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Pygmalion in the genes? On the potentially negative impacts of polygenic scores for educational attainment

Lucas J. Matthews[1] · Matthew S. Lebowitz[1] · Ruth Ottman[1,2,3] · Paul S. Appelbaum[1]

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Abstract

Polygenic scores for educational attainment and related variables, such as IQ and "mathematical ability" are now readily available via direct-to-consumer genetic testing companies. Some researchers are even proposing the use of genetic tests in educational settings via "precision education," in which individualized student education plans would be tailored to polygenic scores. The potential psychosocial impacts of polygenic scores for traits and outcomes relevant to education, however, have not been assessed. In online experiments, we asked participants to imagine hypothetical situations in which they or their classmates had recently received polygenic scores for educational attainment. Participants prompted to answer multi-choice questions as though they had received their own low-percentile score, compared to a control condition, scored significantly lower on measures of self-esteem and of self-perceived competence, academic efficacy, and educational potential. Similarly, those asked to evaluate a hypothetical classmate as though the classmate had received a low-percentile score attributed significantly lower academic efficacy and educational potential, compared to a control condition. Through possible mechanisms of stigma and self-fulfilling prophecies, our results highlight the potential psychosocial harms of exposure to low-percentile polygenic scores for educational attainment.

Keywords Education · Polygenic risk score · Psychosocial · Direct-to-consumer genetic testing (DTC) · Predictive genetic testing · Stigma

✉ Lucas J. Matthews
ljm2189@cumc.columbia.edu

[1] Department of Psychiatry, Center for Research on Ethical, Legal and Social Implications of Psychiatric, Neurologic and Behavioral Genetics, Columbia University Irving Medical Center, New York, NY, USA

[2] Departments of Epidemiology and Neurology, G.H. Sergievsky Center, Columbia University Irving Medical Center, New York, NY, USA

[3] Division of Translational Epidemiology, New York State Psychiatric Institute, New York, NY, USA

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1 Introduction

Genome-wide association studies (GWAS) have given rise to a new era of genomic prediction. By summing the miniscule effects of thousands of genetic associations identified by GWAS, polygenic scores (PGS) permit modest prediction of a wide range of human traits, from height and weight to cardiovascular disease and melanoma (Chan et al. 2011; Cust et al. 2018; Khera et al. 2019; Paquette et al. 2017). Although most applications of GWAS and polygenic prediction are relatively non-controversial, recent efforts to elucidate the genetic bases of socially mediated, non-medical outcomes have generated some contention. Notably, GWAS have been employed by social scientists to identify genetic variants and develop PGS associated with educational attainment (EA), intelligence, mathematics ability, reading ability, social-class mobility, sexual behavior, and household income (Belsky et al. 2018; Chen et al. 2017; Ganna et al. 2019; Paige Harden et al. 2019; Hill et al. 2019; Lee et al. 2018; Luciano et al. 2013; Savage et al. 2017).

Moreover, PGS for these socially mediated outcomes are being used to develop direct-to-consumer (DTC) genetic tests aimed at predicting what might be perceived as an individual's genetic potential for intelligence, education, or wealth (Folkersen et al. 2020; Stéphane 2018). In line with a longstanding interest in the use of genetic information in educational settings (Gason et al. 2005; Grigorenko 2007; Rothstein 1998), some scientists have gone so far as to recommend the development of "genetically sensitive" schools that would involve the use of PGS in educational settings (Asbury and Plomin 2014; Erbeli 2019; Hart 2016; Haworth and Plomin 2012; Morris et al. 2019; Plomin and von Stumm 2018; Plomin and Walker 2003; Plomin et al. 2007). The idea has also received attention in popular media, with advocates for and against debating its merits (Briley and Tucker-Drob 2019; Harden 2018a, b; Martschenko 2019; Regalado 2018; Williamson 2018).

Analogous to "precision medicine"—which involves tailoring patients' medical care to their genetic profiles—"precision education" would involve tailoring students' educational curricula to their polygenic scores for traits and outcomes relevant to schooling, such as EA, IQ, or mathematical ability. Asbury and Plomin (2014) suggest that human behavior genetics demonstrates that not all students are equal in genetic potential, and that genetic tests could be used to identify students at risk to struggle in school:

> Genetics tells us that some children will, by their very nature, find the acquisition of [literacy, numeracy, and technological skills] difficult and that they should be provided with personalized support to whatever extent is necessary to enable them to acquire an adequate toolkit of skills (p. 11).

Further, although the predictive accuracy of PGS is currently very limited, proponents of precision education suggest that individual prediction is just around the corner, as technology will soon be available to "to use DNA 'chips' to predict strengths and weaknesses for individual pupils and to use this information to put personalized strategies in place for them" (Asbury and Plomin 2014, p. 14).

