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Association between depression diagnosis and educational attainment trajectories: an historical cohort study using linked data

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Background: Depression symptoms are thought to be associated with lower educational attainment, but patterns of change in attainment among those who receive a clinical diagnosis of depression at any point during childhood and adolescence remain unclear. **Methods:** We conducted a secondary analysis of an existing data linkage between a national educational dataset (National Pupil Database) and pseudonymised electronic health records (Clinical Record Interactive Search) from a large mental healthcare provider in London, United Kingdom (2007 to 2013). A cohort of 222,027 pupils were included. We used Growth Mixture Modelling (GMM) and stakeholder input to estimate trajectories of standardised educational attainment over School Years 2, 6 and 11. Multinomial logistic regression analyses were then used to investigate the association between resulting educational attainment trajectory membership (outcome) and depression diagnosis any time before age 18 (exposure). **Results:** A five-trajectory GMM solution for attainment was derived: (1) average/high-stable, (2) average-modest declining, (3) average-steep declining, (4) low-improving and (5) low-stable. After adjusting for clinical and sociodemographic covariates, having a depression diagnosis before age 18 was associated with occupying the average-modest declining trajectory (RRR = 2.80, 95% CI 2.36–3.32, $p < .001$) or the average-steep declining trajectory (RRR = 3.54, 95% CI 3.10–4.04, $p < .001$), as compared to the average/high-stable trajectory. **Conclusions:** Receiving a diagnosis of depression before age 18 was associated with a relative decline in attainment throughout school. While these findings cannot support a causal direction, they nonetheless suggest a need for timely mental health and educational support among pupils struggling with depression. **Keywords:** Depression; educational attainment; epidemiologic studies.

Introduction

Depression is a prevalent mental health disorder in the child and adolescent age group (Collishaw, 2015), and can have a detrimental impact on various aspects of life, including educational outcomes (Wickersham, Sugg, et al., 2021). While many studies have investigated the association between depression and attainment, comparatively few have measured attainment dynamically. This might because attainment is often consistent over time for many pupils (Rimfeld et al., 2018). However, it remains important to consider the possibility that for some pupils, grades might fluctuate during their school career, which in many countries spans well over a decade.

We searched the literature for studies which investigated the association between depression and changes in educational attainment over time in the following databases from inception to July 2022: *Embase, Medline, Global Health, PsycINFO, British Education Index* and *Education Resources Information Center*. Keywords related to educational attainment and trajectory modelling (Ovid database search terms: ((academic or educational or school or classroom) adj (achievement or performance or attainment or success or failure or problems or grades)).tw AND GMM.tw OR LGM.tw OR LCGM.tw OR LCGA.tw OR (growth adj (mixture or model or analysis or curve)).tw or (latent adj (class or growth)).tw OR trajector*.tw). We screened for studies investigating educational attainment trajectories in relation to depression or depression symptoms. We identified seven relevant studies which produced inconclusive and sometimes contradictory evidence on the association. Some found depression to be associated with lower or declining attainment over multiple timepoints (Brière, Janosz, Fallu, & Morizot, 2015; Davis et al., 2018; Wickersham, Dickson, et al., 2021), but one found higher baseline depressive affect to be associated with greater improvements in attainment over time among females (Owens, Shippee, & Hensel, 2008). The remaining studies either did not find or did not report evidence for associations between depression and changes in attainment beyond trajectory intercept (Johnson, McGue, & Iacono, 2006; Park, Seo, Park, Kim, & Choi, 2019; Wampler, Munsch, & Adams, 2002). Properly understanding whether, when and how

Conflict of interest statement: See Acknowledgements for full disclosures.

educational attainment changes among pupils with depression is important for informing whether there are particular windows of time when educational and mental health support might need to be targeted.

A previous study conducted using the cohort in this paper was suggestive of relative decline in educational attainment among pupils with depression, but could not model the corresponding trajectories in a control group to contextualise the findings (Wickersham, Dickson, et al., 2021). A structural equation modelling (SEM) technique known as Growth Mixture Modelling (GMM) would enable data-driven identification of unobserved subpopulations who display similar patterns of change, or trajectories, in an outcome over time.

Various studies have employed this technique to identify latent trajectories of attainment, finding anywhere between two and six latent trajectories in their samples, often reflecting combinations of high, average and low attainment which remains stable, increases or decreases over time. The variety of latent trajectory solutions identified by such studies is perhaps unsurprising given the diverse samples they represent, including children with ADHD (DuPaul, Morgan, Farkas, Hillemeier, & Maczuga, 2018), United States immigrant youth (Suarez-Orozco et al., 2010), looked after children (Sutcliffe, Gardiner, & Melhuish, 2017), Chinese elementary school pupils (Fu, Chen, Wang, & Yang, 2016) and New Zealand high-school students (Hodis, Meyer, McClure, Weir, & Walkey, 2011). Their findings may not generalise to other populations. Moreover, few such studies have subsequently investigated the relationship between resulting trajectory membership and mental health or depression-related measures. Those which have focused on general 'psychological symptoms' or internalising problems (Fu et al., 2016; Suarez-Orozco et al., 2010).

Therefore, to understand the association between clinical depression and course of attainment, we aimed to investigate the attainment trajectories that are generally observed among a community sample of pupils, and test the hypothesis that depression diagnosis is associated with membership of lower or declining attainment trajectories.

