Predicting educational achievement

from genomic measures and socioeconomic status

Sophie von Stumm[1], Emily Smith-Woolley[2], Ziada Ayorech[3], Andrew McMillan[3], Kaili Rimfeld[3], Philip S. Dale[4], & Robert Plomin[3]

Author affiliations

[1] Department of Education, University of York, Heslington, York, YO10 5DD, UK

[2] Centre for Education Improvement Science, Institute of Education, University College London, London, WC1H 0AL, UK

[3] Social, Genetic and Developmental Psychiatry Centre, Institute of Psychiatry, Psychology & Neuroscience, King's College London, London, SE5 8AF, UK

[4] Department of Speech and Hearing Sciences, University of New Mexico, Albuquerque, NM 87131, US

Corresponding author: Sophie von Stumm at sophie.vonstumm@york.ac.uk.

ABSTRACT

The two best predictors of children's educational achievement available from birth are parents' socioeconomic status (SES) and, recently, children's inherited DNA differences that can be aggregated in genome-wide polygenic scores (GPS). Here we chart for the first time the developmental interplay between these two predictors of educational achievement at ages 7, 11, 14 and 16 in a sample of almost 5,000 UK school children. We show that the prediction of educational achievement from both GPS and SES increases steadily throughout the school years. Using latent growth curve models, we find that GPS and SES not only predict educational achievement in the first grade but they also account for systematic changes in achievement across the school years. At the end of compulsory education at age 16, GPS and SES respectively predict 14% and 23% of the variance of educational achievement; controlling for genetic influence on SES reduces its predictive power to 16%. Analyses of the extremes of GPS and SES highlight their influence and interplay: In children who have high GPS and come from high SES families, 77% go to university, whereas 21% of children with low GPS and from low SES backgrounds attend university. We find that the effects of GPS and SES are primarily additive, suggesting that their joint impact is particularly dramatic for children at the extreme ends of the distribution.

Word count: 223.

Keywords: Socioeconomic status; genome-wide polygenic scores; educational achievement; longitudinal; gene-environment interplay;

INTRODUCTION

Until recently, parents' socioeconomic status (SES), which typically includes educational attainment and occupational status (von Stumm, Deary, & Hagger-Johnson, 2013), has been the most powerful predictor available from birth of differences in the normal range of children's educational achievement. In meta-analytic reviews, parents' SES has been shown to account for about 9% of the variance in children's educational achievement (Sirin, 2005; Strenze, 2007). In early childhood, children's own intelligence test scores begin to predict educational achievement, accounting for about 5% of the variance (Honzik, Macfarlane, & Allen, 1948). By the school years, children's previous educational achievement becomes the best predictor of their later educational and occupational outcomes. Educational achievement is highly stable throughout the school years, with year-to-year correlations of about .70, which means that earlier achievement accounts for about 50% of the variance of later achievement (Rimfeld et al., 2018).

In recent years, inherited DNA differences have been identified that can also predict educational achievement. For decades it has been known that genetic differences taken as a whole account for most of the variance in educational achievement, with heritability estimates typically around 60% for all subjects at all ages (de Zeeuw, de Geus, & Boomsma, 2015; Rimfeld et al., 2018). Two breakthroughs in DNA research have made it possible to identify inherited DNA differences responsible for this high heritability (Plomin, 2018). The first began over a decade ago with the construction of 'SNP chips', arrays that are able to genotype inexpensively and quickly the most

common type of inherited DNA difference, a difference in a single nucleotide base, called a single-nucleotide polymorphism (SNP).

The second breakthrough was to realise that the tiny effects of individual SNP associations from the GWA results for a trait, even those that do not individually meet the criterion of genome-wide significance, can be aggregated to create powerful predictors of a trait, called genome-wide polygenic scores (GPS) (Plomin & von Stumm, 2018). Because educational attainment (years of education) is obtained as a demographic marker in most GWA studies, it has been possible to include more than a million adults in a meta-analytic GWA study of educational attainment (Lee et al., 2018). A GPS derived from this GWA study predicts up to 13% of the variance in educational attainment in adults in independent samples (Lee et al., 2018). We have shown that a GPS for educational attainment predicts even more variance (15%) in tested educational achievement in 16-year-old adolescents (Allegrini et al., 2018), making this the most predictive GPS for any behavioural trait at present.