Although proponents maintain that precision education would be beneficial to individuals and society in the long term, others are concerned that genetic information could have undesirable consequences in educational settings (Martschenko et al. 2019; Sabatello 2018). Some scholars warn that genetic information is interpreted through the lens of "genetic essentialist" biases, i.e., the belief that genetic causes are fixed, immutable, and deterministic (Dar-Nimrod and Heine 2011; Keller 2005), and that these biases may promote stigma against persons with genetic propensities for socially disfavored traits, such as schizophrenia (Sabatello and Juengst 2019).

No studies have investigated effects of genetic information in educational settings. Nonetheless, a good deal of the prior research on the psychosocial impacts of genetic information regarding disease-related traits is consistent with essentialist interpretations and stigma. In some cases, such information appears to affect beliefs about the controllability of behaviors believed to be influenced by genes or biology. For example, persons led to believe they have a gene for alcoholism report feeling reduced control of their drinking behavior (Dar-Nimrod et al. 2013); genetic attributions for obesity are associated with perceptions of reduced control over eating and weight gain (Dar-Nimrod et al. 2014); and people led to believe they are genetically predisposed to depression have reduced confidence in their ability to cope with depressive symptoms (Lebowitz and Ahn 2018).

Similarly, essentialist biases may influence how persons view the severity or durability of traits believed to be caused by genes or biology. For example, the more people attribute their own depressive symptoms to genetic (and other biological) causes, the longer they expect those symptoms to last (Lebowitz et al. 2013), and when people are told that they are genetically predisposed to depression, they recall having experienced more depressive symptoms in the recent past (Lebowitz and Ahn 2017). In some cases, the impact of genetic information may extend beyond mere self-perceptions to actual performance: in one study, older adults who were informed that they carried an APOE-ε4 allele associated with increased risk of Alzheimer's disease performed worse on memory tasks than APOE-ε4 carriers who were not informed (Lineweaver et al. 2014); in another, participants genotyped and informed of a high risk genetic test result for cardiorespiratory exercise capacity reached a lower maximum capacity for $C0_2$:0_2 gas exchange and decreased ventilatory flow rate compared to those informed of a protected genetic test result (Turnwald et al. 2019).

Consistent with concerns regarding stigma, some prior research suggests that genetic or biological information may negatively influence attitudes and beliefs toward others. In a study of medical students, participants presented with genetic information regarding obesity were less likely to recommend weight loss and exercise to virtual patients (Persky and Eccleston 2011). Another study showed that biological explanations appear to reduce mental health clinicians' empathy for their patients (Lebowitz and Ahn 2014).

If similar negative impacts were to be borne out for genetic tests for education as they have for obesity, depression, alcoholism, and Alzheimer's disease, then EA-PGS may hinder educational achievement, rather than help it. Learning one's own EA-PGS result, for example, could give rise to negative self-fulfilling prophecies. Just as learning about a genetic predisposition to depression may lead people

to perceive themselves as more depressed or less able to overcome depression, students who learn that their genes predict low educational attainment may view themselves as unlikely to succeed in school, which may interfere with their motivation to study for tests or pursue higher education. Likewise, just as learning that one carries a genetic risk factor for Alzheimer's disease can negatively impact performance on memory tests, a low EA-PGS result may negatively impact actual scholastic performance.

Similarly, EA-PGS could hinder educational achievement through the stigmatizing attitudes of others, such as parents, classmates, or teachers. In the event that genetic test results were disclosed in educational settings—perhaps via a genetically sensitive, individualized education plan provided to a parent, educator, or administrator—some students with low EA-PGS results may live down to others' perceptions of limited genetic potential, a negative version of the Pygmalion effect (Rosenthal and Jacobson 1968). Parents and educators may have less confidence in students with a low EA-PGS, and be less likely to encourage studying for school, or discourage pursuit of college or graduate school. In the event that students were to reveal genetic test results to classmates, or perhaps infer test results given course placement, students believed to have low EA-PGS may be stigmatized by their peers and classmates, harming confidence and self-esteem.

Given the increasing popularity of DTC genetic tests for education-related traits and outcomes (Allyse et al. 2018; Regalado 2019; Su 2013), recent calls for precision education, and a growing body of research on the negative psychosocial impacts of genetic information, we sought to assess psychosocial impacts of EA-PGS. We conducted two experiments in which individuals recruited using Amazon's Mechanical Turk (MTurk) platform were prompted to answer multiple-choice questions gauging attitudes and beliefs about self-esteem and beliefs related to school performance, as though they had received a hypothetical EA-PGS result. Experiment 1 examined the potential for EA-PGS to impact self-perceptions relevant to schooling, while Experiment 2 investigated the potential for EA-PGS to impact attitudes towards others. For both experiments, we hypothesized that low EA-PGS would negatively impact self-esteem and perceptions of competence, growth mindset, academic efficacy, and educational potential.

