populations remain uncertain. It may be that the impact of early school experiences, such as achievement in compulsory school, on genetic and environmental influences on intelligence differs from the impact of later more self-motivated school experiences, such as final attainment. To shed light on this, studies of younger populations with longitudinal information on school achievement and intelligence test scores are needed.

The aim of this study was, therefore, to investigate to what extent a measure of school achievement, GPA in lower secondary school, moderated the genetic and environmental variance in intelligence test scores in young adulthood in a population-representative Danish sample.

Materials and Methods

Study Population

This was a register-based cohort study including all Danish male twin pairs who had left lower secondary school since 2002 and appeared before a draft board through 2015 (N = 2,660; 932 MZ & 1,728 DZ born in 1984-1997).

The twin pairs' zygosity was determined using information from the Danish Twin Registry. There, zygosity was based on the twins' responses to four items in a questionnaire about their similarity in appearance, which was sent to all twins. In cases of disagreement between twins, inconsistent responses, and missing responses, zygosity was coded missing. In the present study, 23% of the eligible twins had missing zygosity data. These twins had both lower GPAs in lower secondary school and lower intelligence in young adulthood than twins with non-missing zygosity. The questionnaire-based zygosity has been found correct in 96% of cases where zygosity was also assessed using serological or genetic markers (Christiansen et al., 2003).

In Denmark, all Danish men with residence in the country have to appear before a draft board when they turn 18 years old. However, they can obtain deferment as long as until they turn 25 years old if they can prove that deferment is important because of educational or other considerations specified in the National Service Act. Since most can spend the few hours required for the draft board examination without negatively impact their education, very few obtain deferment. The draft board examination determines whether the men are eligible, limitedly eligible, or unfit for military service based on the results of an intelligence test and a medical examination. During the period from 2003 to 2015, the proportions of men classified as eligible, limitedly eligible, and unfit for military service were 51%, 7%, and 41%, respectively, in the general population (The Defence Command, 2017). About half the men classified as unfit for military service never came before a draft board because they were exempted from military service due to documented health problems. These men were, therefore, not included in the study population. Moreover, men who volunteered for the military forces before draft age also never came before a draft board and were therefore not included in the study population. However, this involved < 0.1% of those eligible for conscription, most of whom of course were singletons.

Variables

Grade point average. GPA was measured in 9th grade, i.e. the last year of lower secondary school, when the study population was approximately 15 years of age. In Denmark, there is compulsory education from 0th grade through 9th grade and pupils follow the same curriculum. Furthermore, the Danish schools have used the same 7-point grading scale ranging from 12 to -3 (12, 10, 7, 4, 2, 0, -3) since 2007. This grading scale is directly comparable with the European Credit Transfer System grading scale. We converted GPAs obtained before the introduction of the 7-point grading scale to this scale using a table for this purpose from the Danish Ministry of Education (2017). Information on grades in lower secondary school was available from Statistics Denmark's registers since the school year 2001/2002.

Intelligence. Intelligence was measured by Børge Priens Prøve (BPP; Teasdale, 2009) when the study population came up before the draft board. The BPP is a group-administered intelligence test in paper-and-pencil format, which consists of 78 items in four domains: Letter Matrices, Verbal Analogies, Number Series, and Geometric Figures. The test is terminated after 45 minutes, after which the number of correct answers is summed to a total score ranging from 0 to 78. A previous study has observed a correlation of .82 between the BPP and the full-scale Wechsler Adult Intelligence Scale (Mortensen et al., 1989).

During the study period, information on intelligence test scores was stored in three different national conscription databases: the Danish National Archives' database, the Danish Defence Personnel Organization's database, and the Conscription Registry. However, in the Danish National Archives' database, the BPP total scores were condensed into 5 categories (Teasdale, 2009), so we recoded these 25 observations as missing. Furthermore, we converted the BPP total scores in the three conscription databases to IQ scores with a mean of 100 and a standard deviation of 15 while taking into account the influence of birth year.