Because inherited DNA differences do not change throughout life, this GPS can predict 16-year-old educational achievement just as well at birth as it can at age 16. The ability to predict from birth is shared with family SES but not with other predictors such as children's intelligence or educational achievement. GPS are also completely reliable in the sense of test-retest reliability, unbiased, and not influenced by test-taking anxiety or coaching.

GPS and SES can be thought of, respectively, as quintessential indices of nature and nurture. GPS is in fact purely genetic in the sense it assesses inherited DNA differences. By comparison, although SES is often assumed to represent solely environmental advantages of wealth and privilege (Conley & Fletcher, 2017), it is actually substantially heritable, with estimates from twin studies of about 50% (Branigan, McCallum, & Freese, 2013). The main ingredients in most SES scores are parents' educational attainment and occupational status, both of which are substantially heritable (Tambs, Sundet, Magnus, & Berg, 1989; Taubman, 1976). Indeed, adult educational attainment, specifically the number of years spent in formal education, is the target trait for the GWA analysis used to create the GPS that predicts children's educational achievement. Therefore, it is not surprising that the prediction of educational achievement from family SES is in part mediated by GPS (Belsky et al., 2016; Belsky et al., 2018; Krapohl & Plomin, 2016).

Previous research has suggested that the prediction of educational achievement from both GPS and SES increases during development (Allegrini et al., 2018; Selzam et al., 2017; von Stumm, 2017), but their relative contribution over time to educational achievement or their interaction have not been explicitly tested before. Longitudinal latent growth curve analysis, which disentangles initial effects on a developmental measure (intercept) from systematic increases and decreases which follow (slope), is particularly useful for this purpose (McArdle, 2009). A growth curve model also allows testing for interaction effects of GPS and SES and thus, exploring the gene-by-environment interaction hypothesis that genetic effects on cognitive

development are weaker in lower-SES families (Gottschling et al., 2019; Tucker-Drob & Bates, 2016).

METHODS

Sample

The sample comes from the Twins Early Development Study (TEDS), a longitudinal twin study that recruited more than 15,000 twin pairs born in England and Wales in 1994 through 1996. The recruitment process and the sample are described in detail elsewhere (Haworth, Davis, & Plomin, 2013). The TEDS sample was at its inception representative of the UK population in comparison with census data and despite some attrition remains considerably representative (Kovas, Haworth, Dale, & Plomin, 2007). Our analyses were based on 4,890 individuals of European ancestry from TEDS for whom genotype data and information on socioeconomic status and educational achievement were available. We also replicated our analyses and findings in a smaller sample, which included only one twin from each twin pair (N =3,297) for maximal independence of data, while the bigger sample included one twin from each monozygotic twin pair and all dizygotic twin pairs. (See Table S2 for descriptive statistics in both samples, and Table S3 for modelling results in the smaller sample.)

Measures

Genome-wide Polygenic Scores (GPS). Saliva and buccal cheek swab samples were collected for these same individuals to compute genome-wide polygenic scores (GPS) based on the latest genome-wide association (GWA) study for years of

education, called educational attainment (EA3) (Lee et al., 2018). Overall 7,363,646 genotyped and well-imputed SNPs were retained for the analyses after stringent quality control, but to ease high computational demands of the software LDpred (Vilhjálmsson et al., 2015) for polygenic scoring in large samples, we further excluded SNPs with info <1, leaving 515,100 SNPs for analysis (see Supplementary Methods for details.) GPS were constructed using the Bayesian LDpred approach, which estimates causal effect sizes from GWA summary statistics by assuming a prior for the genetic architecture and LD information from a reference panel (Vilhjálmsson et al., 2015). Here, GPS are constructed as the weighted sum of trait-increasing alleles for each unrelated genotyped individual in the TEDS sample using a causal fraction of 1, which assumes that all SNPs contribute to the development of the trait. The GPS were adjusted for the first ten principal components of the genotype data, chip, batch and plate effects using the regression method and the standardized residuals were used for all subsequent analyses (see Supplementary Methods S2 for details).

Educational achievement. In the UK, compulsory schooling follows a national curriculum that is organised into blocks of years called 'key stages' (KS). At the end of each key stage, the teacher formally assesses each child's performance. The twins' teachers record their grades in English and mathematics in the National Pupil Database (NPD) following the UK National Curriculum guidelines, which are formulated by the National Foundation for Educational Research (NFER; http://www.nfer.ac.uk/index.cfm) and the Qualifications and Curriculum Authority (QCA; http://www.qca.org.uk). KS1 through KS4 were recorded in the NPD at age 7,

11, 14 and 16, respectively. The English grades assessed students' reading, writing, and speaking and listening; the mathematics grades referred to knowledge of numbers, shapes, space, and to using and applying mathematics and measures. At age 16, twins' grades in English and mathematics were awarded for subtests of the General Certificate of Secondary Education (GCSE) exam, a standardized examination taken at the end of compulsory schooling in the UK, and recorded in the NPD. For each key stage, we built composite scores of children's NPD grades for English and mathematics.