2 Experiment 1: considering one's own EA-PGS

2.1 Methods

2.1.1 Participants

Power analyses revealed that a total sample size of 432 participants would be necessary to detect modest effects ($f = 0.15$) in a three-group one-way ANOVA with 80% power at an alpha cut-off of $p < 0.05$. After receiving approval from the Institutional Review Board of the New York State Psychiatric Institute, we recruited U.S. adults via MTurk ($N = 477$; 45% male; 53% female; 1% other), ranging in age from 18 to 25 years ($M = 24.3$, $SD = 2.68$) to roughly align with the age range

of U.S. college student populations. Seventy-five percent of participants identified as white; 45.5% indicated having a bachelor's degree; and 23.4% indicated a household income between $20,000 to $39,999 (See Table 1: Experiment 1 Demographic Characteristics). Listing a $1 incentive, a link to our survey entitled "Survey about Education" was made available to registered MTurk "workers" who met these criteria.

Table 1 Study 1 demographic characteristics (n = 477)

Demographic variables	N	%
Age		
Mean age = 24.33 (SD = 2.68)		
Gender		
Female	249	53.4
Male	211	45.3
Race		
Black or African American	45	9.7%
White	349	74.9%
American Indian or Alaska Native	5	1.1%
Asian	49	10.5%
Native Hawaiian or Pacific Islander	4	.9%
Other	14	3.00%
Ethnicity		
Latino or hispanic	56	12.0%
Not latino or hispanic	410	88.0%
Education		
Less than high school (less than 9th grade)	1	.2%
Some high school (9th to 12th grade), no diploma	1	.2%
High school graduate (diploma or GED equivalent)	70	15.0%
Some post-high school training (college or occupational, technical, or vocational training), no degree or certificate	122	26.2%
Associate (2-year) college degree, or completed occupational, technical, or vocational program and received degree or certificate	67	14.4%
Bachelors degree (for example: BA, AB, BS)	178	38.2%
Graduate or professional degree (for example: MA, MBA, JD, MD, PHD)	27	5.8%
Household income		
Less than $20,000	63	13.5%
$20,000–$39,999	109	23.4%
$40,000–$59,999	97	20.8%
$60,000–$79,999	80	17.2%
$80,000–$99,999	37	7.9%
$100,000–$139,999	45	9.7%
$140,000 or more	35	7.5%

2.1.2 Procedures

Using the Qualtrics automatic randomizer, participants were randomized to one of three conditions: in the low EA-PGS condition ($n = 161$), participants were asked to imagine they had received a low-percentile polygenic score for educational attainment; in the high EA-PGS condition ($n = 152$), participants were prompted to imagine they had received a high-percentile score; and in the control condition ($n = 153$), participants received no vignette regarding EA-PGS. See Table 2 for the contents of the vignettes presented to participants in the low EA-PGS and high EA-PGS conditions. After reading the vignette, participants were prompted to complete a comprehension check, comprising a single, true-or-false question about whether a person with a low EA-PGS is likely to accrue more education than a person with a high EA-PGS.

Table 2 Stimuli used in experiments 1 and 2

Experiment 1 text: *considering one's own EA-PGS*	"Recently, scientists have developed a new genetic test called a 'polygenic score' that works by analyzing the DNA in a person's blood or saliva. A polygenic score can be used to estimate how many years of school a person might complete. A person with a high polygenic score is likely to complete more years of school in their life than a person with a low polygenic score. Let's say you were in college and that you agreed to do a DNA test, which showed that you have a [high/low] polygenic score for education. How would you answer the following questions if your DNA test suggested that you were likely to complete [more/fewer] years of education than an average person?"
Experiment 2 text: *considering a classmate's EA-PGS*	"Recently, scientists have developed a new genetic test called a 'polygenic score' that works by analyzing the DNA in a person's blood or saliva. A polygenic score can be used to estimate how many years of school a person might complete. A person with a high polygenic score is likely to complete more years of school in their life than a person with a low polygenic score. Let's say you are enrolled in college and you have a classmate named Jane. Jane comes from a middle-class family and lives with her mom and dad. Jane recently had a DNA test, which showed she has a [high/low] polygenic score for education. How would you answer the following questions if Jane's DNA test suggested that she was likely to complete [more/fewer] years of education than an average person?"

Experiment 1 participants were prompted to imagine having received an EA-PGS result of their own, while experiment 2 participants were prompted to imagine a hypothetical classmate with an EA-PGS score

All participants then were prompted to answer a set of multiple-choice questions comprising five scales designed to measure self-stigmatizing attitudes and feelings about education and schooling (See Table 3). First, participants were given the 10-item Rosenberg Self-Esteem Scale (RS-ES) (Rosenberg 1965). By measuring positive and negative feelings about the self, the RS-ES is designed to provide a global measure of self-worth. Second, participants were given a three-item, Growth-Mindset Scale (G-MS) (Dweck 1999, 2006). Measuring general attitudes about the malleability of intelligence, the G-MS is designed to assess beliefs about whether intelligence can be improved through hard work. Third, participants were given an eight-item Competence Scale (CS) (Fiske et al. 2007; Lebowitz et al. 2015). Including items assessing perceptions of intelligence, skill, education, and confidence, the CS is a measure designed to capture a person's ability to act on their intentions.