Methods

Reporting follows RECORD guidelines for cohort studies using linked data (Table S1) and Guidelines for Reporting on Latent Trajectory Studies (Table S2) (Van De Schoot, Sijbrandij, Winter, Depaoli, & Vermunt, 2017; Von Elm et al., 2007).

Design and sample

This was an historical, longitudinal cohort study using an existing individual-level data linkage between the National Pupil Database (NPD) and the South London and Maudsley NHS Foundation Trust (SLaM) Clinical Record Interactive Search (CRIS). Fuzzy and deterministic data linkage was conducted; the linkage process and linkage quality checks have been described in detail elsewhere (Downs et al., 2019). The sample comprised pupils who were resident in the SLaM catchment area (London boroughs of Croydon, Lambeth, Lewisham and Southwark) in the in the years 2007–2013, and those who were referred to SLaM Child and Adolescent Mental Health Services aged 4–18 years from either inside or outside the SLaM catchment area in that period ($n = 276{,}655$). The CRIS data resource, including the linked data here, has received research ethics approval for secondary analyses (Oxford REC C, reference 18/SC/0372).

The NPD contains attainment data at three key timepoints: Year 2 (key stage 1, typically assessed at age 6 or 7), Year 6 (key stage 2, age 10 or 11) and Year 11 (key stage 4, age 15 or 16). As of 2008, statutory assessments are no longer conducted in Year 9 (key stage 3, age 13 or 14), so we were unable to include this timepoint in analysis. We excluded from the sample anyone who the NPD recorded as taking these assessments in a different temporal order (e.g., Year 11 tests prior to Year 6 tests), or who was disapplied, absent, ineligible for tests or unable to access all assessments in Years 2 or 6 ($n = 1{,}427$). We finally excluded anyone who did not have attainment data at any of the three timepoints ($n = 53{,}201$). A resulting $n = 222{,}027$ were included in this analysis.

Measures

Primary outcome: educational attainment (NPD). Mean average point scores for national curriculum assessments were used at Year 2 (based on reading, writing, maths and science assessments) (Department for Education, 2010a) and Year 6 (based on English and maths assessments) (Department for Education, 2010b). Capped total point scores based on each pupil's best eight General Certificate of Secondary Education (GCSE) or equivalent grades were used at Year 11. Point scores at each timepoint were standardised to z-scores using the mean and standard deviation of all pupils in the sample who had attainment data at that timepoint, conducted separately for each academic year group to account for changes in scoring over time. These z-scores were used in trajectory modelling.

Main exposure: depression diagnosis (CRIS). Depression diagnosis was defined as any International Statistical Classification of Diseases and Related Health Problems – 10th Revision (ICD-10) F32x or F33x depressive disorder, recorded before age 18 in CRIS structured primary or secondary diagnosis fields (World Health Organization, 2011).

Covariates. Gender (male or female), ethnicity (White, Black, Asian, Mixed or Other), and relative age in the school year (derived from birth month; autumn-born [September to December], spring-born [January to April] or summer-born [May to August]) were derived from multiple NPD and/or CRIS datasets, assigning from a subsequent dataset if unavailable or missing from the previous in the following order: school census, key stage 1, key stage 2, key stage 4, absence data tables, CRIS. Ever having been eligible for FSM (eligible or ineligible) was used as a proxy for socioeconomic status and was derived from school census and absence data tables.

Neurodevelopmental disorder was derived from CRIS, and defined as any ICD-10 diagnosis of intellectual disability (F70x-79x), pervasive developmental disorder (F84x), or hyperkinetic disorder (F90x), recorded at any age in structured primary or secondary diagnosis fields. Birth year was derived by taking the mean average birth year for each pupil across estimates derived from school census, CRIS and age at key stages 1, 2 and 4. We also generated age at first depression diagnosis for descriptive statistics. This was calculated from depression diagnosis date, and the birth month and birth year variables (birthday was taken as the first of the month).

Statistical analysis

Trajectory modelling. We conducted missing data checks, the results of which are described in more detail in the results section; briefly, they supported a missing at random assumption, and missing attainment data was handled using Full Information Maximum Likelihood Estimation (FIML), which performs well under a missing at random framework. Trajectory modelling was conducted in Mplus version 8.4 (Muthén & Muthén, 1998–2017), and followed a four-step process outlined by Berlin, Parra, and Williams (2013).

Problem definition: A single-trajectory latent growth model (LGM) of attainment over Years 2, 6 and 11 was developed under a SEM framework. We used maximum likelihood estimation with robust standard errors, as attainment data was continuous and skewed at each timepoint. We specified a linear model, with intercept factor loadings fixed to 1, and slope factor loadings fixed to 0, 4 and 9, reflecting the typical number of years between each assessment timepoint (mean age in years at the start of each academic year: 6.00 [$SD = 0.06$] for Year 2; 10.00 [$SD = 0.25$] for Year 6; 15.01 years [$SD = 0.10$] for Year 11). Goodness-of-fit was evaluated with the following values denoting good model fit: comparative fit index (CFI) ≥ 0.95, Tucker-Lewis index (TLI) ≥ 0.95, root-mean-square error of approximation (RMSEA) ≤ 0.06 and standardised root-mean-square residual (SRMR) ≤ 0.08. We also report X^2, although this statistic is heavily influenced by large sample sizes, so we did not use it to assess goodness-of-fit.