Socioeconomic status (SES). Families' SES was assessed at the first contact, with parents reporting their educational qualifications, their occupational positions and the twins' mother's age on the birth of first child. A composite measure of SES (Krapohl & Plomin, 2015) was calculated taking the mean of the standardized scores for mothers' and fathers' educational level, mothers' and fathers' occupational status, and mothers' age at birth of the first child.

Statistical analysis

Students' educational achievement at each key stage was adjusted for age and gender, and standardized regression residuals were used in all subsequent analyses. After testing correlations across all study variables, we fitted a series of latent growth curve (LGC) models using the R package Lavaan (Rosseel, 2012). LGC models differentiate individual differences in the starting point of a trait (i.e., intercept factor), in our case, performance in KS1 at age 7, from individual differences in the rate of change that occurs over time in the same trait (i.e. slope factor), here change

in educational achievement from KS1 through KS4 (i.e. achievement gains and losses).

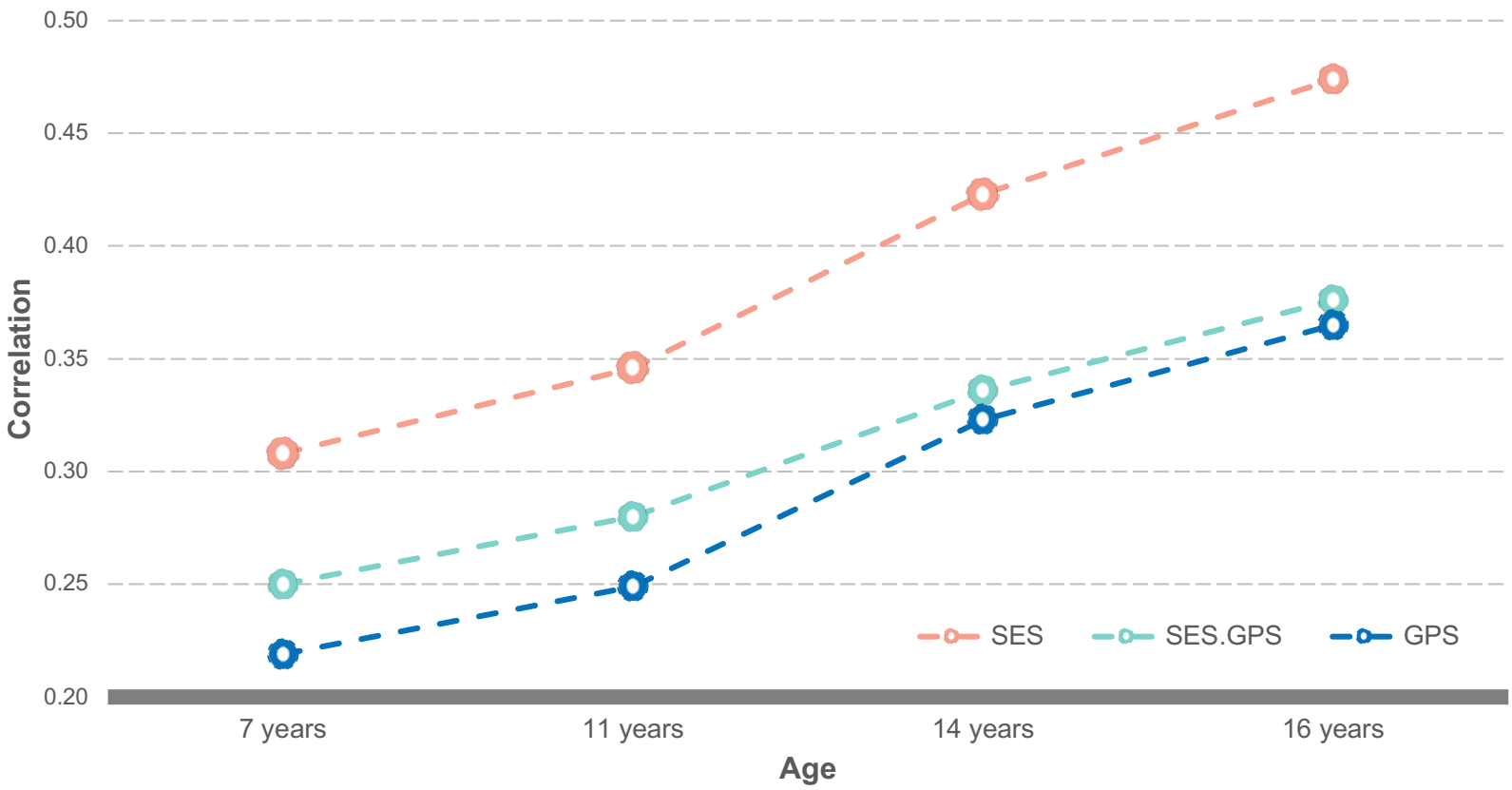
In line with LGC modelling conventions, loadings for the intercept factor were set at 1, while factor loadings for the slope represented the number of KS (i.e. slope loadings were set at 0, 1, 2, and 3), thereby defining the starting point of the slope at KS1. We first tested one-, two-, and three-factor LGC models in order to identify which best represented the data. We then tested the predictive validity of EA3 and SES for educational achievement at KS1 (i.e. intercept factor) and for change in school performance from KS1 through KS4 (i.e. slope factor). We also tested if EA3 and SES interacted in the prediction of educational achievement over time. All models used full information maximum likelihood estimation (FIML) to deal with missing data, which were assumed to be missing at random.