Fourth, participants were given the Academic Efficacy Scale (AES), which is a five-item subscale of the Patterns of Adaptive Learning Scales (PALS). The AES is designed to measure attitudes and beliefs about academic performance and potential (Midgley et al. 2000), and includes items asking whether the respondent can do well in school through hard work and effort. Finally, all participants were given an Educational Potential Scale (EPS), which is a novel, six-item scale that we designed and developed to assess respondents' attitudes and beliefs about past, present, and future school performance and potential. The EPS, which has sufficient inter-item reliability ($\alpha > 0.80$) and is available upon request, prompts participants to rate (on a seven-point Likert type scale) statements such as, "Additional study hours would improve my grades" and "There's no point for me to get a tutor." All items were scored such that higher scores corresponded to greater optimism about one's educational potential and were averaged to compute an overall EPS score for each participant. The order in which participants were presented each scale, and the sequence of items in each scale, were also randomized.

After completing all measures, participants viewed a debriefing, which offered a brief explanation of the currently limited predictive capacities of EA-PGS. The debriefing material also included a blank text box, in which participants were prompted to indicate whether the survey made them feel uncomfortable or stressed.

Table 3 Inter-item reliability of outcome measures (Cronbach's alpha)

Scale	Group 1: $\alpha =$	Group 2: $\alpha =$
Rosenberg Self-Esteem Scale (RS-ES)	.946	.925
Competence Scale (CS)	.943	.936
Growth-Mindset Scale (G-MS)	.949	.922
Academic Efficacy Scale (AES)	.946	.939
Educational Potential Scale (EPS)	.801	.723

2.1.3 Data analysis

Statistical analyses were performed using SPSS. We first calculated inter-item reliability by estimating Cronbach's alpha for each scale (Table 2). We then conducted one-way ANOVAs to assess significant main effects of condition (low EA-PGS, high EA-PGS, or control) on dependent variables (CS, RS-ES, AES, G-MS, and the EPS). Finally, for variables that showed a significant omnibus main effect of condition, we examined pairwise comparisons between the control condition and each of the other conditions using Dunnett's t tests.

2.1.4 Results

Participants asked to imagine having received a low-percentile EA-PGS score of their own reported significantly reduced self-esteem, competence, academic efficacy, and educational potential. The one-way ANOVAs revealed significant main effects of condition on RS-ES scores, $F(2, 464) = 13.57$, $p < 0.001$; CS scores, $F(2,466) = 25.62(2)$, $p < 0.001$; AES scores, $F(2,465) = 25.67$, $p < 0.001$; and EPS scores, $F(2,465) = 9.78$, $p < 0.001$; but not on G-MS scores, $F(2,466) = 0.17$, $p = 0.84$. Follow-up pairwise comparisons using Dunnett t tests revealed that, in comparison with the control condition, participants in the low EA-PGS condition reported lower self-esteem ($p = 0.003$, $d = 0.35$), self-perceptions of competence ($p < 0.001$, $d = 0.59$), academic efficacy ($p < 0.001$, $d = 0.62$), and educational potential ($p = 0.003$, $d = 0.34$) (Fig. 1). There were no significant pairwise differences between the high EA-PGS and control conditions.

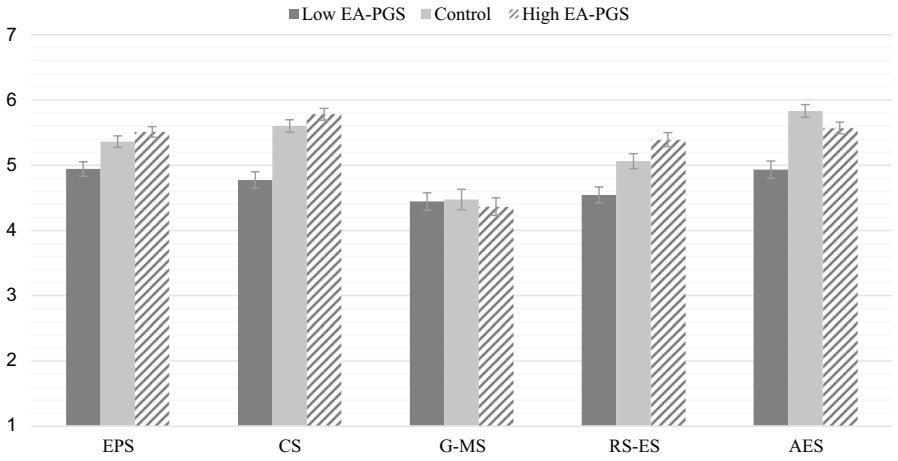

Fig. 1 Mean scores on educational potential scale (EPS), competence scale (CS), growth-mindset scale (G-MS), self-esteem scale (RS-ES), and academic efficacy scale (AES) for participants asked to imagine having received their own EA-PGS, by condition, in Experiment 1. Error bars represent ± 1 SE