Statistical Methods

We investigated the moderating influences of GPA on genetic and environmental variance in intelligence test scores using a dynamic quantitative genetic-environmental model, which is an extension of the standard Cholesky decomposition model measuring the extent to which genetic and environmental influences are correlated across two variables (Purcell, 2002). The standard Cholesky model estimates the genetic (A), shared environmental (C), and non-shared environmental (E) components of the two variables' covariance and total variances and standardizes them. These indicate the extent to which the same sources of influences are involved in both variables. The standard model is based on the fact that MZ twins share effectively all their genes, while DZ twins share on average half their segregating genes in the absence of assortative mating. Moreover, it requires assumption that MZ and DZ twins experience shared environments to the same extents. It also requires assumption that genetic and environmental influences can be independently decomposed and that the genetic and environmental influences on the outcome variable (in this case, intelligence) are constant across the range of the contributing variable (in this case, GPA). The extended model allows relaxation of the assumptions of no gene-environment correlation and no gene-environment interaction, i.e. it allows the genetic and environmental influences on the outcome variable to vary linearly with the level of the contributing variable separately in the covariance between the two variables and in the variance unique to the outcome (Fig. 1).

A limitation of this model is that it does not take into account that covariance may occur due to nonlinear main effects acting uniformly on everyone. A partial way to handle this is to implement another version of this model, which models uniform main effects but in the process does not include consideration of the covariance of the contributing and outcome variables. In other words, it only decomposes the genetic and environmental influences unique to the presumed outcome (Fig. 2).

We implemented both of these models using the umx package in R. First, we checked to what degree our two variables of interest were normally distributed as both models rely on this assumption. We also regressed age, birth year, and their squared terms and interactions and winsorized outliers. Moreover, we investigated whether partitioning the variables in similar-sized scale intervals showed trends in variance over their ranges. This is important to avoid confounding arbitrary measurement scale properties with variance moderation (Falconer & Mackay, 1989). Second, we fit the two above-mentioned models with no moderating parameters such that these could serve as the basis for the complex variance moderation models (Appendix Table 1). Third, we tested the statistical significance of all moderating and main effect parameters in the complex models and dropped those that were not significant and whose absence did not reduce model fit. We did this not to 'rule out' their possible relevance but to focus on the most important moderating effects. We evaluated model fit based on significant differences in log-likelihood, Akaike's Information Criterion (AIC; Akaike, 1983), and Bayesian Information Criterion (BIC; Raftery, 1995). Despite the reciprocal nature of the association, we only investigated the moderating influences of GPA on genetic and environmental variance in intelligence test scores since GPA was measured before intelligence.

Results

Descriptive statistics for the raw variables are shown in Table 1. The study population's mean GPA was consistent with the general population's mean GPA in lower secondary school during the study period. However, the study population's mean IQ score was slightly higher than the mean IQ score observed among all Danish men appearing before a draft board during the study period ($M = 100.4$, $SD = 14.8$), but the difference was small (.7), and reasons for it were not clear. The phenotypic correlation between GPA and IQ score was .67 ($p < .001$), suggesting that the two variables shared 45% of their total variance.

Twin correlations are shown in Table 1. Consistent with extant literature, they suggested both genetic and environmental influences on GPA and IQ score. Standard univariate variance decompositions suggested that the proportions of variance attributable to genetic (A), shared environmental (C), and non-shared environmental (E) influences were A = .50, C = .34, and E = .16 for GPA and A = .67, C = .10, and E = .22 for IQ score.

The fit statistics used to determine the best-fitting version of the full model investigating the extent to which GPA in lower secondary school moderated the genetic and environmental influences on IQ scores are shown in Appendix Table 2. The best-fitting version suggested only moderation of the unique genetic influences. More specifically, the model suggested that genetic variance in IQ scores was greater among individuals with extreme GPAs (Table 2 & Fig. 3). Thus, the genetic variance was .23 among individuals with a GPA of one standard deviation below the mean, .01 among individuals with an average GPA, and .15 among individuals with a GPA of one standard deviation above the mean. The shared environmental variance and the non-shared environmental variance were constant across the range of GPA (.42 and .26, respectively). However, these findings did not reflect the empirical data, which showed a decreasing variance in IQ scores across the range of GPA.