Model specification: We used the single-trajectory LGM as the base model for GMM. Latent class growth analysis (LCGA), which is a more restrictive variant of GMM, was also conducted and its model fit compared to GMM. All variances and covariances were constrained across latent trajectories, while intercept and slope means were freely estimated.

Model estimation: Models with one to five latent trajectories were fitted using the default of 20 random starts and 4 final stage optimisations. Random starts were increased if the best log-likelihood was not replicated, and to check for local solutions. We also checked for negative variance estimates (Heywood cases).

Model selection and interpretation: We assessed the optimal number of trajectories to accept as the final model solution. This decision was informed by entropy, trajectory sizes and shapes, and the following fit statistics: Akaike information criterion (AIC), Bayesian information criterion (BIC), sample size-adjusted BIC (ABIC), Vuong-Lo–Mendell–Rubin likelihood ratio test (VLMR) and Lo–Mendell–Rubin adjusted likelihood ratio test (ALMR).

We also consulted with a Young Person's Mental Health Advisory Group to guide our decision. This group comprises young people aged 16–25 years, resident in the United Kingdom, who have personal experience of using mental health services, or of caring for someone who has. During an advisory group session, we explained that the aim of this part of the study was to describe changes in attainment over time in the general population, and that the general goal of the modelling process was to describe as many pupils in the population as possible, but using as few trajectories as possible, only adding a new trajectory if it is meaningful. We then presented each model solution from one to five trajectories, and with each additional trajectory asked the group to think about the following questions to help decide whether to keep the new trajectory:

- Is the [new trajectory] very different from the [existing trajectories]?
- Can you think of people at school whose grades might look much more like this [new trajectory] than any of the [other trajectories]?

Predicting trajectory membership. We again conducted missing data checks, the results of which are described in more detail in the results section; briefly, they supported a missing at random data pattern in the covariates, and we weighted subsequent analyses for the likelihood of each pupil having complete data.

We conducted univariable and multivariable multinomial logistic regression analyses to investigate whether depression predicted probable trajectory membership after adjusting for gender, ethnicity, FSM eligibility, relative age within the school year and neurodevelopmental disorder as covariates. We included relative age following descriptive exploration of the GMM results which suggested that birth month varied between trajectories. Relative risk ratios (RRR) with associated 95% confidence intervals (95% CI) were calculated from the regression models. Stata version 15.1 was used for regression analyses (StataCorp., 2018).

Sensitivity checks

In the United Kingdom, attainment is sometimes measured as achieving expected thresholds of Level 2 in Year 2, Level 4 in Year 6 and 5 A* to C grades (including English and maths) in Year 11. To ensure that the GMM solution was reflective of various attainment measures, we summarised the proportion of pupils meeting these thresholds in each trajectory. We also investigated missing attainment data in each trajectory, and the possible impact of early or late exam taking.

A known limitation of using probable trajectory membership as an outcome variable is that it disregards known uncertainty over membership (Berlin et al., 2013). Therefore, we also conducted a multivariable linear regression analysis for each trajectory, with the same exposure variables as the main multinomial logistic regression analysis, and the outcome as each pupil's probability of being assigned to the trajectory in question, expressed as a percentage for ease of interpretation.

Results

Trajectory modelling

In the study sample (n = 222,027), attainment data was missing for n = 25,495 (11.5%) in Year 2, n = 61,236 (27.6%) in Year 6 and n = 133,146 (60.0%) in Year 11 (Table S3). This gradient of increasing missingness with each key stage is consistent with the fact that our cohort of pupils were aged 4 to 18 years at the time of extracting their educational records and undertaking data linkage. In this age range, we would expect most pupils to be old enough to have completed Year 2 sometime prior to linkage, fewer to have yet completed Year 6 and a minority to have yet completed Year 11 (Downs et al., 2019). Missingness in attainment data at each timepoint was associated with gender, ethnicity and FSM eligibility (Table S4), and with attainment at the remaining nonmissing timepoints (Table S5). This informed our use of FIML. Attainment was positively correlated between all timepoints, with stronger correlations for more proximate timepoints (Table S6).

We initially fit the single-trajectory LGM with an uncorrelated intercept and slope. The resulting covariance matrix was not positive definite due to slight negative variance in the slope (slope variance estimate = 0.000, estimate/standard error = –5.73). We therefore fixed the slope variance to zero, but the resulting model's fit was poor (CFI = 0.946, TLI = 0.946, RMSEA = 0.089, SRMR = 0.097, $X^2(3)$ = 5239.68, $p < .001$). We then fit the LGM permitting the intercept and slope to correlate, as they commonly do in these models. This resulted in excellent model fit (CFI = 1.000, TLI = 0.999, RMSEA = 0.013, SRMR = 0.004, $X^2(1)$ = 40.43, $p < .001$), and was therefore accepted as the base model.

