Department for Education

The relationship between mental ill health and absence in students aged 13 to 16: Results from the longitudinal study of young people – cohort 2

Research report

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Executive summary

Since the Covid-19 pandemic, there has been a significant increase in school absenteeism. The absence rate for the 2023/24 academic year reached 7.2% across all schools, with one in five students missing 10% or more of possible sessions (Department for Education, 2024a). These figures represent a near doubling of rates of absenteeism compared to pre-pandemic levels.

In conjunction with the rise in school absences, there has been a marked increase in mental health problems among children and adolescents. NHS data from 2023 shows that 21% of 8- to 16-year-olds have a probable mental health problem, which is an increase of 7 percentage points since 2017 (NHS England, 2024). Further, it is estimated that 1.5 million young people and children in England are going to need support for their mental health as a direct result of the pandemic in the coming years (O'Shea 2021).

The simultaneous rise in both school absenteeism and mental ill health raises questions about their potential relationship. Data show that the two are rising alongside each other, but the extent to which poor mental health influences school absences remains unclear. Improving the evidence about this relationship is important for developing effective policies and interventions that can address both absenteeism and the mental health issues that are potentially contributing to it.

This report uses longitudinal data and causal statistical techniques to show the extent to which poor mental health and school absences are related and whether poor mental health contributes to absenteeism.

Data

The findings in this report are primarily based on the second cohort of the Longitudinal Study of Young People in England (LSYPE2), which is a large-scale panel study following a sample of young people born in 1998/1999. The students were first interviewed in the 2012/13 academic year while they were in Year 9. Since then, there have been nine waves of annual interviews. The current study uses the first three waves of interviews, meaning the data run from 2012/13 until 2014/15.

For this analysis, consenting members of the LSYPE2 cohort were matched with relevant variables from the National Pupil Database (NPD). The combination of the administrative data and the mental health, wellbeing, and sociodemographic variables from the survey allowed us to test the hypothesis that poor mental health predicts absenteeism.

Data on attendance was drawn from the NPD. To look at the variation in attendance patterns, multiple binary 'absence threshold' measures were created, in which we looked at whether a student had missed 1%, 3%, 5%, 10%, 15%, 20%, 35%, or 50% of all possible sessions in an academic year. Alongside the various thresholds, we also examined different reasons for absence by looking at overall absence in addition to authorised and unauthorised absences. For this analysis, attendance data was taken from 2014/15, when the cohort members were in Year 11.

Student mental health and personal wellbeing were drawn from the LSYPE2 and defined as follows:

- **Mental health:** Mental health is measured using the 12-item version of the General Health Questionnaire (GHQ-12), which was asked as part of the LSYPE2 in 2013/14. The GHQ-12 is a series of 12 questions designed to measure psychological distress. The outcome of this is a scale running between 0 and 12, in which a higher score indicates poorer mental health, with poor mental health here referring to the level of distress reported.
- **Personal wellbeing:** Personal wellbeing is measured using the ONS4, which evaluates participants' life satisfaction, happiness, feelings of worthwhileness, and feelings of anxiety. These domains are measured using four distinct questions administered by the LSYPE2 in 2014/15. These are subjective measures, and each is measured independently on a Likert item that ranges from 0 to 10, where a higher score indicates poorer personal wellbeing.

Key findings

Mental health

- Mental ill health is found to be one of the causal factors of absence in Year 11 students.
- Poorer mental health strongly predicts authorised absences. The odds of being absent for authorised reasons increase as the student's mental health becomes worse, with the amount of school being missed being strongly related to poorer mental health after controlling for other factors.
- Unauthorised absences are not predicted well by poor mental health. Across most of the absence thresholds, the effect size is negligible and insignificant, with other factors (e.g., socioeconomic variables) better predicting unauthorised absence rates.

Personal wellbeing

- The relationship between poor personal wellbeing and increased levels of school absence is weak and statistically insignificant. Individuals with lower levels of life satisfaction, feelings of worthwhileness, happiness, and higher levels of anxiousness were more likely to miss school, but the observed relationships were not strong.

Socioeconomic and school factors

- Several variables were included as covariates in the analysis, including household composition, school experiences, parental aspirations, ethnicity, free school meal eligibility, drug use, and whether the student had identified special educational needs or a long-standing illness/disability.
- Variables related to school belonging and school enjoyment predicted absence. Particularly, students who reported enjoying school less were more likely to be absent for both authorised and unauthorised reasons.
- High levels of absence were predicted by a student being eligible for free school meals and having special educational needs or a long-standing illness or disability.
- Children from single-parent households were also more likely to have missed more sessions than those from two-parent households.

Concluding thoughts

This analysis suggests that poorer mental health contributes to absenteeism, particularly for authorised absences. Specifically, it indicates that students facing more severe mental health challenges are more likely to miss school. However, this association was not found with measures of personal wellbeing. This may be due to the timing of the measures and the intended usage of the tools. The two measures of mental health and personal wellbeing were administered at different times in LSYPE2: the personal wellbeing measures were collected at age 15/16, which is the same time point as the attendance data, while the GHQ-12 was administered a year earlier at age 14/15. The tools also capture different dimensions of mental health. The GHQ-12 is designed to detect persistent psychological distress, while the ONS4 measures are designed to measure personal wellbeing and ask about more immediate feelings, such as recent feelings of anxiety ("How anxious were you *yesterday*?"). This temporal framing means that ONS4 responses may reflect short-term fluctuations in mood rather than stable psychological patterns. Consequently, the timing of data collection in relation to periods of absence becomes critical. For instance, a student's wellbeing score could vary depending on whether it was recorded during a particularly challenging week (e.g., due to a recent bereavement) or a more stable period. This variability might dilute any potential association with school attendance, as the ONS4 captures a narrower, momentary snapshot rather than sustained experiences of distress. Further, the differing objectives of the tools likely play a role. The GHQ-12, as a clinical instrument, is more attuned to identifying psychological distress that could interfere with attendance. In contrast, the

ONS4 personal wellbeing measures may be less sensitive to the kinds of mental health issues that directly impact school attendance. Together, these differences underscore the importance of using appropriate measures to capture the complex relationship between mental ill health and absenteeism.

Nonetheless, the results demonstrate that poor mental health – as measured by the GHQ-12 – is associated with higher rates of absence, particularly authorised absence. Good mental health is something that is built in a child over time, and an important part of any response must be prevention and early support to prevent escalation to more serious issues that might lead to higher rates of absence. Given these findings, it is crucial that future research explores which interventions are most effective in improving students' mental health *and* encouraging school attendance.

It is important to note that the data used in this study were collected before the Covid-19 pandemic, a period during which the social landscape underwent significant changes. These changes include a rise in mental health issues among young people and a shift in societal attitudes towards mental health and school attendance. Therefore, future longitudinal studies are required to replicate the findings in the current context.

1 Introduction

1.1 Background

Absenteeism is a growing concern for schools in England. Recent statistics show that in the 2023/24 academic year, 20.7% of pupils missed at least 10% of sessions, with this figure reaching 37.6% in special schools and 26.7% in state-funded secondary schools (Department for Education, 2024a). This means at least 1 in 5 children missed 10% or more of their possible school sessions.