Therefore, we fit the more limited version of the genetic and environmental variance moderation model, which models uniform main effects but only decomposes the genetic and environmental influences unique to the presumed outcome. The fit statistics used to determine the best-fitting version of this model are shown in Appendix Table 3. The best-fitting version suggested a quadratic main effect of GPA on IQ scores but allowed only moderation of the shared environmental influences. The quadratic main effect of GPA on IQ scores suggested that the positive influence of education on intelligence was larger among individuals with low GPAs (Table 3 & Fig. 4). More specifically, we observed an average IQ difference of .63 SD among individuals with a GPA of -1 SD and 0 SD, respectively, whereas we observed an average IQ difference of .53 SD among individuals with a GPA of 0 SD and 1 SD, respectively. Since this model treated the substantial covariance of GPA and IQ score as a main effect on the mean, the model mean was above the real mean (Fig. 4). The model also suggested that shared environmental variance in IQ scores was greater among individuals with low GPAs (Table 3 & Fig. 5). Thus, the shared environmental variance was .08 among individuals with a GPA of one standard deviation below the mean, .02 among individuals with an average GPA, and .00 among individuals with a GPA of one standard deviation above the mean. The genetic variance and the non-shared environmental variance were constant across the range of GPA (.28 and .21, respectively).

Discussion

Main Findings

Although conceptually the more complete model, the full model produced results that clearly did not reflect the empirical data. Therefore, we fit the alternate, more limited version that modelled uniform main effects but in the process did not include consideration of the substantial covariance of GPA and IQ scores. Using this model, we observed that GPA in lower secondary school had a quadratic main effect on IQ scores in young adulthood and that GPA moderated the shared environmental influences on IQ scores so that IQ variation was greater among individuals with low GPAs. GPA did not moderate the genetic or non-shared environmental influences on IQ scores. However, since the model treated the covariance of GPA and IQ scores as a uniform main effect, we cannot exclude the possibility that part of the suggested non-linear main effect is due to moderated covariance, e.g. due to a third variable influencing both GPA and IQ scores. In other words, both our statistical models carried restrictions that were unlikely to hold in overtly developmentally intertwined traits such as school achievement and intelligence. Unfortunately, however, the field currently lacks statistical models we could have applied that address this kind of intertwinement.

Comparison with the Existing Literature

Taken at face value, the positive non-linear main effect of GPA on IQ scores suggested that the positive influence of education on IQ scores was larger among individuals with poor school achievement. The observation of a positive influence of education on IQ scores was consistent with the existing literature (e.g. Ritchie & Tucker-Drob, 2018). However, the suggested size of the positive influence was most likely inflated, since the covariance of GPA and IQ scores was treated as a uniform main effect on the mean. The observation that the positive influence of education on IQ scores was larger among individuals with poor school achievement was consistent with a recent Danish study, in which an interaction analysis suggested that the influence of length of education on IQ scores in midlife was larger among individuals with low IQ scores at age 12 (Hegelund et al., 2020). Here, we observed more specifically that the positive influence among individuals with poor school achievement was 1.2 times greater than among individuals performing well (mean IQ difference of .63 SD among individuals with a GPA of -1 SD and 0 SD, respectively, versus .53 SD among individuals with a GPA of 0 SD and 1 SD, respectively). However, our model included no consideration of the substantial covariance of GPA and IQ scores, which was confounded with what was treated as a uniform main effect on everyone. Still, total moderating and uniform main effects must reproduce the empirical pattern, and our nonlinear model did this reasonably well. But, as mentioned above, we cannot rule out the possibility that part of the suggested non-linear main effect is due to moderated covariance, e.g. due to a third variable influencing both GPA and IQ scores. If so, the gene-environment correlation involved in socioeconomic position is the most likely driver given its well-established underlying genetic influences and observable associations with both variables (e.g. Krapohl & Plomin, 2016; Trzaskowski et al., 2014). This makes it difficult to draw clear inferences from our results and points to the need to develop more complete models integrating consideration of uniform main effects with considerations of variance and its moderating factors.