3 Experiment 2: considering a classmate's EA-PGS

3.1 Methods

3.1.1 Participants

A second group of U.S. adults ages ($N = 439$; 35.54% male; 63.33% female; 1.14% 'other') 18–25 years ($M = 24.43$, $SD = 2.56$) was recruited to take a "Survey about Education" via MTurk, using the same approach as in Experiment 1. 74.1% of participants identified as white; 45.5% indicated having a bachelor's degree; and 24.2% indicated a household income between $20,000 to $39,999 (See Table 4: Experiment 2 Demographic Characteristics).

3.1.2 Procedures

All participants were prompted to read a vignette about a hypothetical classmate who had recently received the results of a genetic test for education (Table 1). As in experiment 1, participants were randomized to one of three conditions: control ($n = 145$), low EA-PGS ($n = 144$), and high EA-PGS ($n = 152$). Scales identical or similar to those in experiment 1 were used to assess impacts of EA-PGS on growth mindset (G-MS), and perceptions of the classmate's educational potential (EPS), competence (CS), self-esteem (RS-ES), and academic efficacy (AES). Items on the RSES, EPS, and AES were reworded to reflect attitudes towards others, rather than oneself. On the RSES, for example, the item "All in all, I am inclined to feel that I am a failure" was altered to assess participant attitudes toward a hypothetical classmate ("Jane") described in the vignette: "All in all, I am inclined to feel that my classmate Jane is a failure." These revised versions of the RSES, EPS, AES showed satisfactory inter-item reliability (alpha > 0.7) and are available upon request. All other procedures, including the comprehension check and debriefing, were identical to those in Experiment 1.

3.1.3 Data analysis

Statistical analyses were performed using SPSS. We first calculated inter-item reliability by estimating Cronbach's alpha for each scale (Table 2). We then conducted one-way ANOVAs to assess significant main effects of condition (low EA-PGS, high EA-PGS, or control) on dependent variables (CS, RS-ES, AES, G-MS, and the EPS). Finally, for variables that showed a significant omnibus main effect of condition, we examined pairwise comparisons between the control condition and each of the other conditions using Dunnett t tests.

Table 4 Experiment 2 demographic characteristics (n = 477)

Demographic variables	N	%
Age		
Mean age = 24.43 (SD = 2.56)		
Gender		
Female	278	63.3%
Male	156	35.5%
Race		
Black or African American	44	10.0%
White	326	74.1%
American Indian or Alaska Native	5	1.1%
Asian	38	8.6%
Native Hawaiian or Pacific Islander	1	.2%
Other	26	5.9%
Ethnicity		
Latino or Hispanic	70	16.0%
Not Latino or Hispanic	368	84.0%
Education		
Less than high school (less than 9th grade)	0	0%
Some high school (9th to 12th grade), no diploma	2	.5%
High school graduate (diploma or GED equivalent)	39	8.9%
Some post-high school training (college or occupational, technical, or vocational training), no degree or certificate	101	23.0%
Associate (2-year) college degree, or completed occupational, technical, or vocational program and received degree or certificate	47	10.7%
Bachelors degree (for example: BA, AB, BS)	200	45.4%
Graduate or professional degree (for example: MA, MBA, JD, MD, PHD)	51	11.6%
Household income		
Less than $20,000	54	12.3%
$20,000–to $39,999	106	24.2%
$40,000–$59,999	75	17.1%
$60,000–$79,999	77	17.5%
$80,000–$99,999	56	12.8%
$100,000–$139,999	37	8.4%
$140,000 or more	34	7.7%

3.1.4 Results

Participants attributed reduced academic efficacy and educational potential to hypothetical classmates who had received low-percentile EA-PGS scores. The one-way ANOVAs revealed significant main effects of condition for AES scores, $F(2,439) = 12.52$, $p < 0.001$; CS scores, $F(2,439) = 9.19$, $p < 0.001$; and EPS scores, $F(2,438) = 7.2$, $p = 0.001$; but not for G-MS scores, $F(2,440) = 1.66$, $p = 0.192$; or RS-ES scores, $F(2,439) = 0.59$, $p = 0.555$. Follow-up pairwise

comparisons using Dunnett t tests revealed that, in comparison with the control condition, participants in the low EA-PGS condition ascribed lower academic efficacy ($p < 0.001$, $d = 0.40$) and educational potential ($p = 0.002$, $d = 0.38$) to the hypothetical classmate; while participants in the high EA-PGS ascribed greater competence ($p = 0.014$, $d = 0.30$) (Fig. 2).