RESULTS

The prediction of educational achievement from GPS and SES increased steadily throughout the school years, as shown in Figure 1. From ages 7 to 16 years, the association of GPS with educational achievement increased from .22 to .36 (i.e. from 5% to 14% of the variance) and that of SES from .31 to .48 (i.e. from 10% to 23% of the variance). The substantial gains in the predictive power of GPS and SES from age 7 to age 16 are especially impressive because educational achievement was highly stable across the school years, with longitudinal correlations ranging from .61 to .87 (Supplementary Table S1). GPS and SES were correlated at .35, which suggests

genetic influence on SES, as discussed earlier. In Figure 1, the middle line, which is labelled 'SES.GPS', represents the residual correlation between SES and educational achievement after regressing out GPS (i.e. estimate of the effect of SES after controlling for genetic influences).

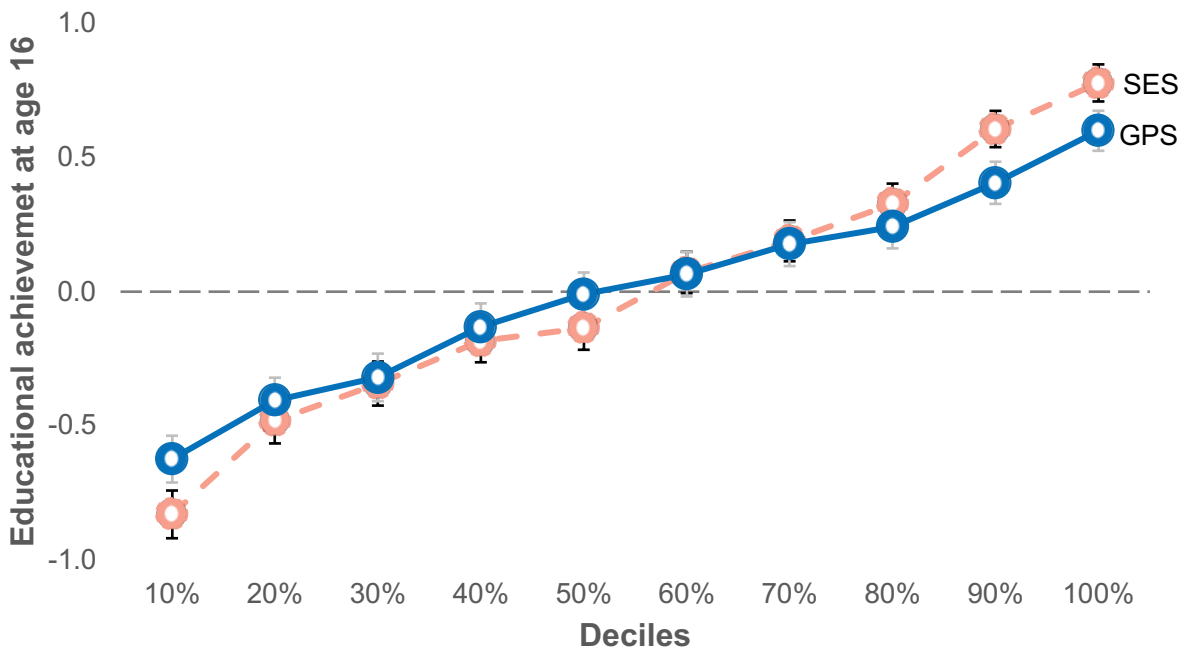
Figure 1. GPS and SES correlations with educational achievement at 7, 11, 14 and 16 years