The observed greater shared environmental variance among individuals with poor school achievement may reflect the suggestion that anyone can obtain a low GPA irrespective of their genetic propensities for ability or family background by ignoring student responsibilities, while doing well may require considerable ability. Because individuals with poor school achievement tend to come from socially disadvantaged families (e.g. Thomson, 2018), related social forces, such as lack of parental interest and involvement in schoolwork and larger numbers of life stressors, might work to stunt or limit these individuals' genetic propensities, which would explain their low mean IQ scores. However, not all individuals with poor school achievement come from socially disadvantaged families. Some individuals come from socially advantaged families and have grown up in intellectually stimulating family environments working to reinforce or compensate for their genetic propensities, but they might have found the school regiment demotivating and, as a result, underperformed academically. Despite these individuals' poor school achievement, they might therefore still obtain relatively high IQ scores.

However, as previously mentioned, our observations were based on only 55% of the total variance in IQ scores. Since the model that included all the variance did not track the data well, we examined its suggested genetic and environmental correlations with all moderation paths fixed to 0 (equivalent to the standard Cholesky model) to get an idea of their overall magnitudes. The genetic correlation was 1.00, the shared environmental correlation .77, and the non-shared environmental correlation .49. These substantial correlations strongly suggested that not only were genetic influences correlated with genetic influences on the two variables, shared environmental with shared environmental, and so on, but genetic influences were correlated with both shared environmental influences and non-shared environmental influences (and the two forms of environmental influences were probably correlated as well, though perhaps to a lesser degree). This would be a large violation of the full model's underlying assumptions, so it could easily have contributed to its unrealistic indications. There is considerable evidence that both passive and active gene-environment correlation occurs (e.g. Belsky et al., 2016), involving intergenerational and peer-level transmission of cultural values associated with social status and individual life choices. Individuals from socially advantaged families tend to grow up in more intellectually stimulating family environments and themselves seek or create similar experiences when they grow older and more independent. These often work either to reinforce or compensate for their genetic propensities, which tend to be favourable for intellectual development because their parents tend to have more education and higher than average intelligence. At the same time, individuals from socially disadvantaged families tend to grow up in less intellectually stimulating family environments and themselves seek or create other kinds of experiences when they grow older and more independent. These often either work to stunt or limit their genetic propensities, which tend to be less favourable because their parents tend to have less education and lower than average intelligence. This population stratification can constrain the total variance in intelligence test scores. In our study, the total variance was constrained to similar degrees within all the intervals of school achievement (31-47% of total), suggesting that population genetic stratification was present rather strongly throughout the range. In other words, it appears that the Danish male population is sorted both genetically and environmentally for school achievement with individuals quite constrained in propensity (opportunity) to manifest ‘potential’ via both school achievement and intelligence by family background. Furthermore, because restriction of the range is often associated with restricted observable correlations, this situation, which we will call a social problem, may actually be worse than it appears here.

Strengths and Limitations

The major strength of the study was its large study population comprising 1,330 male twin pairs who had left lower secondary school since 2002 and appeared before a draft board through 2015. Other strengths were the use of information from Danish administrative registers due to their high validity and completeness and use of the BPP as the measure of intelligence due to its high correlation with the full-scale Wechsler Adult Intelligence Scale. Furthermore, the prospective nature of the study in combination with the adopted statistical methods made it possible to gain at least some insight into the genetic and environmental interplay involved in the influence of school achievement on intelligence in young adulthood.

However, as previously mentioned, the statistical models used both had major limitations and pointed to the need for better models of gene-environment interplay, which can integrate uniform main effects with considerations of variance and its moderating factors. Furthermore, although our study findings suggested that school achievement moderated the shared environmental influences on intelligence, we could not rule out that other moderation paths might exist that we did not have the statistical power to identify since the kind of genetic and environmental interaction effects we examined often are small and hard to identify (Rowe, 2003). This issue might have been exacerbated by the statistical models' implicit boundary conditions, which can lead to deviations from the expected Type I error rate and also induce bias in the parameter estimates (Verhulst et al., 2019). Finally, it was not clear whether the study findings could be generalised to women or countries other than Denmark.