4 Discussion

The present research revealed a number of potential negative psychosocial impacts of exposure to one's own or others' low-percentile EA-PGS results. In Experiment 1, participants prompted to answer multiple-choice questions as though they had received a low EA-PGS scored lower on measures of self-esteem, as well as self-perceived competence, academic efficacy, and educational potential, compared to those who received no information regarding EA-PGS (i.e., control condition). In Experiment 2, participants attributed significantly lower academic efficacy and educational potential to a hypothetical classmate with a low EA-PGS, compared to one who had received no EA-PGS. Our results suggest that exposure to one's own or another's low EA-PGS could negatively impact attitudes and beliefs directly relevant to success in school.

In addition to a general negative effect of the low EA-PGS condition, Experiment 1 showed that there was no difference between control and high EA-PGS, which could suggest most participants assume their own polygenic scores are above average. This condition of perceived superiority is consistent with previous research on the relationship between self-assessment and actual performance, such as the above-average effect, the Downing effect, and the Dunning-Kruger effect (Davidson and Downing 2000; Furnham et al. 2005; Kruger and Dunning 1999; Schmidt

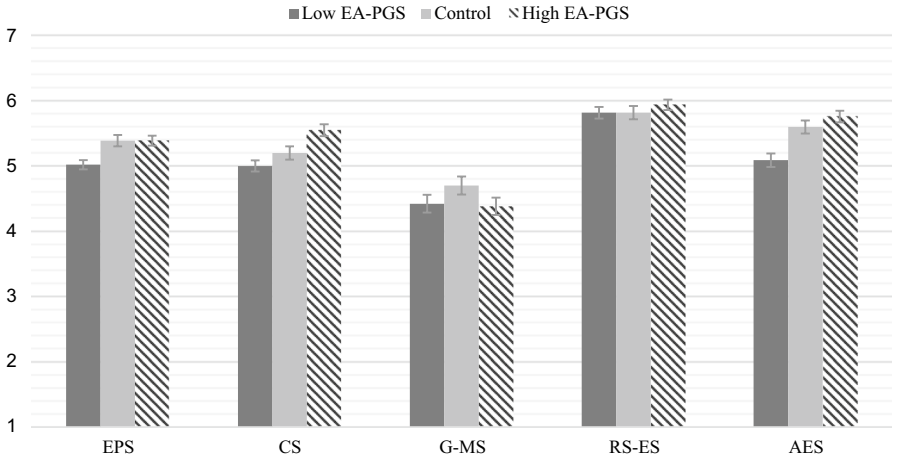

Fig. 2 Mean scores on educational potential scale (EPS), competence scale (CS), growth-mindset scale (G-MS), self-esteem scale (RS-ES), and academic efficacy scale (AES) for participants asked to imagine having received their own EA-PGS, by condition, in Experiment 2. Error bars represent ± 1 SE

et al. 1999). The result is also consistent with the notion that negative information is more impactful than positive information (Baumeister et al. 2001). Similarly, in experiment 2, the high EA-PGS scenarios generally did not produce significant differences from the control condition. However, in one exception, participants attributed significantly higher competence (i.e., CS) to a hypothetical classmate with high EA-PGS than the control. The explanation for this one exception is unclear; future research could examine whether there may be some dimensions on which high EA-PGS scores cause people to be perceived as superior.

One possible implication of our findings is that individual EA-PGS results should be used or interpreted with caution, especially in educational settings. Given that EA is highly correlated with, and treated as a proxy for, IQ (Deary et al. 2007), genetic tests generating polygenic scores aimed at predicting intelligence or related outcomes, such as math and reading ability, should also be approached with caution. Whether through exposure to results via precision education or DTC genetic testing, learning of one's own or another's low score may result in harmful beliefs and attitudes about academic capability and educational potential. Our findings suggest that genetic tests may give rise to a negative Pygmalion effect (i.e., negative self-fulfilling prophecies) in educational settings. Students who receive low EA-PGS may have reduced confidence in their ability to succeed in school and may be exposed to harmful stigmatizing attitudes from parents, classmates, or educators. These impacts could conceivably lead them to be less likely than others to study for tests and pursue college or graduate school, or to stay in school.

Our findings may be especially worrisome considering the limited ability of PGS to predict individual outcomes, especially in individuals of non-European backgrounds (von Stumm et al. 2020). Although persons who receive test results may respond to them as if they were true predictors, the actual predictive capacities of PGS for highly complex behavioral traits and outcomes—including EA and IQ—are subject to a host of conceptual and methodological caveats (Berg et al. 2019; Bulik-Sullivan et al. 2015; Coop, 2019; Dai et al. 2019; Duncan et al. 2019; Janssens, 2019; Krapohl et al. 2014; Martin et al. 2017, 2019; Mostafavi et al. 2019; Rosenberg et al. 2019).