GMM consistently provided a better model fit than the more restrictive LCGA (Table S7); therefore we proceeded with GMM (Figure S1). Each additional trajectory appeared to represent a distinct pattern of change in attainment, and improved model fit, although entropy declined (Table 1, Figures S2 and S3). The five-trajectory model therefore had the best model fit, but also the lowest entropy (0.750), introduced a trajectory which represented a very small proportion of the sample (n = 5,364; 2%), and had two trajectories representing a decline in educational attainment (one steeper than the other). We explored the possibility of a sixth trajectory, but the resulting variances for Year 2 and Year 11 were not positive definite unless fixed to zero – we decided that this was too great a departure from the model specification for one to five trajectories to be comparable, and did not consider it as a candidate solution during model selection.

We consulted with the Young Person's Mental Health Advisory Group on how many trajectories to accept, based on the considerations outlined in the methods section above. They generally agreed that three trajectories were preferable to two, and four were preferable to three. Choosing between four and five trajectories generated more discussion, and the group suggested gathering more information to inform the decision.

One suggestion was to investigate whether the two declining trajectories in the five-trajectory model were significantly different in statistical terms. We conducted a post hoc comparison between the two declining trajectories, which produced a statistically significant result (Wald test of parameter constraints = 2,263.83, $p < .001$).

Another suggestion was to estimate the difference between the two declining trajectories in terms of GCSE grades, to understand how substantially they differ in real-world terms. On average, pupils in the modestly declining trajectory received 191.2 capped total point scores in Year 11 (SD = 35.9), while pupils in the more steeply declining trajectory received 48.2 (SD = 41.0) (Table S8). This difference of 143 point scores could translate to multiple possible grade combinations, but as an example would be roughly equivalent to attaining three additional GCSEs between A and B grade (Department for Education, 2016).

Finally, the group suggested considering the practical implications of belonging to the steeply declining trajectory versus the modestly declining trajectory. Based on the above information, the levels of educational support needed for pupils in each trajectory could be very different. Therefore, the inclusion of both declining trajectories was agreed to be important, and we accepted the five-trajectory GMM solution (Figure 1, Table S9).

Table 1 Model fit information for Growth Mixture Modelling of educational attainment

	Number of trajectories				
Fit statistics	1	2	3	4	5
Number of free parameters	8	11	14	17	20
AIC	1120115.45	1075587.08	1062643.31	1054094.81	1051405.38
BIC	1120197.94	1075700.50	1062787.66	1054270.09	1051611.59
ABIC	1120172.51	1075665.54	1062743.17	1054216.07	1051548.03
VLMR	N/A	$p < .001$	$p < .001$	$p < .001$	$p < .001$
ALMR	N/A	$p < .001$	$p < .001$	$p < .001$	$p < .001$
Entropy	N/A	0.805	0.797	0.794	0.750
Group size (%)					
Trajectory 1	222,027 (100%)	201,980 (91%)	192,365 (87%)	190,243 (86%)	186,580 (84%)
Trajectory 2	..	20,047 (9%)	18,357 (8%)	10,363 (5%)	8,243 (4%)
Trajectory 3	..	..	11,305 (5%)	12,332 (6%)	13,275 (6%)
Trajectory 4	..	..	..	9,089 (4%)	8,565 (4%)
Trajectory 5	..	..	..	–	5,364 (2%)

ABIC, Sample size-adjusted Bayesian Information Criterion; AIC, Akaike Information Criterion; ALMR, Lo–Mendell–Rubin adjusted likelihood ratio test; BIC, Bayesian Information Criterion; N/A, Not Applicable; VLMR, Vuong-Lo–Mendell–Rubin likelihood ratio test.

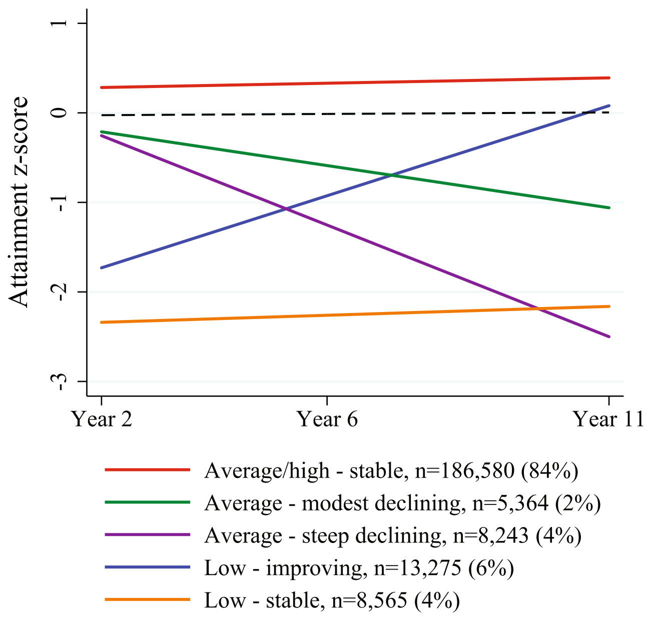

Figure 1 Five-trajectory Growth Mixture Modelling solution. *Note*: The dashed line shows the trajectory of the overall base latent growth model as a reference point

Sensitivity checks indicated that the proportion of pupils meeting expected attainment thresholds was consistent with the trajectory shapes resulting from the five-trajectory solution, suggesting that the trajectories were reflective of various attainment metrics (Table S10). However, the trajectories and the likelihood of pupils occupying them varied slightly according to underlying attainment data missingness (Tables S11 and S12). To explore the potential role of early and late exam taking, we calculated the proportion of pupils in each trajectory who were the 'expected' age at the start of each academic year (Table S13). Compared to the other trajectories, there was a slightly higher proportion of pupils in the average-modest declining trajectory who were older than 15 years at the start of Year 11. However, this difference was minimal, so the trajectories do not seem to have been heavily influenced by early or late exam taking.