Note: SES = socioeconomic status. GPS = genome-wide polygenic score. SES.GPS = SES corrected for GPS, referring to the residual correlation between SES and educational achievement after regressing out GPS.

The potential practical implication of these predictions is especially apparent at the extremes. Dividing the sample into 10 equal-sized groups (deciles) from low to high GPS and similarly from low to high SES, Figure 2 depicts the mean standardised educational achievement (GCSE) scores at age 16. The lowest and highest deciles differed by more than 1.2 SD for GPS and 1.5 SD for SES. These average GCSE scores for the lowest and highest deciles translate into grades of C+ and A-, respectively, for GPS, and C- and A for SES. It is also noteworthy that the association of both GPS and SES with educational achievement was linear.

Figure 2. GPS and SES decile means for standardised educational achievement scores at age 16



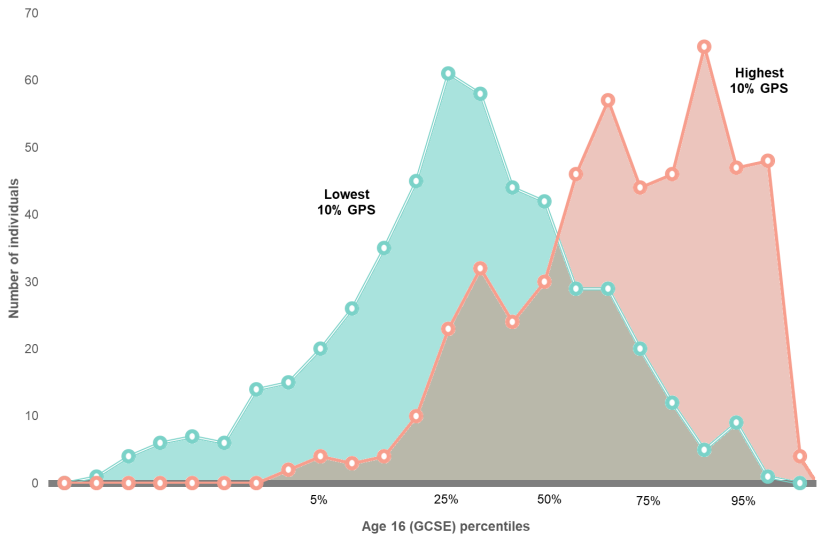
Note: The error bars show the 95% confidence intervals of the decile means.

The impressive mean differences mask a considerable range of individual differences. Figure 3 shows the substantial overlap between the distributions of scores within the lowest and highest deciles for GPS and for SES (i.e. grey area). For example, 9% of the individuals in the lowest GPS decile had higher educational achievement scores than the mean score of the highest GPS decile (Figure 3a). Conversely, 10% of those in the highest GPS decile had lower educational achievement scores than the mean of the lowest GPS decile. For SES, the analogous overlap is 5% and 3%, respectively (Figure 3b).

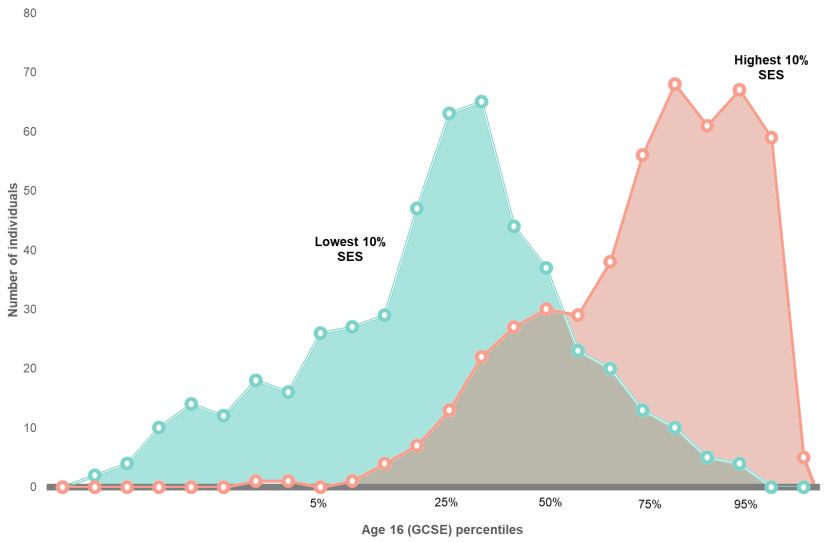
The 95% confidence intervals for the decile means in Figure 2 indicate that accurate estimates of educational achievement can be made on average for extreme groups. However, the overlap in distributions in Figure 3 highlights the limits of prediction at the level of individuals.