First, DNA variants discovered in large-scale GWAS for EA explain proportions of variance too small to be usefully predictive of individual outcomes. Genetic differences between participants explained only approximately 14% of the total variance in EA in a GWAS of over one million participants (Lee et al. 2018), and only 4% of the total variance in IQ in a GWAS of 280,000 participants (Savage et al. 2017). These results are characteristic of genomic studies of highly complex traits and outcomes known to be mediated by social and environmental factors. With such limited predictive capacity at the population level, individual-level PGS predictions of EA, IQ, and similarly complex traits related to education are highly likely to misidentify individual outcomes. That is, children who go on to lead highly successful lives and accrue many years of education may have low-percentile EA-PGS scores, while conversely, children who will ultimately drop out of high school may have high-percentile scores. If a student with truly high educational potential, however, were to receive a low EA-PGS score, our two experiments point to the possibility that such a score could negatively impact the student's educational trajectory via

negative self-perceptions and stigmatizing attitudes among others made aware of the student's EA-PGS result.

Second, PGS for EA and IQ are more likely to misidentify the outcomes of people of non-European ancestry. PGS are subject to a "problem of portability"; that is, they are less predictive in populations with characteristics different from the population characteristics of the original GWAS sample. Specifically, PGS exhibit variable predictive accuracy within samples of differing sex, age, and socioeconomic status, and between populations of different genetic ancestry (Martin et al. 2019; Mostafavi et al. 2019). Notably, PGS for height derived from populations of European ancestry inaccurately predicted Africans to be shorter than Europeans and slightly taller than East Asians (Martin et al. 2017). Given that greater than 70% of GWAS participants are of European descent (Need and Goldstein 2009; Popejoy and Fullerton 2016; N. A. Rosenberg et al. 2010), the implications of this problem of portability are that PGS for EA and IQ are more likely to misidentify the outcomes of individuals of non-European ancestry who were historically and are currently disadvantaged in American classrooms.

4.1 Study limitations

There are four primary limitations of our study. First, our study is strictly hypothetical in design, which limits the capacity of our findings to extrapolate to real-world cases of exposure to EA-PGS results. We did not assess the psychosocial impacts of real EA-PGS results, nor did we use a nationally representative sample of US students. Rather, our studies asked predominantly White MTurk workers to complete a survey as though they had been exposed to an EA-PGS result. Although our experimental design cannot rule out the possibility, we believe it is unlikely that real genetic tests would be less impactful than hypothetical genetic tests.

Rather, it seems likely that individuals would be *more* strongly affected by the results of an actual genetic test than by those entertained by imagination. Moreover, our results mirror the empirical results of previous studies on the attitudes of individuals who were led to believe that they had taken real genetic tests. For example, participants given a sham genetic test for susceptibility to depression (Lebowitz and Ahn 2018), who were then told that they had tested positive for a genetic predisposition for major depression, showed diminished confidence in their ability to cope with symptoms of depression.

Similarly, the results of our study of MTurk workers may not be generalizable to individuals most likely to be impacted by EA-PGS results. Actual students or parents of students might be more or less likely to be impacted by genetic tests that are believed to predict their educational potential. For example, the results of an EA-PGS may impact a high school student's decision to pursue college or a college student's decision to pursue graduate school. Or such results may have much less effect on students' choices than their educational performance to date. Therefore, further investigation into the impacts of EA-PGS is required to assess their influence in real-life educational settings.

Second, our study relies on self-reports of competency, rather than actual assessments of performance. It could be, for example, that although individuals who are asked to imagine a hypothetical low EA-PGS report lower self-perceptions of competence in educational settings, an actual assessment of performance in educational settings would reveal no effect. Although this outcome cannot be ruled out by our experimental design, our results are consistent with some prior research in which exposure to genetic information is significantly correlated with reduced performance on actual tasks. In the study of Alzheimer's patients cited above, for example, genotype-by-disclosure interaction effects were demonstrated in which older adults who knew their ApoE4 genotype performed worse on verbal memory tests than older adults who also carried ApoE4 but did not know their genotype (Lineweaver et al. 2014). However, further investigation is needed to assess whether actual EA-PGS results influence real-life performance on tasks related to educational assessment.

Third, our findings are limited in that they do not speak to the potential psychosocial impacts of alternative kinds of non-genetic diagnostic testing. That is, our findings are informative about the potential psychosocial impacts of exposure to low-percentile polygenic scores for educational attainment, but do not address the impacts of receiving other kinds of information (e.g., aptitude tests) relating to educational attainment. Further studies that compare the impacts of low-percentile EA-PGS to alternative educational diagnostics are required to address this limitation.

Fourth, participant comprehension of genetics may have influenced our results. That is, our studies did not seek to measure participants' genetic literacy, which could potentially moderate negative psychosocial impacts. It may be, for example, that individuals with above-average comprehension of genetics are more likely to be aware of the limitations of EA-PGS and thus less likely to be negatively impacted by them. To address this limitation, we are currently conducting studies that seek to identify factors that influence the impacts of EA-PGS, such as information regarding the predictive and explanatory limitations of individual polygenic scores.