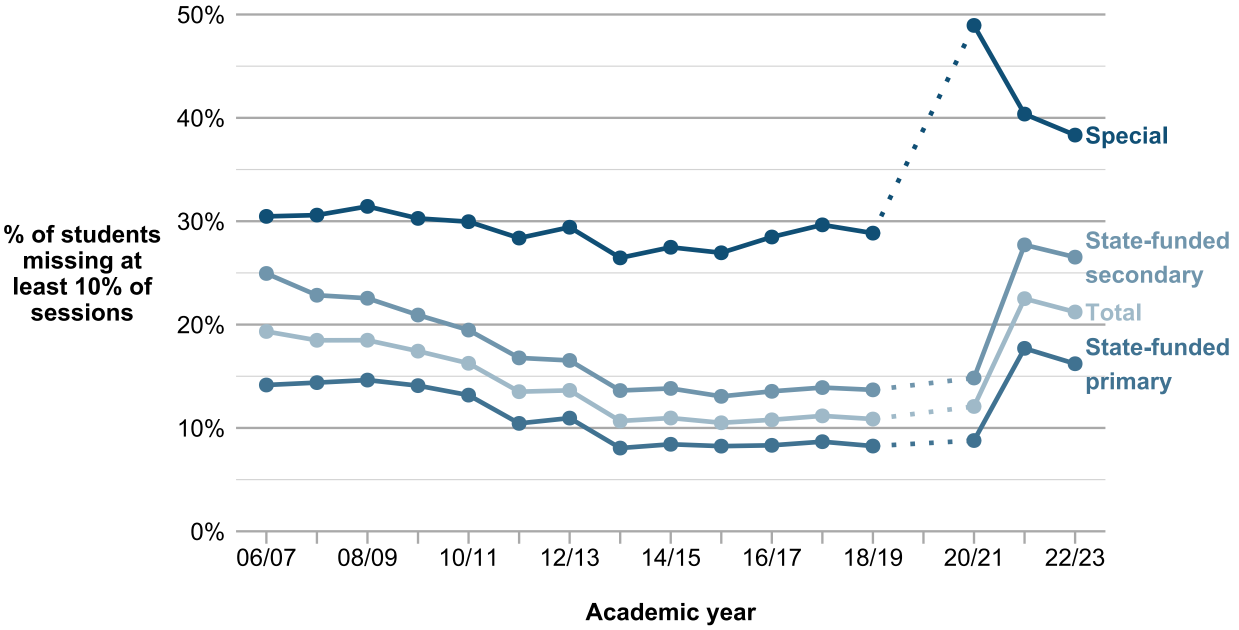
A large body of research has shown that high levels of absence in school is detrimental to the student's future academic and non-academic prospects. For example, poor school attendance is believed to contribute to poor attainment, which in turn can have long-term consequences, such as reduced lifetime earnings (Hodge et al. 2021). At KS2, students who achieved the expected standard of reading, writing, and maths had an absence rate of 3.5%, while those who did not meet the expected standards had an absence rate of 4.7%. Similarly, at KS4, students who achieved a grade of 3 or lower in maths and English had an absence rate of 8.8%, compared to an absence rate of 5.2% in students who achieved at least a grade of 4 (Department for Education 2024a). In addition to academic outcomes, poorer school attendance is also associated with worse working memory and cognitive flexibility in early childhood (Ansari and Gottfried 2021; Gottfried and Ansari 2021) and increased difficulties in social and emotional development (Santibañez and Guarino 2021).

School attendance has been identified as a protective factor that reduces the odds of negative outcomes across many non-academic domains. Students who missed fewer school sessions were less likely to become engaged in risky behaviour, with higher rates of absence being found to predict involvement in criminal behaviour (e.g., knife crime) (Ministry of Justice and Department for Education 2019), earlier and more frequent alcohol consumption, and an increased likelihood of having used drugs (Department for Education 2011a). Schools have also been identified as a setting that promotes resilience in children, thereby making them less susceptible to mental health problems later in life (Brooks 2006). High levels of school absence have also been found to have long-reaching consequences into adulthood, as those who were frequently absent in school were more likely to not obtain any formal qualifications and be out of the labour force in mid-adulthood (Dräger et al. 2024).

Given the benefits of school attendance, it is important to ensure that children and young people attend as many sessions as possible. However, in recent years, rates of absenteeism have increased. The overall absence rate reached 7.2% in the 2023/24[1]

[1] Note that 2023/24 data is based on daily data, rather than Census data.

Figure 1.1. Percentage of persistent absentees from 2006/07 to 2023/24, stratified by school type. The dotted lines indicate missing data due to Covid-19.



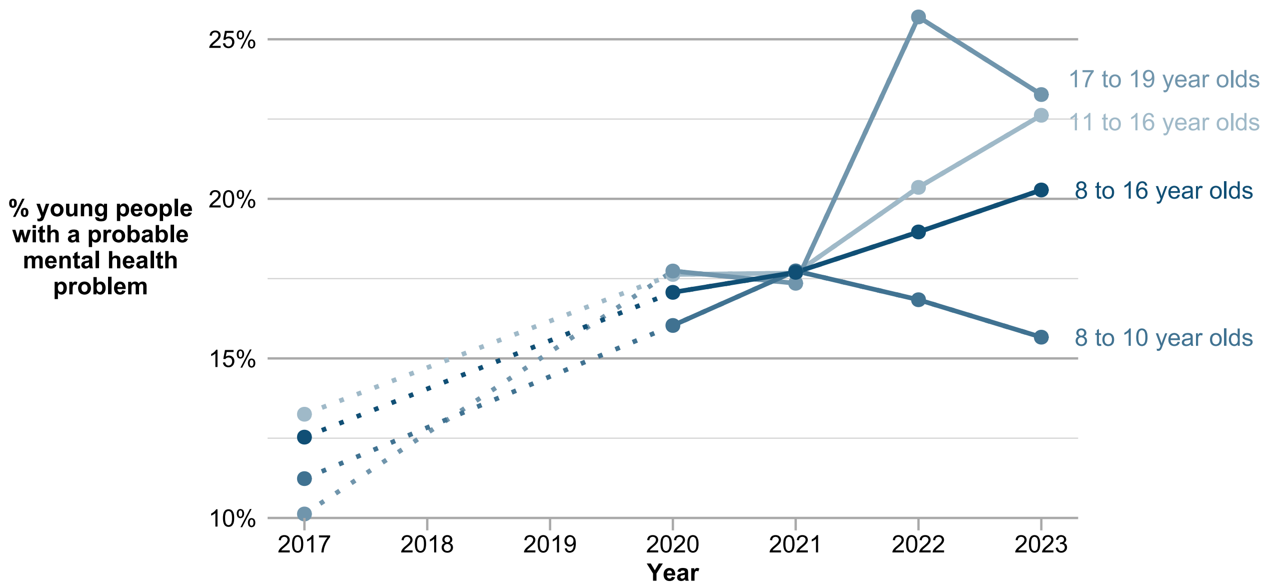
Source: Explore education statistics.
Note that 2023/24 data is daily data rather than Census data.

academic year, which is a 2.5 percentage-point increase from pre-pandemic levels in 2018/19 (Department for Education, 2020). Among the missed sessions, 4.7% were authorised (mainly due to illnesses), and 2.5% were unauthorised. Further, rates of persistent absence – which is defined as a student missing 10% or more of their possible sessions – have doubled since the pandemic. Prior to the pandemic, approximately 1 in 10 students were persistently absent, but this has now risen to 1 in 5 in 2023/24 (see Figure 1.1).

To address absenteeism, it is essential to understand why children and young people are missing an increasing number of school sessions. Poor mental health and wellbeing have been identified as possible contributing factors. Since the pandemic, number of young people experiencing poor mental health has risen significantly. In 2017, 12.1% of those aged 8 to 16 were identified as having a probable mental disorder, a figure that increased to 20.3% by 2023 (Figure 1.2).

The concurrent rise in absenteeism and poor mental health has led to suggestions that these trends may be linked, with poor mental health potentially being a factor causing children and young people to miss more school. Descriptive research from the NHS indicates that students with mental health problems miss more days of school per year than those without. In the Autumn term of 2022, 11.2% of students aged 8 to 16 with probable mental health problems missed more than 15 days of school, compared to just 1.5% of their peers without identified mental health issues (NHS England, 2024). This

Figure 1.2. Percentage of students with a probable mental health problem by age. The dotted lines indicate years with no data.



Source: Mental Health of Children and Young People in England.
Note that the y-axis does not start at 0.

report examines this correlation further using pre-Covid data, exploring whether poor mental health itself contributes to higher school absences.