Figure 3. Overlap in distributions of educational achievement (GCSE) at age 16 for lowest and highest deciles of (a) GPS and (b) SES

(a) GPS



(b) SES



Note. GCSE scores at age 16 were standardised and adjusted for age and sex and then binned at equal intervals over the range of -3.55 to +1.95. Frequencies in these bins are reported separately for the lowest and highest deciles of GPS and SES.

Our LGC analysis indicated that a two-factor model including slope and intercept fit better than a one-factor model (χ^2_{diff} (3) = 639.93, $p < .001$) but worse than a three-factor model (χ^2_{diff} (4) = 150.23, $p < .001$). Because the third factor, a curvilinear factor, correlated -.86 with the slope factor, we retained the more parsimonious two-factor solution that differentiated latent factors representing individual differences in intercept and in slope for educational achievement (model fit: CFI = 0.990; RMSEA = 0.077, 90% confidence interval = 0.067 to 0.088).

We used GPS, SES and their interaction as joint predictors of the two LGC factors as parameters of educational achievement throughout the four ages. GPS and SES were significantly and independently associated with latent growth factors representing individual differences in intercept and slope of educational achievement, as reported in

Table 1. In other words, both GPS and SES independently contributed to the prediction of educational achievement not only at the beginning of school (intercept) but also to systematic increases and decreases (slope) in achievement across the school years.

Table 1: Parameter estimates for GPS, SES and their interaction as predictors of latent growth factors (intercept and slope) of educational achievement

	$Beta_i$	**SE_i**	**P_i**	**R^2_i**	**$Beta_s$**	**SE_s**	**P_s**	**R^2_s**
GPS	.154	.014	< .001		.183	.004	< .001	
SES	.314	.014	< .001		.233	.004	< .001	
GPS*SES	-.046	.013	.003		.001	.004	.977	
				.154				.116

Note: N = 4,890; $_i$ = intercept; $_s$ = slope; Beta = standardized coefficient; SE= standard error; P = p-value; R^2 = Adjusted R^2.

Table 1 also shows that the effects of GPS and SES interacted in the predictions of the intercept but not for the slope. These results might seem support the gene-by-environment interaction hypothesis that genetic effects on cognitive development vary across different levels of family SES (Gottschling et al., 2019; Tucker-Drob & Bates, 2016). However, the negative beta of the interaction term for the intercept suggest a result in the opposite direction than originally proposed (Tucker-Drob & Bates, 2016): It appears here that GPS scores were more predictive of educational achievement at age 7 in children from low SES families than in those from high SES backgrounds. That said, the effect size associated with the interaction effect was small (i.e. 0.2% of the variance; see also our additional analyses in

Supplementary Materials), suggesting that the effects of GPS and SES on educational achievement are primarily additive.

Together, GPS and SES accounted for 15.4% of the variance of the intercept and 11.6% of the slope, as indicated by R^2 in Table 1. The independent effects of GPS and SES, which we estimated by squaring the betas in Table 1, contributed 12.3% (i.e., 2.4% + 9.9%) to the variance of the intercept and 8.7% (i.e., 3.3% + 5.4%) to the variance of the slope. The difference between R^2 and these independent contributions of GPS and SES represents overlapping prediction by GPS and SES: 3.2% for the intercept and 2.8% for slope.

DISCUSSION

Unlike other correlations in the behavioural sciences, which typically do not imply causation, the GPS-SES correlation is causal from GPS to SES in the sense that there can be no backward causation of GPS from SES because nothing changes inherited DNA sequence variation. Controlling for this genetic confound on SES by regressing parents' SES on children's GPS reduced the predictive power of SES in our analyses. Specifically at age 16, the variance in educational achievement explained by SES was reduced from 22.5% to 15.8%, closer to the level of prediction by GPS (13.3%; middle line labelled 'SES.GPS' in Figure 1).