Conclusions

Using a very limited model by necessity, we observed that GPA in lower secondary school had a positive influence on mean intelligence level in young adulthood and that GPA moderated intelligence variation, such that shared environmental variance unique to intelligence was greater among individuals with poor school achievement. These observations were consistent with existing literature suggesting that education increases intelligence and contributed further to this literature by suggesting that causal mechanisms linking school achievement with intelligence vary with level of school achievement. This suggested that, whatever the specific mechanisms may be, they originate in environmental contexts that have similar effects on everyone experiencing them. Examples might include classroom, family-level socioeconomic circumstances, and broader contexts such as community-level socioeconomic climate and access to and quality of medical care. Most important though, the study observations suggested strong links between genetic and environmental influences common to school achievement and intelligence and pointed to need for better models of gene-environment interplay.

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Table 1

Descriptive Statistics and Twin Correlations

	GPA at age 15	IQ score at age 18
Descriptive statistics		
M	6.3	101.1
SD	2.4	14.2
Twin correlations		
MZ	.84	.79
DZ	.59	.44

Note. GPA is grade point average.

Table 2

Parameter Estimates from the Best-Fitting Full Moderation Model and Derived Variance Components and Genetic and Environmental Correlations

Parameter	Estimate		95% CI
Common genetic influences			
Common A	.11		-.02, .24
Common A moderation	.00*		
Common shared environmental influences			
Common C	.49		.42, .56
Common C moderation	.00*		
Common non-shared environmental influences			
Common E	.29		.25, .33
Common E moderation	.00*		
Unique genetic influences			
Unique A	.05		-.01, .10
Unique A moderation	-.42		-.47, -.36
Unique shared environmental influences			
Unique C	.43		.36, .49
Unique C moderation	.00*		
Unique non-shared environmental influences			
Unique E	.42		.39, .45
Unique E moderation	.00*		
Variance components	-1 SD	0 SD	1 SD
Genetic	.23	.01	.15
Shared environmental	.42	.42	.42
Non-shared environmental	.26	.26	.26
Correlations	-1 SD	0 SD	1 SD
Genetic	.23	.92	.29
Shared environmental	.75	.75	.75
Non-shared environmental	.57	.57	.57

Note. Using the parameter labels in Figure 1, the genetic variance components were derived with the formula: $(a_c+\beta_1 M)^2 + (a_u+\beta_4 M)^2$. The genetic correlations were derived with the formula: $(a_c+\beta_1 M) / ((a_c+\beta_1 M)^2 + (a_u+\beta_4 M)^2)^{0.5}$. The environmental variance components and correlations were derived with corresponding formulas. *Parameter was fixed to 0.

Table 3

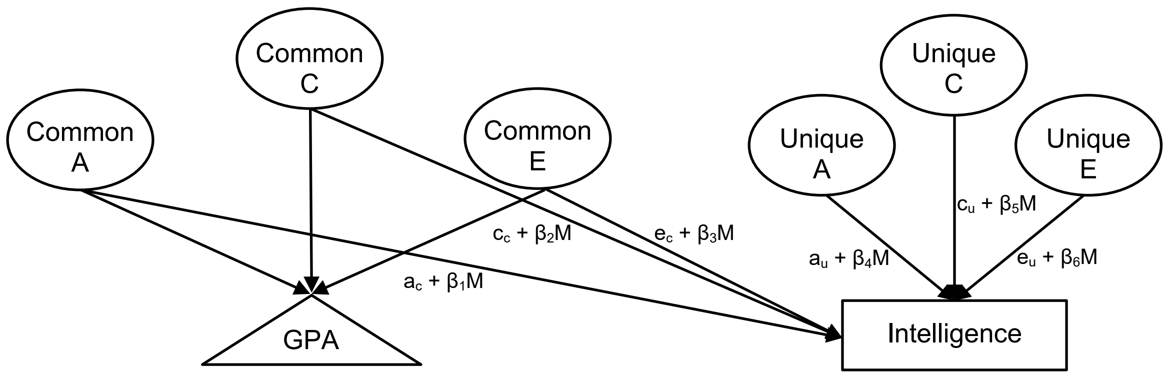
Parameter Estimates from the Best-Fitting Non-Linear Moderation Model and Derived Variance Components