Predicting trajectory membership

Sample characteristics are provided in Table 2; they varied according to trajectory and depression diagnosis status. In particular, the proportion of the sample who received a depression diagnosis before age 18 was highest in trajectories representing a decline in attainment (4.2% in the average-steep declining trajectory, 3.0% in the average-modest declining trajectory). The median age at first depression diagnosis was 15 years in all trajectories.

Data was missing for ethnicity and FSM eligibility covariates only (Table 2). Missingness was associated with the remaining fully observed variables and with birth year (Table S14), supporting a missing at random assumption, and informing our use of complete case analyses with inverse probability weighting. Univariable multinomial logistic regression analysis supported a positive association between depression diagnosis and membership of the declining trajectories (Table S15, Figure 2). This was also observed after adjusting for other clinical and sociodemographic characteristics, with depression predicting membership of the average-modest declining trajectory (RRR = 2.80, 95% CI 2.36–3.32, $p < .001$) and the average-steep declining trajectory (RRR = 3.54, 95% CI 3.10–4.04, $p < .001$) (Table 3, Figure 2). A Wald test comparing the depression coefficients for the two declining trajectories was statistically significant ($X^2(1) = 5.40$, $p = .020$), suggesting that for those with depression, the risk associated with being in the average-steep declining trajectory was greater than the risk associated with being in the average-modest declining trajectory. Associations between depression diagnosis and membership of either the low-improving or low-stable trajectories were not statistically significant.

As part of our sensitivity checks, fully adjusted multivariable linear regression sensitivity analyses indicated that, compared to pupils without depression, pupils with depression had, on average, lower mean posterior probabilities of 7.18% for the average/high-stable trajectory, 0.88% for the low-improving trajectory and 1.31% for the low-stable trajectory (Table S16). These findings are slightly different to the main analysis, which showed null findings for the low-stable and low-improving trajectories, likely because these linear models can compare the likelihood of being in each trajectory with the remaining trajectories, whereas the main analysis had a single fixed reference group (the average/high-stable trajectory). Conversely, compared to pupils without depression, pupils with depression had 2.11% higher mean posterior probabilities for the average-modest declining trajectory, and 7.26% higher mean posterior probabilities for the average-steep declining trajectory. This aligns with the findings for these trajectories from the main analysis.

Discussion

In a large cohort of 222,027 pupils, receiving a depression diagnosis before age 18 was associated with declining trajectories of educational attainment. This is consistent with some previous studies. Suarez-Orozco and colleagues found that young people self-reporting more 'psychological symptoms' were more likely to occupy a trajectory showing a precipitous decline in school performance, but unlike this study they did not find this for their slower declining trajectory (Suarez-Orozco et al., 2010). Fu and colleagues, meanwhile, did not find any association between internalising symptoms and attainment trajectory membership (Fu

Table 2 Descriptive statistics for the overall sample, and broken down by probable trajectory membership and depression diagnosis