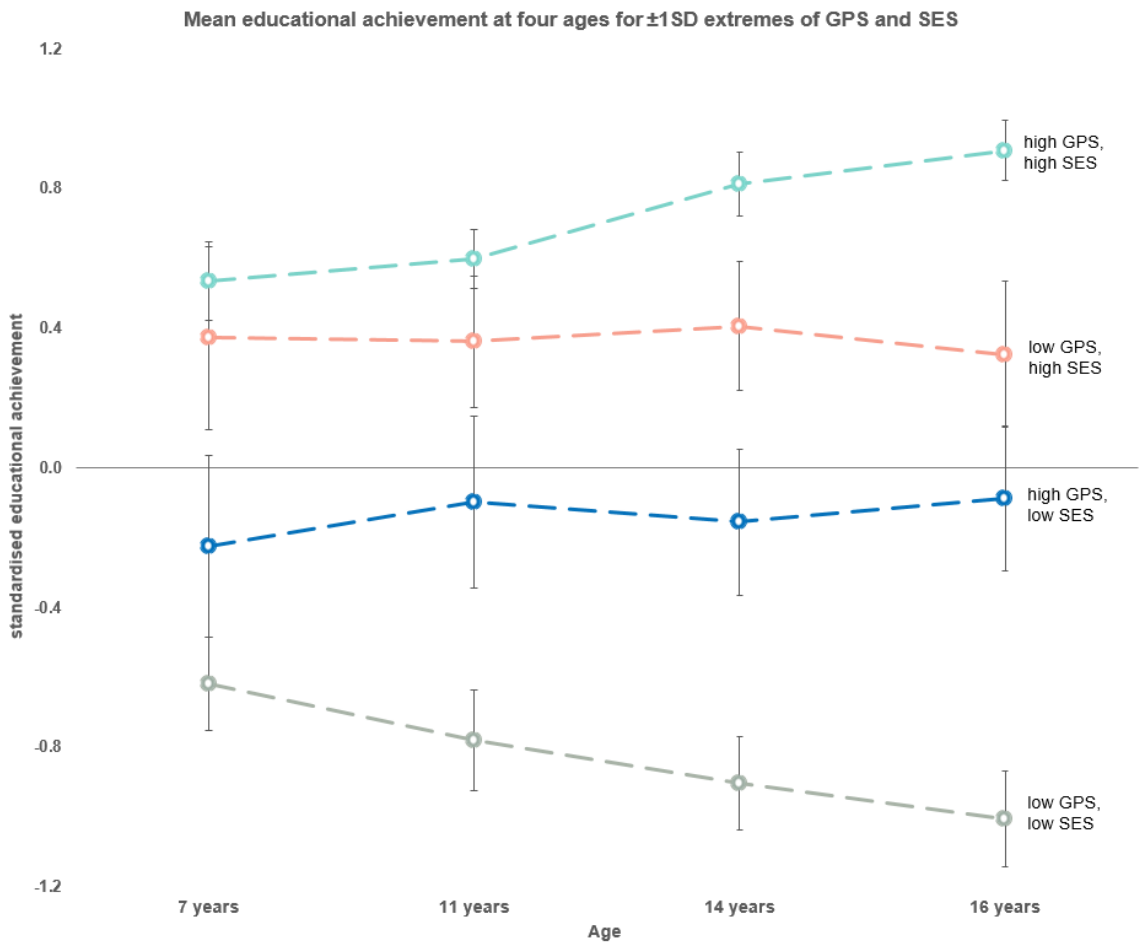
Controlling for genetic influence on SES by correcting parents' SES for children's GPS is conservative as compared to correcting parents' SES for parents' own GPS, as it may lead to underestimating the influence of SES. However, GPS data for parents are not available in the TEDS sample. Moreover, even using parents' own GPS would be a conservative correction

for genetic influence on SES. The heritability of SES has been estimated as about 50% in twin studies (Tambs et al., 1989; Taubman, 1976), which means that the GPS used in the present study accounts for only about a quarter of the heritability of SES, an issue known as missing heritability (Plomin & von Stumm, 2018). Correcting SES for the 50% heritability of SES estimated in twin studies is likely to make the environmentally mediated predictive power of SES less than that of GPS.