4.2 Educational impacts and implications

Despite the predictive limitations of EA-PGS, there are numerous avenues by which individuals may be in a position to interpret either their own or another person's EA-PGS. First, individuals may acquire EA-PGS via direct-to-consumer (DTC) genetic reporting companies, such as GenePlaza, Genomelink, Xcode, and Promethease (Stéphane 2018). These companies allow users to upload their genomic data, which may be obtained from services such as 23andme, Ancestry.com, FamilyTreeDNA, and Genos, and purchase individual genetic reports for anything from "educational attainment" and "mathematical ability" to "depression" and "addictions." The upshot is that DTC genetic testing opens the door for individuals to obtain, use, and interpret highly inaccurate and misleading genetic tests for traits and outcomes, which may negatively impact attitudes and beliefs about education and schooling.

Until more is understood about the complex relationships between genetics, environments, and educational outcomes, and EA-PGS can be used to reliably and accurately predict outcomes at the level of individuals—which may not be an attainable

goal, for the reasons noted above—we encourage extreme caution. Ideally, individuals seeking to interpret the results of genetic tests for traits and outcomes relevant to education ought to receive accessible information that helps explain what the tests mean and emphasizes predictive and explanatory limitations. Such information ought to explain, for example, that genetic tests for education and related outcomes are moderately predictive of group outcomes (on average, individuals with high EA-PGS are likely to accrue more years of schooling than individuals with low EA-PGS), but cannot usefully predict individual life trajectories.

Individuals, parents, educators, administrators, and educational policy-makers seeking to make decisions about the use and interpretation of education-related PGS ought to familiarize themselves with information regarding the nature and limitations of the underlying genetic studies, such as FAQs frequently published with genetic studies for non-medical traits. These FAQs, which often explain in clear language what genomic studies do and do not reveal, attempt to counter common misconceptions and misinterpretations of results by highlighting limitations of the science. For example, in a brief FAQ regarding genetic associations with mathematical achievement, researchers emphasized that PGS are "NOT 'fortune-tellers'" or free of influence from environmental or social processes (Harden 2020).

Parents and educators may also refer students to a growing number of online resources, including videos, designed to provide accessible explanations of genetic studies of educational outcomes. For example, in an animated YouTube video co-scripted by a behavior geneticist, a narrator offers a public-facing account of polygenic scores and their relation to educational attainment, and warns of their potential for misunderstanding (Genes, Education, and Equity 2020). Such resources may be useful for helping individuals understand the results of EA-PGS. In sum, the potential psychosocial harms highlighted by this study, combined with the severely limited predictive and explanatory potential of PGS relevant to education, warrants extreme caution about application of EA-PGS, especially in educational settings.

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Author contributions LJM confirms that he had full access to all the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis. All of the authors gave final approval of this version to be published and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Data availability Data will be made available to qualified researchers upon request.

Code availability SPSS syntax will be made available to qualified researchers upon request.

Declarations

Conflict of interest Authors Lucas J. Matthews, Matthew S. Lebowitz, Ruth Ottman, and Paul S. Appelbaum declare that they have no conflict of interest.

Ethics approval and informed consent Approval to conduct this human subjects research was obtained from the New York State Psychiatric Institute's Institutional Review Board. All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional and national) and with the Helsinki Declaration of 1975, as revised in 2000. Informed consent was obtained from all patients for being included in the study.

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Lucas J. Matthews, Ph.D, is a postdoctoral researcher in the Columbia University Center for Research on Ethical, Legal and Social Implications of Psychiatric, Neurologic and Behavioral Genetics. He is co-appointed as a research fellow at The Hastings Center. Matthews' research scholarship addresses conceptual and ethical issues regarding recent technological developments in human behavior genetics, such as the missing heritability problem and potential psychosocial impact of polygenic prediction of non-medical traits and outcomes.

Matthew S. Lebowitz, Ph.D, is an assistant professor in the Department of Psychiatry at Columbia University. Dr. Lebowitz's research examines the ways in which attitudes and beliefs—about mental disorders and other health conditions, as well as about behavior and identity more broadly—are affected by causal reasoning and related psychological processes. This research has had a particular focus on understanding the effects of genetic and other biomedical explanations for behavior, mental and physical health, and other life outcomes.

Ruth Ottman, Ph.D., is a professor in the Columbia University departments of Epidemiology and Neurology, and the G.H. Sergievsky Center, Columbia University Irving Medical Center. Dr. Ottman's recent research examines the psychosocial impacts of receiving genetic information about risk for neurologic disorders

Paul S. Appelbaum, M.D., is Dollard Professor of Psychiatry, Medicine and law, and Director of the Center for Research on Ethical, Legal and Social Implications of Psychiatric, Neurologic & Behavioral Genetics, Department of Psychiatry, Columbia University Irving Medical Center. Dr. Appelbaum's recent research has focused on the ethical and social issues raised by advances in genomics.