Parameter	Estimate		95% CI
Genetic influences			
A	.53		.49, .58
A moderation	.00*		
Shared environmental influences			
C	-.12		-.22, -.02
C moderation	.16		.09, .23
Non-shared environmental influences			
E	.46		.43, .49
E moderation	.00*		
Main effect on the mean			
Mean	.11		.06, .15
Linear mean moderation	.58		.55, .62
Quadratic mean moderation	-.05		-.08, -.02
Variance components	-1 SD	0 SD	1 SD
Genetic	.28	.28	.28
Shared environmental	.08	.02	.00
Non-shared environmental	.21	.21	.21

Note. Using the parameter labels in Figure 2, the genetic variance components were derived with the formula: $(a+\beta_a M)^2$. The environmental variance components were derived with corresponding formulas. *Parameter was fixed to 0.

Figure 1

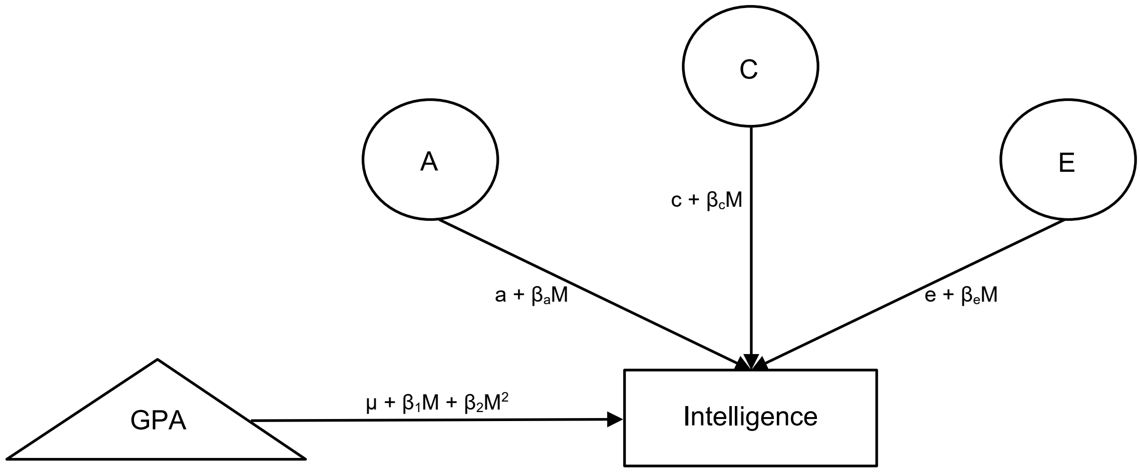
Diagrammatic Model of Grade Point Average (GPA) Moderating Intelligence (Full Moderation Model)



Note. A refers to genetic influences, C to shared environmental influences, and E to non-shared environmental influences. The paths in the model allow the level of GPA (M) to moderate the genetic and environmental influences on intelligence. Subscript c refers to influences common to GPA and intelligence, and subscript u refers to influences unique to intelligence.