1.2 Report aims

The primary aim of this report is to understand whether poor mental health contributes to higher school absences. Though there are a number of studies showing the two are associated, but there is currently limited published evidence demonstrating that mental health is a factor causing increased absence.

1.3 Structure of the report

The next section of this report outlines the methods used, including the data, variables, and statistical techniques. The subsequent three sections then present the results of the analyses. Section 3 describes the univariate patterns of all the variables included in the analyses. Section 4 presents bivariate descriptive statistics, including 1) the relationship between absence and mental health and wellbeing, 2) the variation in mental health and wellbeing by the sociodemographic covariates, and 3) the variation in absence by the sociodemographic covariates. The main analysis is then presented in Section 5, in which causal methods are used to understand whether poor mental health and wellbeing are contributing to absence rates. The report then concludes with a summary of the main findings.

2 Methodology

2.1 Data

To explore whether mental ill health contributes to higher school absences, data from the Longitudinal Study of Parental and Children Cohort 2 (LSYPE2, known as “Our Future” to participants) was used. The LSYPE2 is a large-scale panel study that began in 2012/2013, in which students who were aged 13/14 and in Year 9 were interviewed. Since then, there have been nine additional waves, with the most recent having been carried out in 2023. The study includes participants who were typically residing in England at the time of sampling, who were chosen through a two-stage process involving firstly school selection and then pupil selection. The sample includes students from local authority-maintained schools, academies, and special schools. Though the study was designed to be representative, the sample design boosted those eligible for free school meals (FSM) and those with identified special educational needs (SEN).

Participants of the LSYPE2 had the option to consent to linkage with the National Pupil Database (NPD), which is an administrative resource curated by the Department for Education (Jay et al. 2019). The NPD provides data on attendance (amongst other things), and therefore, we are able to use the rich sociodemographic data from the LSYPE2 in conjunction with administrative data held in the NPD. Here, attendance data from the 2014/15 academic year are drawn from the NPD and matched with Wave 3 of LSYPE2 to measure absence in Year 11.

Figure 2.1. LSYPE2 data collection information, Waves 1 to 3.

	Wave 1 2013	Wave 2 2014	Wave 3 2015
Age	13/14	14/15	15/16
Academic year	2012/13	2013/14	2014/15
School/HE year*	9	10	11
Mode	CAPI CATI	CAPI CATI	CAPI CATI
Sample size	13,100	11,166	10,010

CAPI = Computer-assisted personal interview; CATI = Computer-assisted telephone interview

Further information on the sample and survey design can be found in the technical reports released alongside the data via the ONS SRS (Department for Education 2024b), and a cohort profile can be found in Baker et al. (2014).

The current study uses data from Wave 1 (2012/13), Wave 2 (2013/14) and Wave 3 (2014/15) of the LSYPE2, which is when the participants were aged 13/14, 14/15, and 15/16 (Figure 2.1). These three waves were selected as they are the only waves of LSYPE2 when the participants are in compulsory formal schooling, with Wave 4 onwards following the student into further and higher education and employment. Though many of the students do carry on into further education, beyond Year 11, educational establishments are not required to submit attendance data to the Department for Education, and therefore, it would not be possible to conduct the proposed analysis.

2.2 Analysis

The current analysis comprises three sections – two descriptive and one predictive – with the former exploring the variation in attendance and mental health/wellbeing based on various demographic characteristics and the second examining whether there is a causal relationship between poor mental health and absence. The contents of these sections are summarised below.

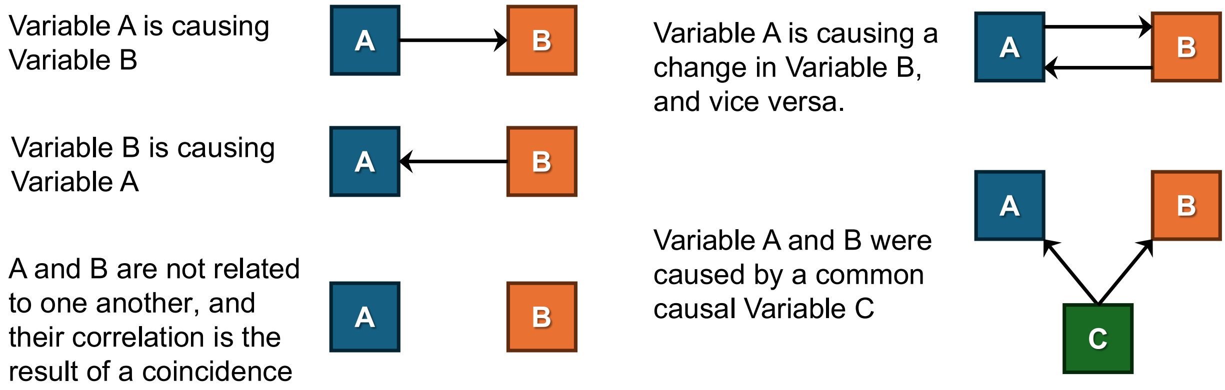
2.2.1 Sample characteristics, and patterns of mental health and attendance

The first stage of this analysis describes the characteristics of the young people included in this sample. Here, the aim is to understand the patterns of the variables without any causal assumptions. Univariate descriptive statistics are first presented in Section 3. Bivariate relationships between mental health, absence, and other demographic factors are then presented using simple descriptive statistics in Section 4.

2.2.2 Is there a causal relationship between mental health/wellbeing and absence?

The primary focus of this report is looking at whether poor mental health/wellbeing is causally related to increased odds of being absent from school. Previous research has established a correlational relationship between the two variables; however, it remains unclear whether this correlation exists because poor mental health directly causes an increased likelihood of being absent from school or due to other factors. A correlation between variables can arise for various reasons (displayed graphically in Figure 2.2). It may be that mental ill health does lead to reduced attendance, meaning there is a true causal relationship. However, it is also possible that low attendance

Figure 2.2. Illustration of possible reasons why two variables may be associated with each other.



negatively impacts the mental health of the student, meaning there would be reverse causation occurring. It may also be that there is a third variable (e.g., socioeconomic disadvantage) that affects both mental health and school attendance separately, which would result in a statistical association between poor mental health and absenteeism. Lastly, the correlation might be spurious, indicating a statistical relationship that is occurring purely by chance.

To understand whether there is a true causal relationship between the two variables, the analysis employs causal methods in the a) data selection, b) variable selection, and c) statistical methods:

a) **Data selection.** The study uses longitudinal data, which can allow us to establish the temporal sequence of variables, strengthening the ability to make causal claims. However, longitudinal data alone cannot completely eliminate other explanations for covariance between variables. For instance, the effect of a third variable – as illustrated in Figure 2.2 – may still be present. Therefore, longitudinal data alone cannot allow us to establish a causal relationship or make causal claims.

b) **Variable selection.** When selecting the covariates for inclusion in the analysis, careful consideration needs to be given to how these variables are causally related to each other and to the primary variables of interest (Figure 2.3). This step is important because the relationships between the exposure (mental health/wellbeing) and the outcome (absence) can be influenced by various confounding factors. These are variables that are related to both the exposure and the outcome and that, if not properly accounted for, could distort the observed relationship. If covariates were selected indiscriminately without regard to their causal connections, various issues could be encountered. Firstly, including irrelevant or weakly related covariates could introduce noise and reduce the clarity of the results, making it harder to discern the true causal relationships. More importantly, failing to include key confounding factors could lead to biased estimates of the effect of mental health/wellbeing on absence. This occurs because the omitted confounders might be the true drivers of both the exposure and the outcome, creating a spurious or misleading association between them. To mitigate this risk, the selection of covariates was informed by a strong theoretical understanding of the causal relationships among the variables. This approach helps ensure that the analysis accurately reflects the true nature of the relationships, leading to more reliable and valid conclusions about the impact of mental health/wellbeing on absenteeism (McElreath 2020). This process is briefly outlined in Section 2.3.3 and then described in more detail in Appendix B.

c) **Statistical methods.** Causal statistical methods can also be used to understand whether poor mental health and wellbeing are contributing to the odds of being absent. In this case, methods are used that adjust the data so that it mimics the conditions of a randomised controlled trial. This method helps to control for confounding variables by assigning weights to each observation based on the likelihood of receiving the exposure given certain covariates. Hence, these methods adjust the sample so that the distribution of the covariates is balanced across different measures of the exposure, allowing us to isolate the causal effect of mental health and wellbeing on absence. These methods are described in detail in Appendices B and C, with the results from the causal analysis presented in Section 4.