	Stratified by probable trajectory membership					Stratified by depression diagnosis		
	Average/high – stable (n = 186,580)	Average – modest declining (n = 5,364)	Average – steep declining (n = 8,243)	Low – improving (n = 13,275)	Low – stable (n = 8,565)	No record of depression diagnosis before age 18 (n = 219,403)	Received a depression diagnosis before age 18 (n = 2,624)	Total (n = 222,027)
Trajectory membership								
Average/high – stable	..	..	..	..	..	184,693 (84.2%)	1,887 (71.9%)	186,580 (84.0%)
Average – modest declining	..	..	..	..	..	5,205 (2.4%)	159 (6.1%)	5,364 (2.4%)
Average – steep declining	..	..	..	..	..	7,900 (3.6%)	343 (13.1%)	8,243 (3.7%)
Low – improving	..	..	..	..	..	13,146 (6.0%)	129 (4.9%)	13,275 (6.0%)
Low – stable	..	..	..	..	..	8,459 (3.9%)	106 (4.0%)	8,565 (3.9%)
Received a depression diagnosis before age 18	1,887 (1.0%)	159 (3.0%)	343 (4.2%)	129 (1.0%)	106 (1.2%)	..	..	2,624 (1.2%)
If yes, age of first depression diagnosis in years (median, interquartile range)	15 (14, 16)	15 (14, 16)	15 (15, 16)	15 (14, 17)	15 (13, 16)	..	..	15 (14, 16)
Gender								
Female	95,709 (51.3%)	2,257 (42.1%)	3,517 (42.7%)	5,510 (41.5%)	2,966 (34.6%)	108,145 (49.3%)	1,814 (69.1%)	109,959 (49.5%)
Male	90,871 (48.7%)	3,107 (57.9%)	4,726 (57.3%)	7,765 (58.5%)	5,599 (65.4%)	111,258 (50.7%)	810 (30.9%)	112,068 (50.5%)
Ethnicity								
White	65,303 (39.5%)	2,076 (50.8%)	3,350 (49.9%)	4,498 (37.1%)	3,300 (46.4%)	76,991 (39.9%)	1,536 (59.1%)	78,527 (40.2%)
Black	59,855 (36.2%)	1,335 (32.6%)	2,196 (32.7%)	4,734 (39.0%)	2,504 (35.2%)	70,106 (36.4%)	518 (19.9%)	70,624 (36.1%)
Asian	13,421 (8.1%)	114 (2.8%)	203 (3.0%)	903 (7.4%)	387 (5.4%)	14,928 (7.7%)	100 (3.9%)	15,028 (7.7%)
Mixed	19,806 (12.0%)	470 (11.5%)	796 (11.9%)	1,282 (10.6%)	676 (9.5%)	22,682 (11.8%)	348 (13.4%)	23,030 (11.8%)
Other	7,013 (4.2%)	95 (2.3%)	166 (2.5%)	719 (5.9%)	247 (3.5%)	8,143 (4.2%)	97 (3.7%)	8,240 (4.2%)
Ever FSM eligible	73,762 (39.8%)	2,560 (49.2%)	4,560 (58.4%)	8,355 (63.1%)	5,233 (62.2%)	93,300 (42.9%)	1,170 (45.4%)	94,470 (43.0%)
Ever received a neurodevelopmental disorder diagnosis	3,530 (1.9%)	339 (6.3%)	1,002 (12.2%)	776 (5.9%)	2,073 (24.2%)	7,402 (3.4%)	318 (12.1%)	7,720 (3.5%)
Relative age in school year								
Autumn-born	65,074 (34.9%)	1,797 (33.5%)	2,876 (34.9%)	2,768 (20.9%)	2,370 (27.7%)	74,006 (33.7%)	879 (33.5%)	74,885 (33.7%)
Spring-born	59,895 (32.1%)	1,773 (33.1%)	2,768 (33.6%)	4,194 (31.6%)	2,806 (32.8%)	70,555 (32.2%)	881 (33.6%)	71,436 (32.2%)
Summer-born	61,611 (33.0%)	1,794 (33.5%)	2,599 (31.5%)	6,313 (47.6%)	3,389 (39.6%)	74,842 (34.1%)	864 (32.9%)	75,706 (34.1%)

n = 222,027. Percentages are reported unless otherwise specified. Ethnicity was missing for n = 26,578 (12.0%), and FSM eligibility was missing for n = 2,125 (1.0%). FSM, Free School Meals.

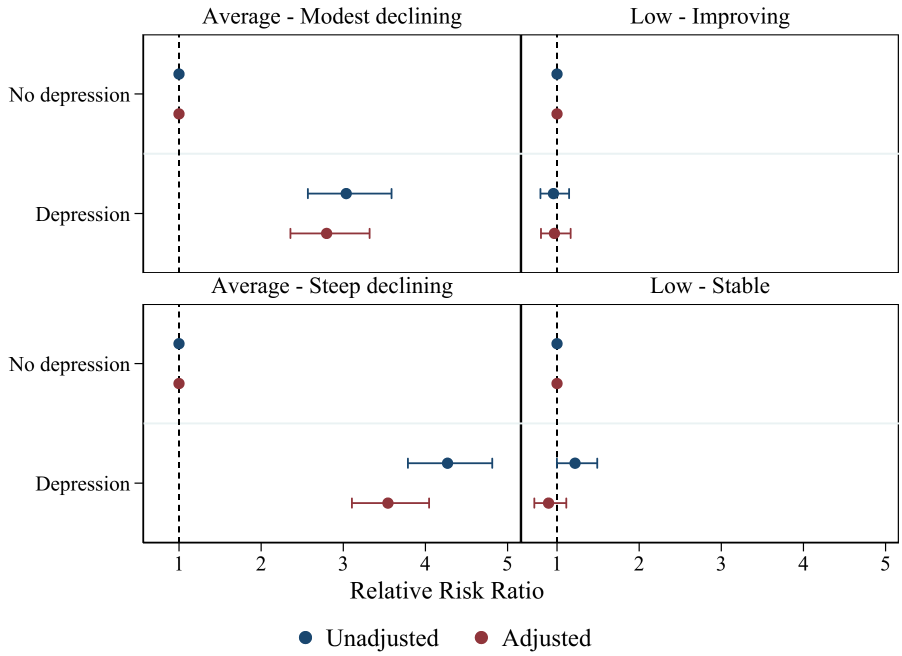

Figure 2 Unadjusted and adjusted associations between receiving a depression diagnosis before age 18 and latent trajectory membership ('Average/high – stable' trajectory as the reference group). *Note*: Relative Risk Ratios derived from univariable and multivariable multinomial logistic regressions

Table 3 Results of multivariable, multinomial logistic regression analysis predicting membership of each trajectory, with the 'Average/high – stable' trajectory as the reference group