Figure 2

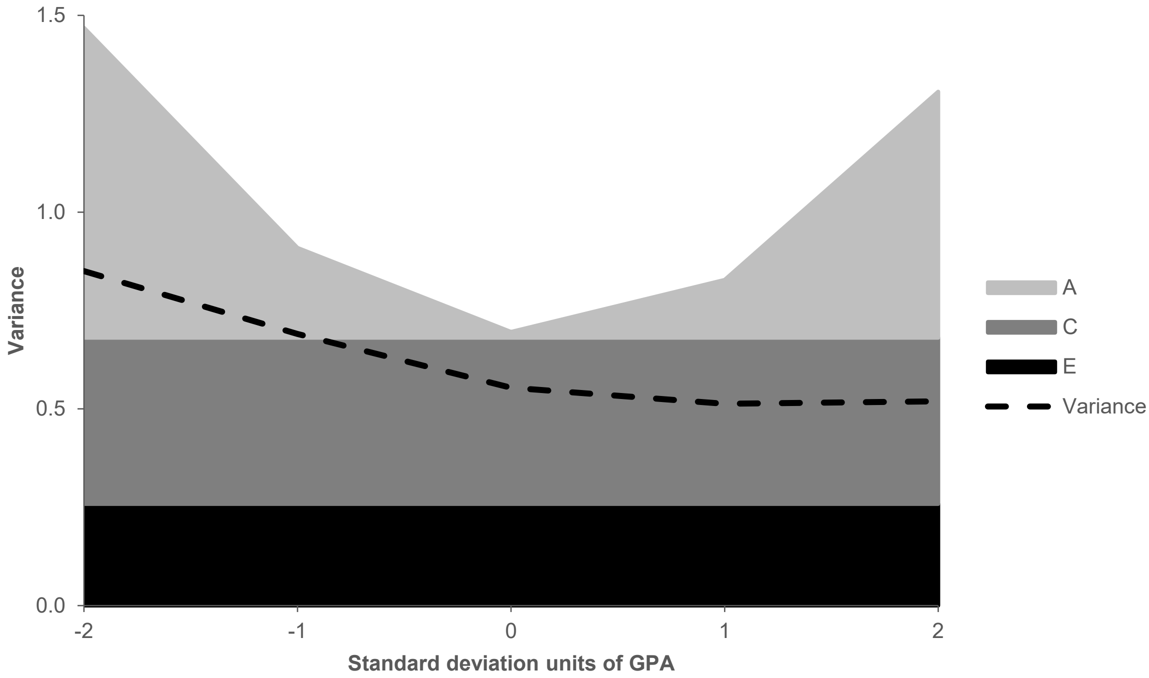
Diagrammatic Model of Grade Point Average (GPA) Moderating Intelligence (Non-Linear Moderation Model)



Note. A refers to genetic influences, C to shared environmental influences, and E to non-shared environmental influences. The paths in the model allow the level of GPA (M) to moderate the genetic and environmental influences on intelligence.

Figure 3

Variance in IQ Scores as a Function of Grade Point Average (GPA) in Lower Secondary School, by Source of Variance



Note. A refers to genetic variance, C to shared environmental variance, and E to non-shared environmental variance. The dotted line shows the empirical variance.