2.3 Variables

2.3.1 Measuring attendance

The current definition of persistent absence in the Department for Education is a student who misses 10% or more sessions annually. However, this cut-off is historically variable, as the definition of persistent absence has changed over the years (e.g., prior to 2015/16, it was 15% of sessions, and before 2011/12, it was 20% of sessions) (Department for Education 2011b, 2024c). As the definition has changed over the years, this research uses multiple different binary ‘absence thresholds’ to try and capture the breadth of absence patterns across students, with the different absence thresholds being:

1. A student who missed 1% or more of possible sessions
2. A student who missed 3% or more of possible sessions
3. A student who missed 5% or more of possible sessions
4. A student who missed 10% or more of possible sessions (Department for Education’s definition of persistent absence)
5. A student who missed 15% or more of possible sessions

6. A student who missed 20% or more of possible sessions
7. A student who missed 35% or more of possible sessions
8. A student who missed 50% or more of possible sessions (Department for Education’s definition of severe absence)

Hence, the outcome in each analysis will be a binary for each threshold, in which the student’s absence rate either exceeded the threshold or did not exceed the threshold.

In addition to looking at overall absence patterns across these eight definitions, we also look at specifically authorised and unauthorised absence (e.g., a student who has missed 10% or more sessions for authorised reasons only). This is because it appears that the recent uptick in absences in England is primarily driven by authorised absences (Department for Education 2023) and also because the profile of a student who is absent for authorised versus unauthorised reasons is not always the same. Hence, there are 24 outcomes in total, which are binary in nature (absence threshold met vs. absence threshold not met).

Absence variables are derived from the NPD, using data from the academic year 2014/15, which is in line with the LSYPE2 Wave 3 when students were in Year 11. This year was selected for analysis primarily for pragmatic reasons. Firstly, this academic year is the third year of LSYPE2, meaning that there are two waves of data that exist prior to the absence measure, meaning longitudinal methods can be employed. Secondly, it is timely in terms of the education stage, as it is when students are carrying out their KS4 assessments, and understanding attendance patterns this year can have possible implications for understanding attainment.

2.3.2 Measuring mental health and wellbeing

To measure mental health and wellbeing, data from the LSYPE2 was used, which offers a number of proxies of participant mental health and wellbeing, five of which are used in this study.

Firstly, responses to the 12-item version of the General Health Questionnaire (GHQ-12) are used in this study to measure mental health. This variable was collected in Wave 2 of LSYPE2 when the participants were in Year 10 (aged 14/15). The GHQ-12 is a commonly used measure to assess whether a respondent is experiencing any psychological distress and detect common mental disorders such as depression and anxiety (Goldberg 1972). Therefore, in the case of this piece of research, poor mental health refers to increased psychological distress. The GHQ-12 comprises 12 questions related to factors such as sleep, concentration, and happiness, each of which is measured as a 4-point Likert item (see Appendix A for more detail). From this, a 12-point Likert scale can be derived, in which a higher score indicates poorer mental health and higher levels of psychological distress.

Secondly, personal wellbeing is measured using responses to the ONS4 (Office for National Statistics 2024), which were asked in Wave 3 of the LSYPE2 when the students were in Year 11 and aged between 15 and 16. The ONS4 consists of four measures designed to capture subjective personal wellbeing and measure:

1. How satisfied the participant is with their life;
2. To what extent the participant feels like their life is worthwhile;
3. How happy the participant felt yesterday, and,
4. How anxious the participant felt yesterday.

These measures are all collected as 11-point Likert items (0-10), where 10 indicates poorer personal wellbeing (i.e., poorer life satisfaction, higher levels of anxiousness), and a lower score indicates more positive personal wellbeing (see Appendix A for additional variable information).

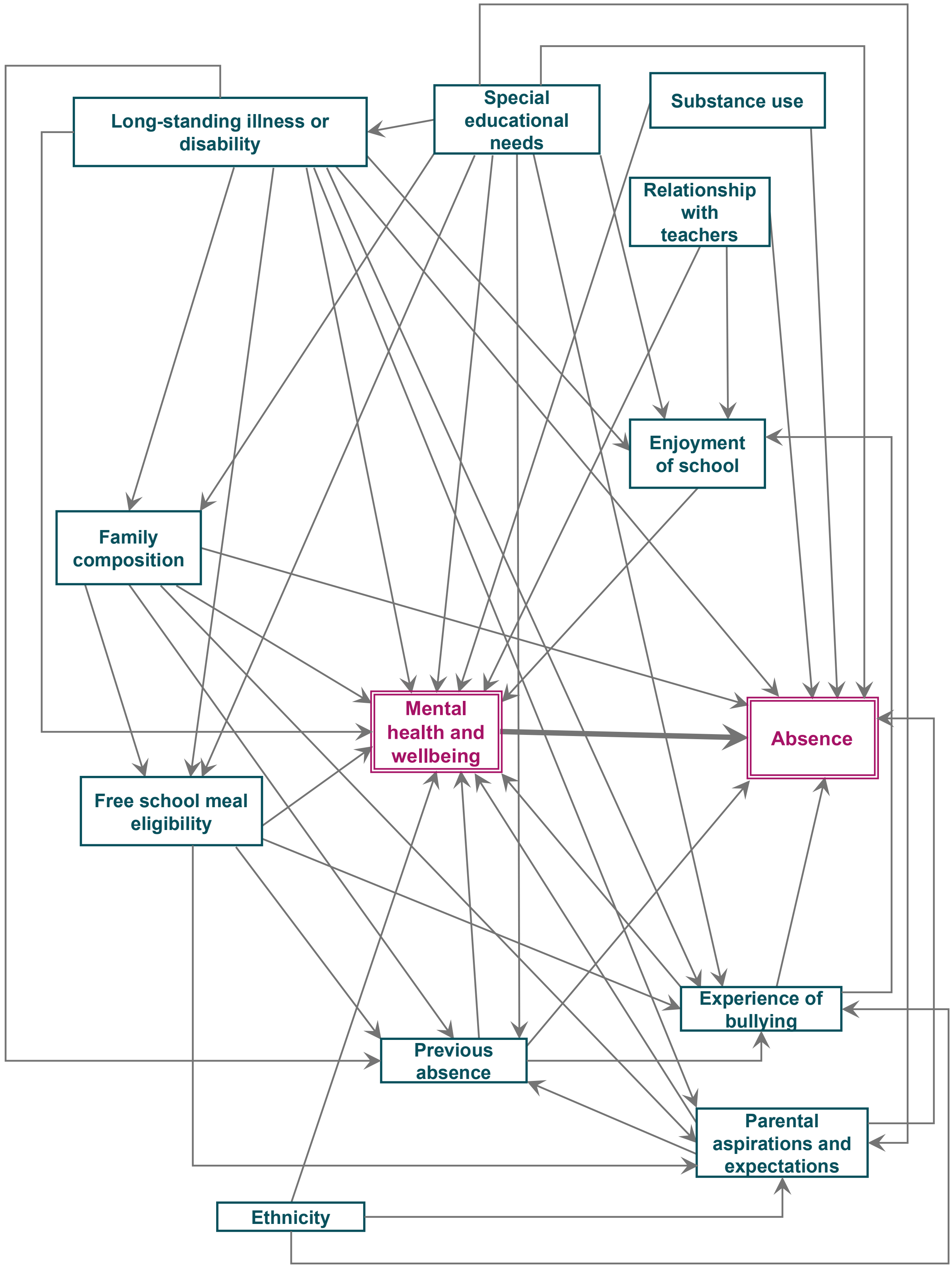
Throughout this report, where the term “mental health” is used, it is referring to the participant’s GHQ-12 score and refers to higher levels of psychological distress (e.g., poorer mental health equates to a higher GHQ-12 score). “Personal wellbeing” throughout this report refers to the ONS4 personal wellbeing measures, which measure subjective life satisfaction, happiness, anxiousness, and feelings of worthwhileness. Additional information relating to the derivation of the mental health and wellbeing measures, including the specific questions asked, can be found in Appendix A.