	Average – modest declining (n = 4,046)		Average – steep declining (n = 6,581)		Low – improving (n = 12,127)		Low – stable (n = 7,047)	
	RRR (95% CI)	p	RRR (95% CI)	p	RRR (95% CI)	p	RRR (95% CI)	p
Received a depression diagnosis before age 18								
No	Reference	–	–	–	–	–	–	–
Yes	2.80 (2.36–3.32)	<.001	3.54 (3.10–4.04)	<.001	0.97 (0.80–1.17)	.737	0.90 (0.72–1.11)	.324
Gender								
Female	Reference	–	–	–	–	–	–	–
Male	1.41 (1.32–1.50)	<.001	1.32 (1.25–1.39)	<.001	1.45 (1.40–1.51)	<.001	1.71 (1.62–1.81)	<.001
Ethnicity								
White	Reference	–	–	–	–	–	–	–
Black	0.70 (0.65–0.75)	<.001	0.68 (0.64–0.72)	<.001	1.02 (0.98–1.07)	.344	0.83 (0.78–0.88)	<.001
Asian	0.29 (0.24–0.36)	<.001	0.32 (0.27–0.37)	<.001	1.06 (0.98–1.14)	.154	0.71 (0.64–0.80)	<.001
Mixed	0.72 (0.65–0.80)	<.001	0.72 (0.66–0.78)	<.001	0.84 (0.79–0.90)	<.001	0.62 (0.57–0.68)	<.001
Other	0.41 (0.33–0.51)	<.001	0.43 (0.36–0.50)	<.001	1.35 (1.24–1.47)	<.001	0.72 (0.63–0.82)	<.001
Ever FSM eligible								
No	Reference	–	–	–	–	–	–	–
Yes	1.65 (1.54–1.76)	<.001	2.36 (2.24–2.49)	<.001	2.59 (2.49–2.70)	<.001	2.68 (2.54–2.83)	<.001
Ever received a neurodevelopmental disorder diagnosis								
No	Reference	–	–	–	–	–	–	–
Yes	2.78 (2.47–3.15)	<.001	5.36 (4.94–5.83)	<.001	2.92 (2.68–3.17)	<.001	13.54 (12.65–14.50)	<.001
Relative age in school year								
Autumn-born	Reference	–	–	–	–	–	–	–
Spring-born	1.01 (0.94–1.09)	.774	1.00 (0.94–1.06)	.998	1.67 (1.59–1.76)	<.001	1.32 (1.24–1.41)	<.001
Summer-born	1.03 (0.96–1.12)	.381	0.93 (0.87–0.99)	.017	2.55 (2.43–2.68)	<.001	1.63 (1.53–1.74)	<.001

n = 194,897. The multivariable analysis adjusted for all variables in this table. CI, confidence interval; FSM, free school meals; RRR, relative risk ratio.

et al., 2016). This may reflect the varying effects that mental health disorders could have on educational outcomes, such that conflating them as 'psychological symptoms' or 'internalising symptoms' could obscure their independent effects (Weidman, Augustine, Murayama, & Elliot, 2015). It may also reflect the greater severity and impact of depression among those accessing mental health services: by focusing on depression diagnosis rather than symptom scales, we demonstrate that clinically significant depression is indeed associated with an overall decline in school performance.

While we cannot draw causal inferences from this study, it is notable that the median age of depression diagnosis (15 years) fell between a drop in attainment in Year 6 (age 11 years) and a further drop in Year 11 (age 16 years). This might reflect bidirectional effects between depression and attainment, with pupils experiencing a vicious cycle between lower school performance and poor mental health (Weidman et al., 2015). It is therefore possible that at least some pupils who go on to struggle with their mental health show early signs of difficulty through a decline in their attainment between Year 2 and Year 6, and if this is successfully identified, the time leading up to Year 11 might present a critical period for targeting mental health and educational support. However, a previous study conducted using this cohort was more suggestive of a nonlinear pattern, with the decline in performance only taking place in Year 11 after the median age of diagnosis (Wickersham, Dickson, et al., 2021). In the current study, we did not investigate a quadratic relationship; doing so might have found further support for a nonlinear pattern, but could have led to overfitting. Therefore, the timing of these effects needs clarification in future work.

GMM is a flexible method of identifying unobserved subpopulations with similar trajectories, and to our knowledge, this is the largest study to have adopted this technique in educational data. Where previous studies have been hampered by sometimes unreliable self- and informant-reported education and mental health data, we leveraged linked administrative data with known clinical significance.

Stakeholder consultation guided the model selection process. This was a key strength of this study because it ensured that the model solution carried real-world relevance. Prior to consulting the group, we were in favour of accepting the four-trajectory solution based on its higher entropy. Opinions on how many trajectories to accept were mixed within the group, but they generally agreed that additional analyses would inform this decision, and ultimately those analyses gave support to the five-trajectory solution. This demonstrates the value of using stakeholder feedback to challenge researcher preconceptions and guide the analysis process.

Some limitations should be highlighted. Linked administrative datasets overcome many biases of primary data collection, but the exact cause of missing data is often unclear. Nonetheless, we explored and managed missing data. We did not conduct validation work on data fields, thus misclassification bias remains possible, as does unmeasured confounding. In order to maximise our sample size, we included children who were resident in the local area, and children who were both in-borough and out-of-borough referrals to SLaM. Given the resulting slight overrepresentation of clinically severe cases in our cohort, caution about the external validity of these findings is warranted.

Due to the very small number of children receiving depression diagnoses at younger ages, we were unable to explore depression as a dynamic variable, instead creating a binary variable indicating any depression diagnosis before age 18. Some were therefore diagnosed with depression after Year 11, the final timepoint in trajectory modelling, limiting ability to infer a direction of effect. However, this ensured that depression diagnosis was captured for the small proportion of pupils included in trajectory modelling who took their GCSE's later than expected, and who were more likely to occupy declining or consistently low trajectories (Table S13). Furthermore, for pupils whose depression diagnosis did occur after Year 11, it remains likely that their actual onset of depression was much earlier, due to known delays in treatment-seeking (Wang et al., 2007).