Figure 4

IQ Score as a Function of Grade Point Average (GPA) in Lower Secondary School

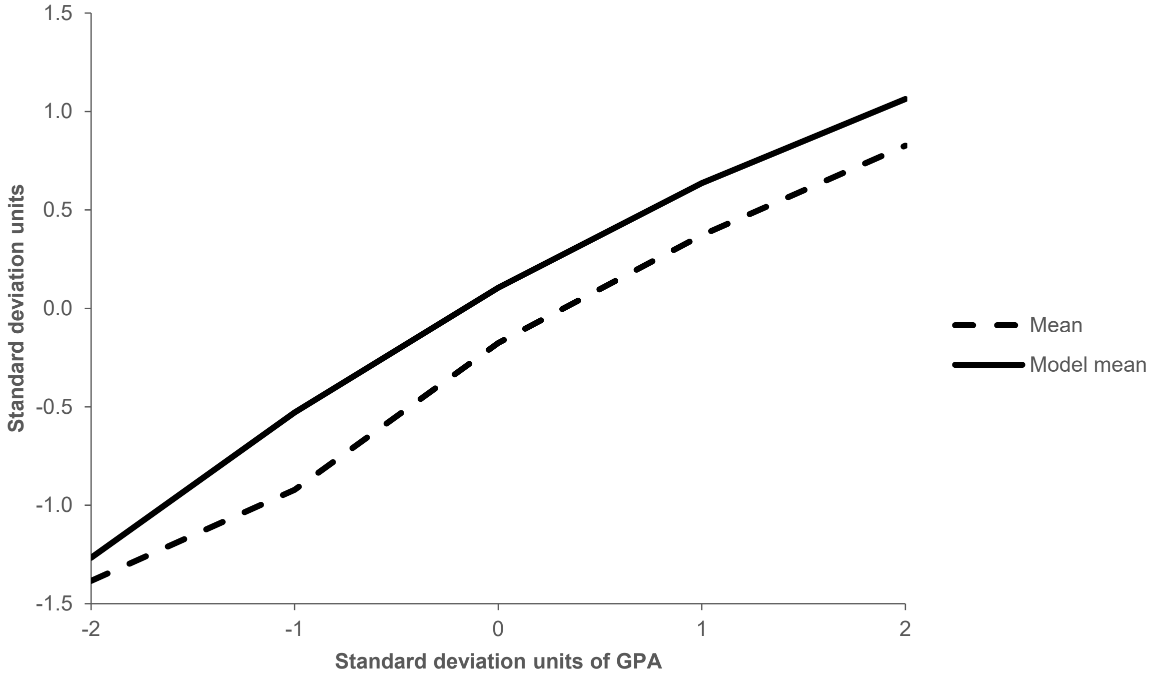
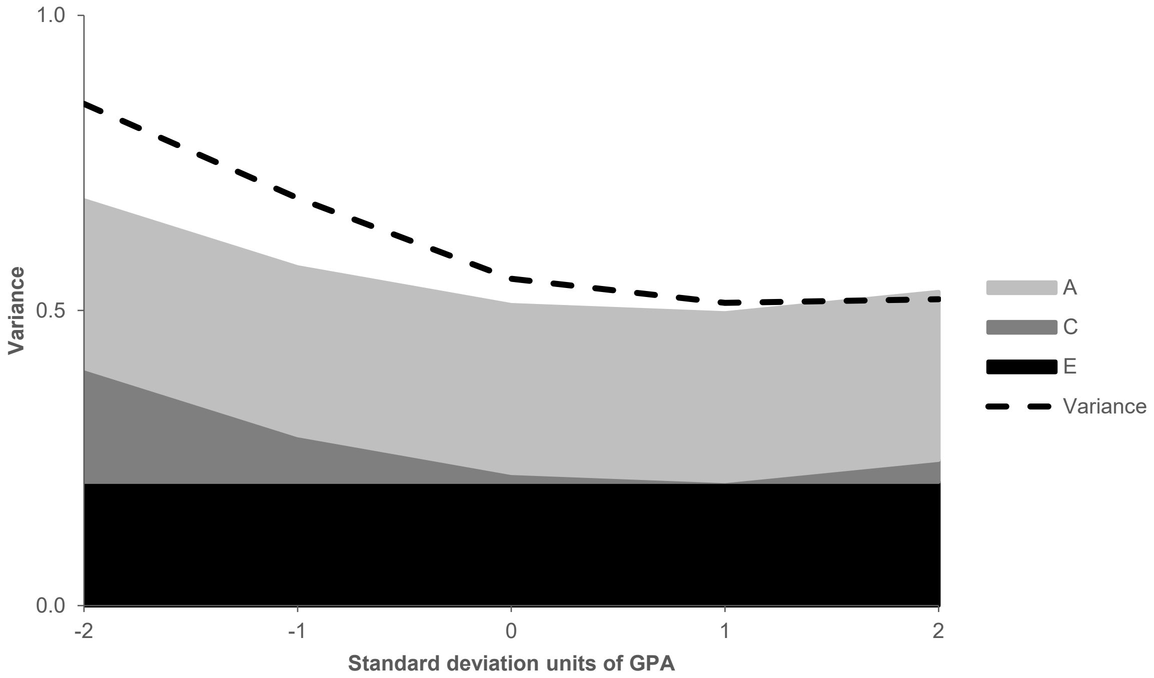


Figure 5

Variance in IQ Scores as a Function of Grade Point Average (GPA) in Lower Secondary School, by Source of Variance



Note. A refers to genetic variance, C to shared environmental variance, and E to non-shared environmental variance. The dotted line shows the empirical variance.