As mental health and personal wellbeing are measured at different waves (mental health at Wave 2, personal wellbeing at Wave 3), slightly different datasets are used depending on whether it is mental health or personal wellbeing that is included as a covariate. Information on this dataset construction can be found in Appendix C.

2.3.3 Covariates

As we are trying to establish whether there is a causal relationship between poor mental health/wellbeing and absence, causal methods were used to select covariates included in the analysis. In this case, a Directed Acyclic Graph (DAG) was used, which is a graphical representation of the relationship between various variables. The final DAG used for this analysis is shown in Figure 2.3. Mapping the hypothesised causal pathway between selected covariates helps us to identify which variables need to be included in the analysis and which variables may mask any causal relationship if they were to be included (Pearl 1995). More information about variable selection (including the construction of the full DAG) can be found in Appendix B.

Figure 2.3. Directed acyclic graph showing the minimally sufficient adjustment set required to estimate the effect of mental health and wellbeing on absence. Pink text with a double lined box indicated variables of interest; blue text with a solid lined box indicates adjusted for covariates.



3 Sample characteristics

As previously stated, two separate datasets are used depending on whether mental health or personal wellbeing is the exposure of interest. The mental health dataset comprised 7737 participants, and the personal wellbeing dataset 7374 participants. In the following sections, unless otherwise stated, the descriptives refer specifically to the mental health dataset, as it has a slightly larger sample size. However, full descriptive statistics for both datasets are presented in Appendix D Table 1, where it can be seen here that the sample characteristics do not differ between the datasets.

3.1 Mental health and personal wellbeing

In this sample of the LSYPE2 cohort, the mean GHQ-12 score was 1.89 (standard deviation [SD]: 0.03). Across the literature, different cut-offs have been proposed whereby a score greater than or equal to the cut-off would indicate that the participant has a probable mental illness. These cut-offs mainly range between 2 and 4 (Anjara et al. 2020); however, it has been suggested that the mean score for the overall population of respondents can be used as an approximation of the best threshold for indication of a probable mental illness in the sample (Goldberg et al. 1998). As the mean GHQ-12 score is 1.89, we can use a GHQ-12 score of 2 as a cut-off for probable mental illness, meaning 26% (n = 2006) of the participants could be considered to have a "high" GHQ-12 score, and therefore a probable mental illness (Figure 3.1).

The average wellbeing scores were 2.11 (SD: 1.81) for life satisfaction, 2.17 (SD: 1.95) for feelings of worthwhileness, 2.24 (SD: 2.15) for happiness, and 2.90 (SD: 3.05) for anxiousness. The ONS provides thresholds to interpret these values, which are

Figure 3.1. The distribution of GHQ-12 scores within LSYPE2. The black line represents the sample mean (1.89).

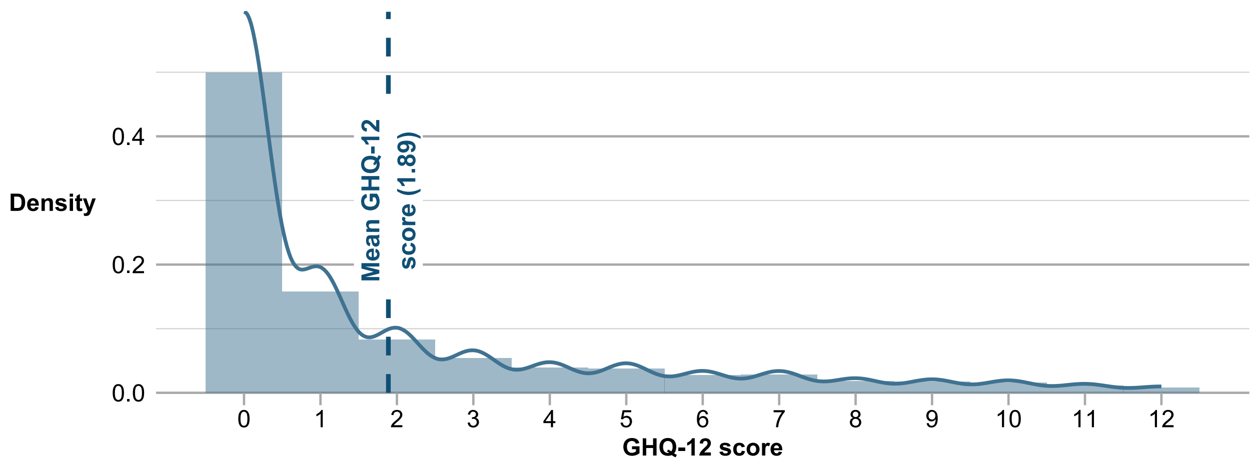
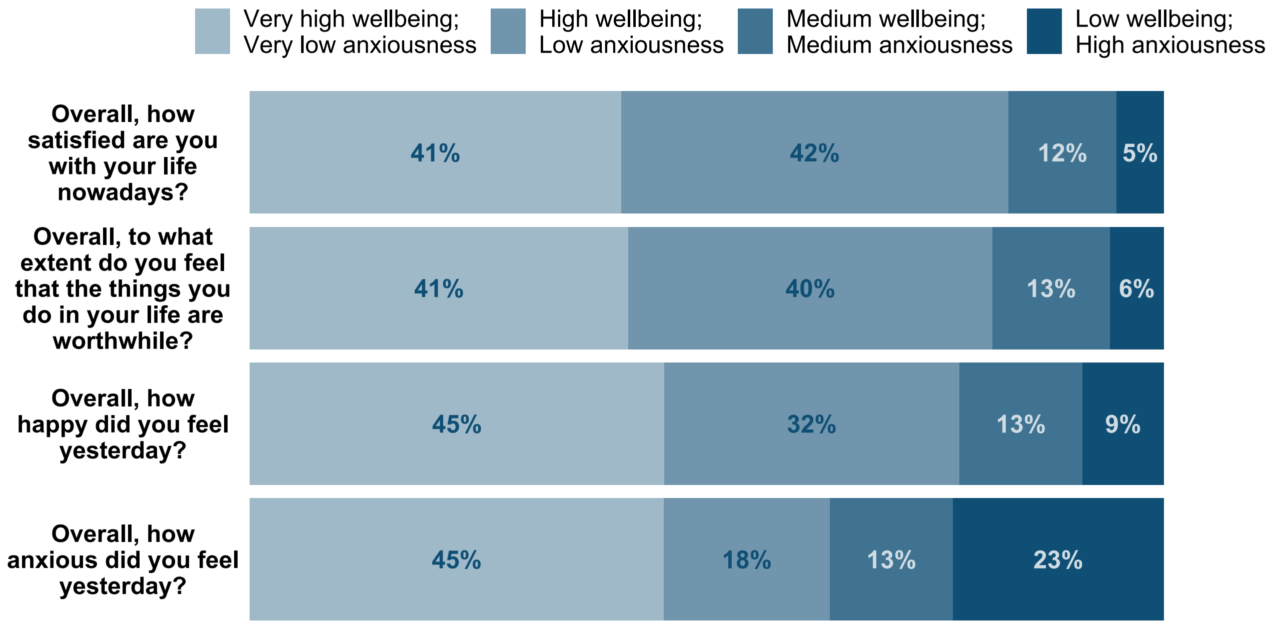


Table 3.1. Personal wellbeing thresholds

Response on an 11-point scale	Threshold for life satisfaction, feelings of worth, and happiness	Threshold for feelings of anxiety
0-1	Very high wellbeing	Very low levels of anxiousness
2-3	High wellbeing	Low levels of anxiousness
4-5	Medium wellbeing	Medium levels of anxiousness
6-10	Low wellbeing	High levels of anxiousness

Source: Adapted from the Office for National Statistics[2]

Figure 3.2. Percentage of participants in each personal wellbeing threshold.



presented in Table 3.1. Based on these thresholds, it can be seen that – on average – the LSYPE2 participants have high personal wellbeing and low levels of anxiousness.