Correcting SES for GPS is an example of the usefulness of GPS to create purer environmental measures by correcting them for genetic confounds indexed by GPS. When we corrected SES for GPS, this purer measure of the environmental impact of SES on the variance of educational achievement was reduced from 23% to 16%. Correcting SES for genetic confounding will provide better targets for future research on equality of opportunity and social mobility (Plomin, 2018).

Analyses of the extremes of GPS and SES highlight our developmental findings. We divided the sample into four groups using cut-offs of ±1SD in SES and GPS (Figure 4; see also Supplementary Figure S1). Children with high GPS from high SES family backgrounds and those with low GPS from low SES families (i.e. high-high and low-low groups, respectively) differed significantly in achievement at age 7 and the achievement gap steadily widened between the groups throughout the school years. By age 16, the mean educational achievement of the two groups differed by 1.9 SD, which is equivalent to a grade of A- in the high-high group and C- in the low-low group. In the high-high group, 77% went on to attend university at age 18 as compared to 21% in the low-low group.

Figure 4. Mean educational achievement at four ages for ±1SD extremes of GPS and SES



Note: The error bars show the 95% confidence intervals of the means.

We found that GPS contributed as similarly to children's differences in growth in educational achievement (3.3% of the variance) as it did to their differences at the beginning of compulsory schooling (2.4%). This is likely to explain why heritability is not much reduced by attempts to produce fairer measures of 'added value' of schools (more recently called measures of 'progress' in the UK), which correct educational achievement for ability and earlier achievement (Haworth, Asbury, Dale, & Plomin, 2011). Specifically, we speculate that correcting for ability and earlier achievement does not correct for the genetic contribution to growth, which is independent of intercepts (von Stumm, 2017).

In contrast our analyses showed that SES contributed much less to the growth in educational achievement (5.4%) than it did to children's performance differences in the beginning of compulsory schooling (9.9%). This finding suggests that measures of 'added value' do a better job of controlling for the effects of SES than they do for GPS. This interpretation is supported by twin analyses that found that estimates of shared environmental influence, which include the effects of SES, are halved using measures of added value (Haworth et al., 2011).

Turning to the two middle, 'mixed' groups in Figure 4, it appears that high GPS may help compensate for disadvantages in school performance in children from low SES families. Our analyses showed that at age 16, children with high GPS from low SES backgrounds had mean GCSE scores that were close to average (-.09 standard score) and 47% of these children went on to attend university, as compared to only 21% in the low-low group. We note, however, that to an even greater extent high SES helped compensate for the disadvantage of low GPS children. Their mean GCSE scores were slightly above average (.32 standard score) and they were much more likely to later go to university (62%). Nonetheless, these effects of GPS and SES were largely independent and additive (see Supplementary Figure S2). That is, we found no evidence for an interaction between genes (GPS) and environment (SES), in line with a meta-analysis on this issue (Tucker-Drob & Bates, 2016).

CONCLUSIONS

Our major finding is that inherited DNA differences aggregated in GPS are powerful predictors of educational achievement, both by accounting for some of the prediction by

SES and by going substantially beyond it by accounting for variance not associated with SES. The GPS derived from GWA results for adult educational attainment predicted 14% of the variance in educational achievement at age 16, which approximates the prediction from family SES after controlling for genetic influence (16%). This is currently the most powerful GPS predictor of any behavioural trait (Allegrini et al., 2018). In future, bigger and better GWA studies of educational traits are likely to increase the predictive power of GPS even more.

The impact of GPS is particularly dramatic at the extremes of the distribution.
We suggested, for example, that high GPS partially compensates for the disadvantages of children from low-SES families, increasing their chances of going to university from 21% to 47%. This raises the possibility of doing more to help this group reach its full potential. Nonetheless, the substantial overlap between the distributions of scores within the lowest and highest deciles for GPS and SES indicates the limits of prediction at the level of individual students.

AUTHOR CONTRIBUTIONS

S.v.S and R.P. conceived and designed the study. S.v.S. and A.M. analysed the data. S.v.S. and R.P. drafted the paper and E.S.-W., Z.A., A.M., K.R. and P.S.D. helped to revise the paper. All authors approved the final draft of the paper.

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OPEN PRACTICES STATEMENT

The analyses reported in this manuscript were not pre-registered. The data and materials are available from the permanent TEDS archive upon request to R.P. (robert.plomin@kcl.ac.uk).

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