Another limitation of investigating depression diagnosis before age 18 as a binary variable is that our findings are not sensitive to how diagnosis at various stages of development might result in different attainment trajectories. However, it is notable that in every attainment trajectory we identified, the average age of depression diagnosis was 15 years. If trajectories varied between pupils who were diagnosed earlier versus later in development, we might expect the average age of diagnosis in each trajectory to reflect this. Nonetheless, future studies which are able to measure depression diagnosis or symptom emergence in a more dynamic way would shed further light on the respective timings of depression and changes in attainment.

We also did not explore the effects of depression severity. While ICD-10 codes can be used to differentiate between mild, moderate and severe depression with or without psychotic symptoms, this was not always specified in our sample. These codes may also not be consistently applied within or between clinicians. The pupils in our sample who had depression diagnoses had been referred to mental health services, so it is likely that many of them were experiencing moderate or severe mental health symptoms. Nonetheless, future studies might further explore the impact of depression severity if this can be reliably ascertained.

Conclusion

With depression and declines in attainment strongly associated, there is a clear need to recognise that investment in pupil wellbeing is a critical component of school success (Bonell et al., 2014). Tentatively, mitigating against child and adolescent depression may moderate its potential impact on attainment. Timely educational interventions may also be beneficial, particularly among those showing an early drop in attainment, so that strategies can be put in place before later and often important educational milestones. Depending on individual need, educational strategies might entail extra tuition, covering material missed due to school absence, or developing contingency plans such as staggering or deferring exams, making use of exam boards' exceptional circumstances policies, or pursuing alternative educational pathways which place less emphasis on exam performance. Any such strategy should be decided in collaboration with pupils, families, teachers and care coordinators.

Existing strategies which have shown promising effectiveness for improving the school performance of underachieving pupils might also be adapted to cater specifically for pupils struggling with depression and other mental health disorders (Snyder et al., 2019). Programs designed to help pupils catch up on missed learning during the coronavirus pandemic could also be extended and made available to adolescents whose education is disrupted due to depression and other mental health issues (Department for Education, 2020). Overall, this study emphasises the need for timely mental health and educational support among pupils with depression.

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article:

Table S1. The RECORD statement – checklist of items, extended from the STROBE statement, that should be reported in observational studies using routinely collected health data. Items specific to cross-sectional/case-control studies have been removed.
Table S2. Guidelines for reporting on latent trajectory studies.
Table S3. Missing data patterns in the final sample.
Table S4. Percentage missing attainment data at each timepoint stratified by sociodemographic characteristics, and results of Chi-squared tests on cross-tabulations between attainment data availability at each timepoint and sociodemographic characteristics.
Table S5. Associations between attainment data availability at each timepoint and attainment *z*-scores at the remaining timepoints.
Table S6. Pearson's correlation coefficients between attainment *z*-scores at each timepoint.
Table S7. Bayesian information criterion resulting from latent class growth analysis and growth mixture modelling.
Table S8. Mean capped total point scores in each trajectory.
Table S9. Unstandardised parameter estimates for the five-trajectory Growth Mixture Modelling solution.
Table S10. Proportion of pupils meeting expected educational attainment thresholds in each trajectory.
Table S11. Proportion of pupils in each trajectory with available attainment data.
Table S12. Proportion of pupils with observed/missing attainment data assigned to each trajectory group.
Table S13. Proportion of pupils in each trajectory who were the expected age at the start of each academic year.
Table S14. Results of multivariable logistic regression analysis predicting data completeness.
Table S15. Results of univariable, multinomial logistic regression analyses predicting membership of each trajectory, with the 'Average/high – stable' trajectory as the reference group.
Table S16. Results of multivariable linear regression analyses predicting pupils' probabilities of being assigned to each trajectory.
Figure S1. Theoretical path diagram used in Growth Mixture Modelling.
Figure S2. Bayesian Information Criterion for Growth Mixture Modelling solutions with one to five latent trajectories.
Figure S3. Trajectory shapes for Growth Mixture Modelling solutions with one to five latent trajectories.

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The data that support the findings of this study are not publicly available but can be accessed with permissions from both the Department for Education and South London and Maudsley NHS Foundation Trust. A.W. and J.D. had full access to the study data. Supporting Mplus and Stata code will become publicly available via A.W.'s GitHub account on publication: https://github.com/AliceWickersham.

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Key points

- Depression can have a detrimental impact on educational outcomes, yet there is contradictory evidence on how depression is associated with changes in attainment throughout the school career.
- We modelled trajectories of attainment in a large, UK-based cohort of pupils, conducting stakeholder consultation to guide the modelling process.
- Harnessing linked health and education records, we investigated the association between clinical depression diagnosis and the attainment trajectories.
- Our findings suggest that pupils who receive a depression diagnosis before age 18 are at significantly greater risk of occupying trajectories illustrating a relative decline in attainment.
- There is a clear need for timely mental health and educational support among pupils with depression, using strategies decided in collaboration with pupils, families, teachers and care coordinators.

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