The percentage of participants in each ONS4 threshold is shown in Figure 3.2. 9% (n = 655), 5% (n = 381), and 6% (n = 435) of the sample had low levels of happiness, life satisfaction, and feelings of being worthwhile, respectively, while 23% (n = 1702) had high levels of anxiousness. However, almost half of all participants were considered to have high wellbeing (life satisfaction: 41%, n = 2998; worthwhile: 41%, n = 3054; happy: 45%, n = 3344) and low levels of anxiousness (45%, n = 3338).

[2] The wellbeing measures have been reversed from the original ONS4 scale (see Appendix A). Anxiousness remains the same as the original measure.

3.2 Absence

Across the absence variables, there was a downward trend in those who were over the binary absence threshold in Year 11 as the threshold became larger. Around three-quarters of students (77%, n = 5980) missed at least 1% of possible sessions, half missed 3% (52%, n = 4047), and a third missed 5% (34%, n = 2668).

Over the years, the Department for Education's methods of classifying persistently absent students have changed. The current definition is 10% or more sessions, and therefore, within this sample, 12% (n = 963) can be classified as persistently absent. This figure is similar to the national statistics for persistent absence in 2014/15, where the absence rate for secondary schools was 13.8% (Figure 1.1), suggesting LSYPE2 is representative of England in terms of absence rates. Prior to 2015/16, students were considered persistently absent if they missed 15% of possible sessions or more. In this sample, 6% (n = 425) of students fit this criterion. Very few students missed 20% of sessions (3%, n = 235), and less than 1% (n = 36) of students were severely absent, meaning they missed 50% of all possible sessions (Figure 3.3). Again, this figure is in line with national statistics, in which 0.9% of secondary school students were severely absent in 2014/15.

A large amount of the overall absence rates appears to be explained by authorised absences (Figure 3.3). At the 5% threshold, 28% (n = 2168) of students were absent for authorised reasons, while only 6% (n = 436) were absent for unauthorised reasons, suggesting that many students are missing school for sanctioned reasons, e.g., sickness.

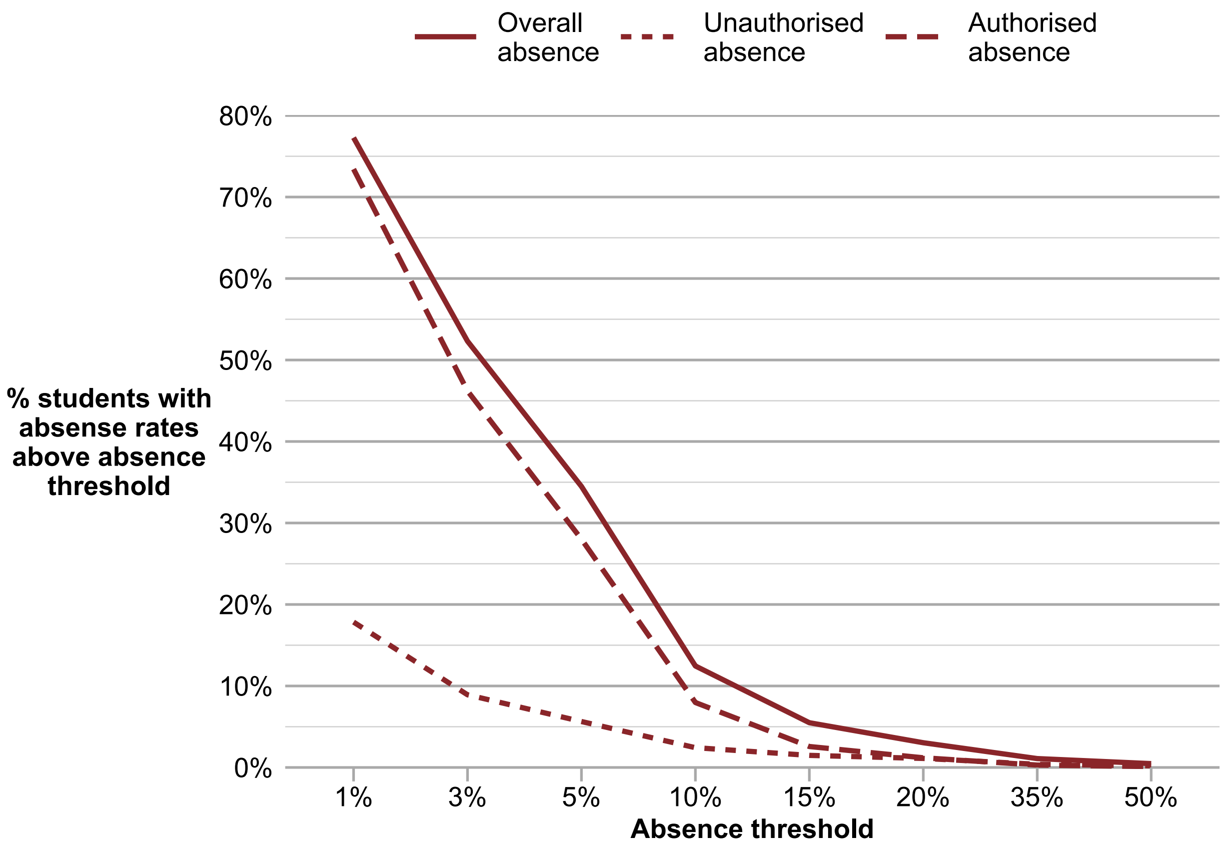
3.3 Covariates

Most of the sample was white (81%, n = 6286) and did not have a long-standing illness or disability (LSID) (85%, n = 6607) or SEN (92%, n = 7127). Just over two-thirds of participants lived in a two-parent household (62%, n = 4785), and a quarter lived with just one biological parent in a single-parent household (28%, n = 2176). The remaining participants either lived as part of a stepfamily (9%, n = 711) or with neither biological parent (1%, n = 65). Most of the participants had never been eligible for FSM (70%, n = 5418) and had never tried cannabis (97%, n = 7471).

The majority of the cohorts' parents hoped that their child would carry on in full-time education when they leave Year 11 (87%, n = 6727), with only 9% (n = 687) hoping their child would do an apprenticeship and 4% (n = 286) wanting their child to start work with some education or training. A further 0.5% (n = 37) wished for their child to do something else (e.g., start a family).

Many students had what could be considered a positive school experience, with the average school enjoyment score being 3.15 out of 4 (SD: 0.44). Very few students stated

Figure 3.3. Perentage of students with absence rates greater than the absence thresholds at age 15/16, stratified by absence type.



that they did not like any of their teachers (1%, n = 63) or hardly any of their teachers (9%, n = 670). The most common responses were that students liked most of (45%, n = 3506) or some of (39%, n = 2981) their teachers, and 7% (n = 516) of the sample liked all of their teachers. Around a third of the sample (36%, n = 2822) also stated that they had been bullied.

Full descriptive statistics can be found in Appendix D Table 1.

4 Patterns of mental health and attendance

4.1 Variation in mental health and wellbeing by absence thresholds

4.1.1 Mental health

Across all absence thresholds and all absence types, those who were classified as absent had poorer mental health, with students who fit within the absence threshold consistently having a GHQ-12 score over the sample.

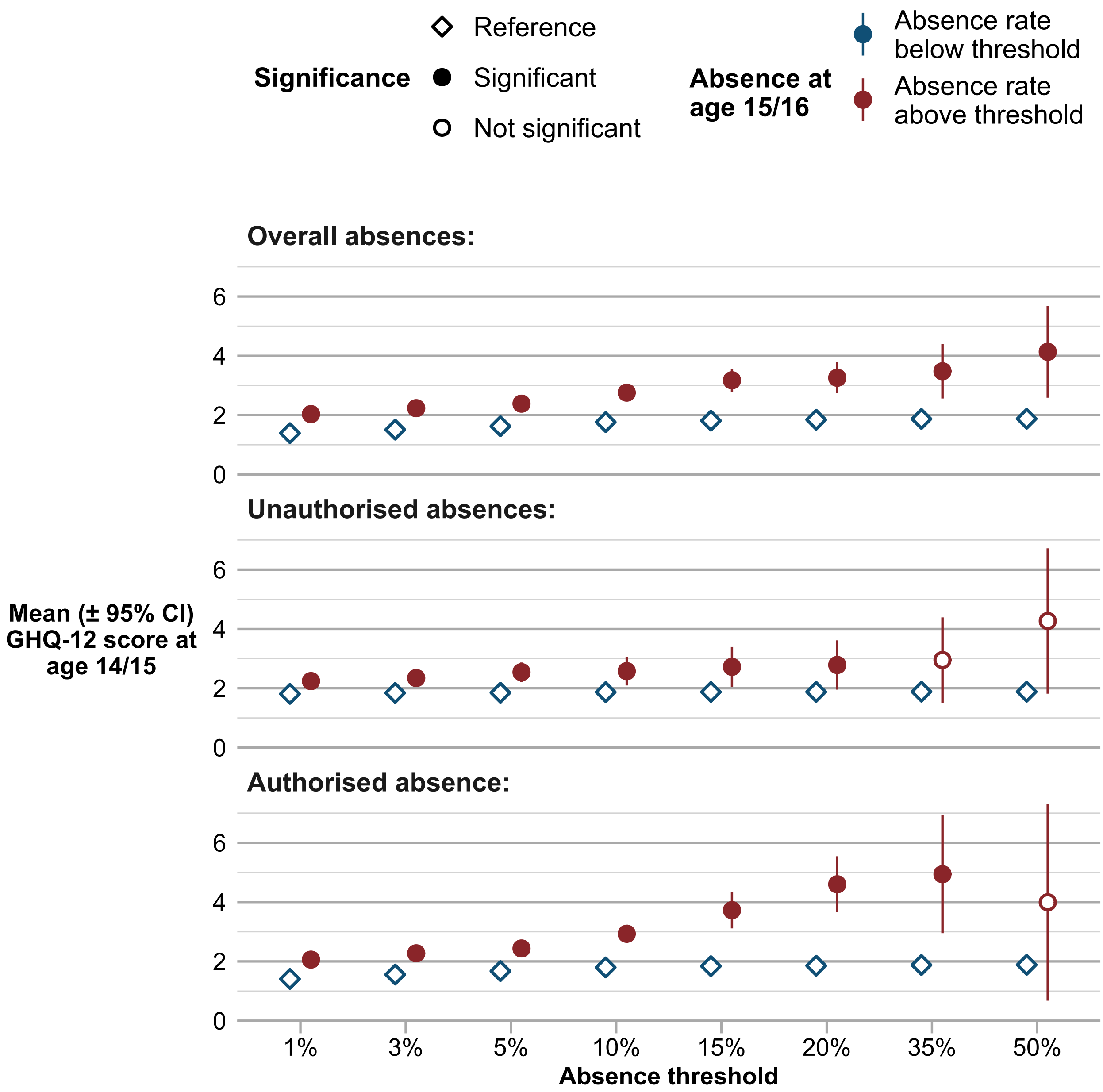
As presented visually in Figure 4.1. The relationship between mental health and absence was most pronounced when looking at authorised absences. Students who had missed 10% of sessions for authorised reasons had an average GHQ-12 score of 2.93 (SD: 3.70; n = 617), while students with the same absence patterns for unauthorised reasons had an average GHQ-12 score of 2.58 (SD: 3.35; n = 188). However, the differences in mental health between absent students become wider as the absence threshold becomes larger. When looking at the 15% absence threshold, students who missed these sessions for authorised reasons (n = 199) had a mean GHQ-12 score 1 point higher than those who had missed the sessions for unauthorised reasons (n = 115), and this difference increased to 2 points when the absence threshold shifted to missing 35% of possible sessions.

4.1.2 Personal wellbeing

A similar relationship is seen between personal wellbeing and absence.

Those who were less satisfied with their lives were more likely to be absent, with those missing a larger percentage of sessions having significantly worse life satisfaction than those who missed fewer sessions (Figure 4. 2). Like with the GHQ-12 score, this relationship appears to be driven by authorised absences. Though those who were absent for unauthorised reasons did have worse life satisfaction than those who were not absent, the difference in life satisfaction was relatively small. For example, at the 15% threshold, those who were not absent for unauthorised reasons had a life satisfaction score of 2.11 (SD: 1.81), and those who were absent only had a life satisfaction score that was 0.57 points worse. However, when looking at the same threshold in authorised absence, there is a whole point difference in life satisfaction between those whose absence rates were greater than the threshold and those whose were not (3.07 vs. 2.09). The difference in life satisfaction relative to absence status was most marked in the larger thresholds. Those who missed 35% of sessions for authorised reasons had a life satisfaction score of 3.72 (SD: 2.64), which is 1.61 points worse than

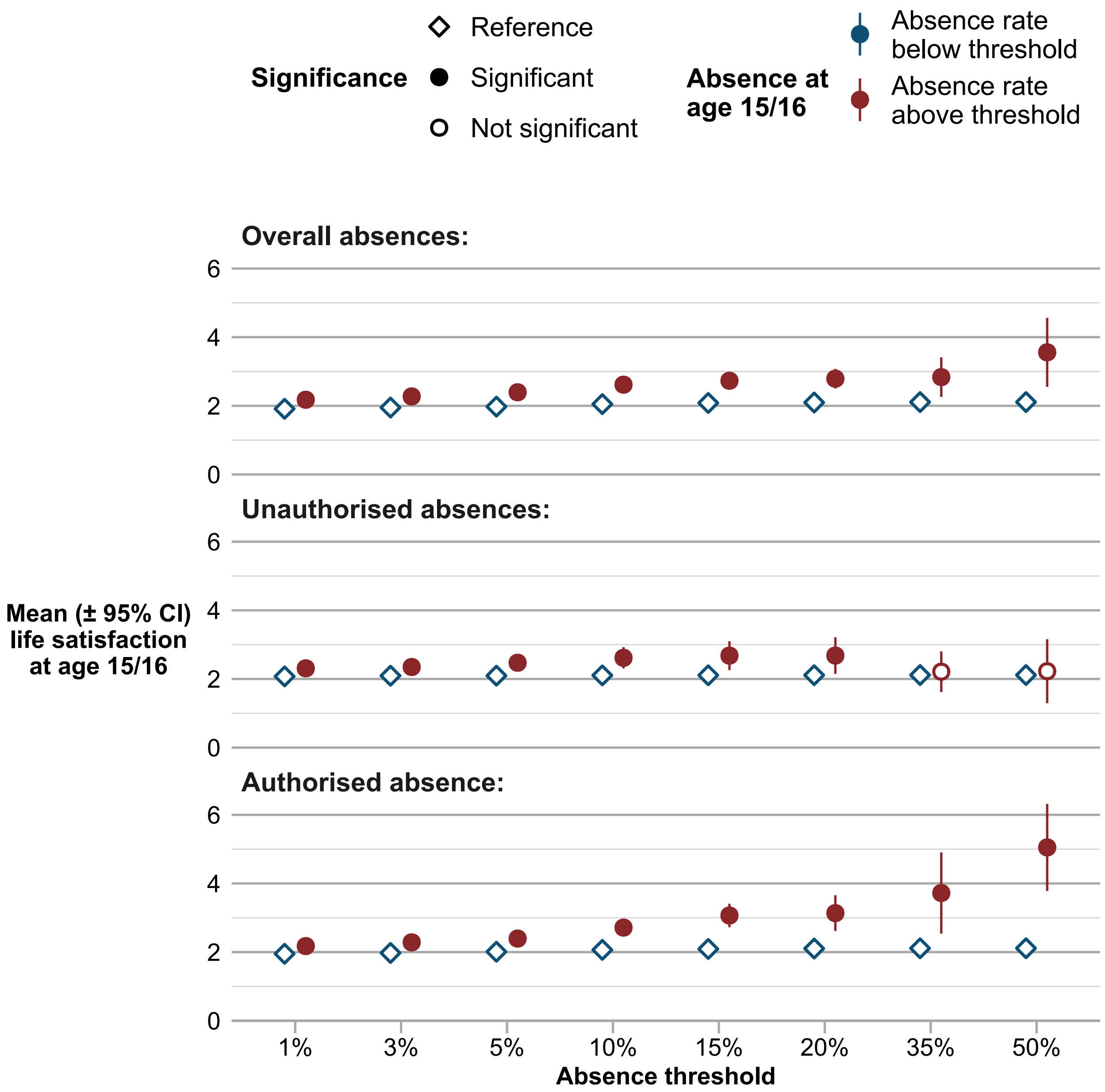
Figure 4.1. Mean GHQ-12 score and 95% confidence interval, by type of absence and absence threshold.



students who were not absent. The difference was widest at the 50% threshold, where the life satisfaction of students who were severely absent was over two times worse than that of non-severely absent students (5.05, SD: 2.08 vs. 2.11, SD: 1.81).

Feelings of worth, happiness, and anxiousness (Figure 4.3) have a similar pattern to life satisfaction. There is a general trend in which students who miss more sessions have worse wellbeing, with the difference in wellbeing more pronounced in the higher thresholds and in authorised absences. In most cases, those who are missing

Figure 4.2. Mean life satisfaction rating and 95% confidence interval, by type of absence and absence threshold

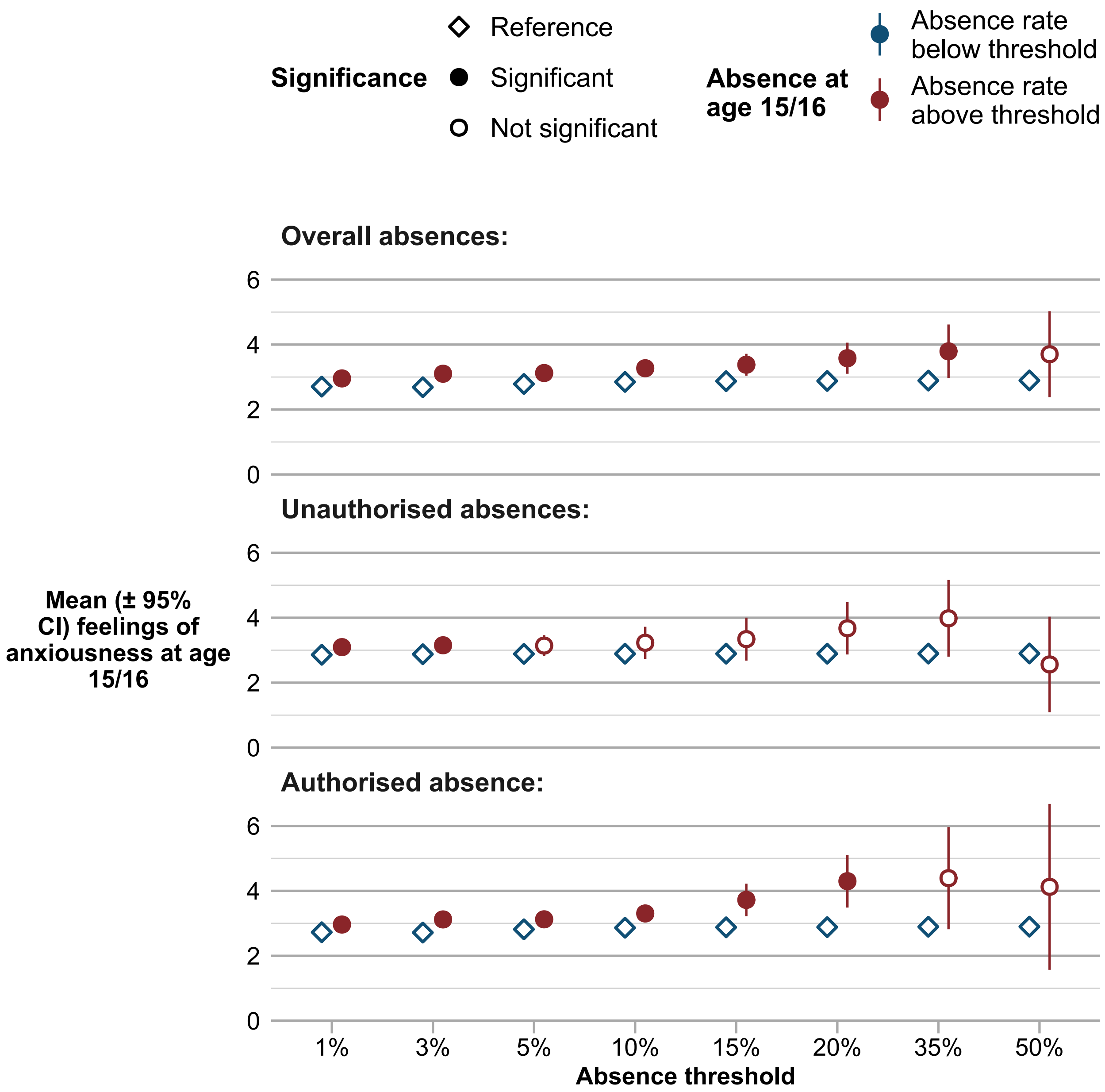


school for unauthorised reasons do not have lower scores for the wellbeing measures, particularly in the higher thresholds.

4.1.3 Summary

This analysis highlights that – without taking other factors into account – mental health/wellbeing and absence are associated. The differences in mental health and wellbeing are most notable at higher absence thresholds (e.g., missing more than 15% of

Figure 4.3. Mean feelings of anxiousness and 95% confidence interval, by type of absence and absence threshold.



sessions), where students who were classified as absent had significantly poorer mental health and personal wellbeing.

The differences in mental health and wellbeing are particularly pronounced when looking at authorised absences. This suggests that authorised absences may drive higher mental health-related absences in schools, rather than poor mental health leading to an increase in unauthorised school absences. For many of the thresholds, though students who are absent for unauthorised reasons do tend to have poorer mental health, the differences are not statistically significant. In contrast, there is a clear linear the relationship between the amount of school missed for authorised reasons and poorer mental health and personal wellbeing.

4.2 Variation in mental health and wellbeing by sociodemographic factors

4.2.1 Mental health

Within the ethnic groups, those classified as being in an "other" ethnic group had the highest GHQ-12 score on average (2.04, SD: 0.3), indicating poorer mental health. This was followed by white (1.92, SD: 0.04) and mixed (1.92, SD: 0.16) ethnicities. In contrast, Asian (1.64, SD: 0.11) and black (1.66, SD: 0.11) students had the lowest average GHQ-12 scores. However, the difference from white students was only significant in black and Asian students (Figure 4.4).

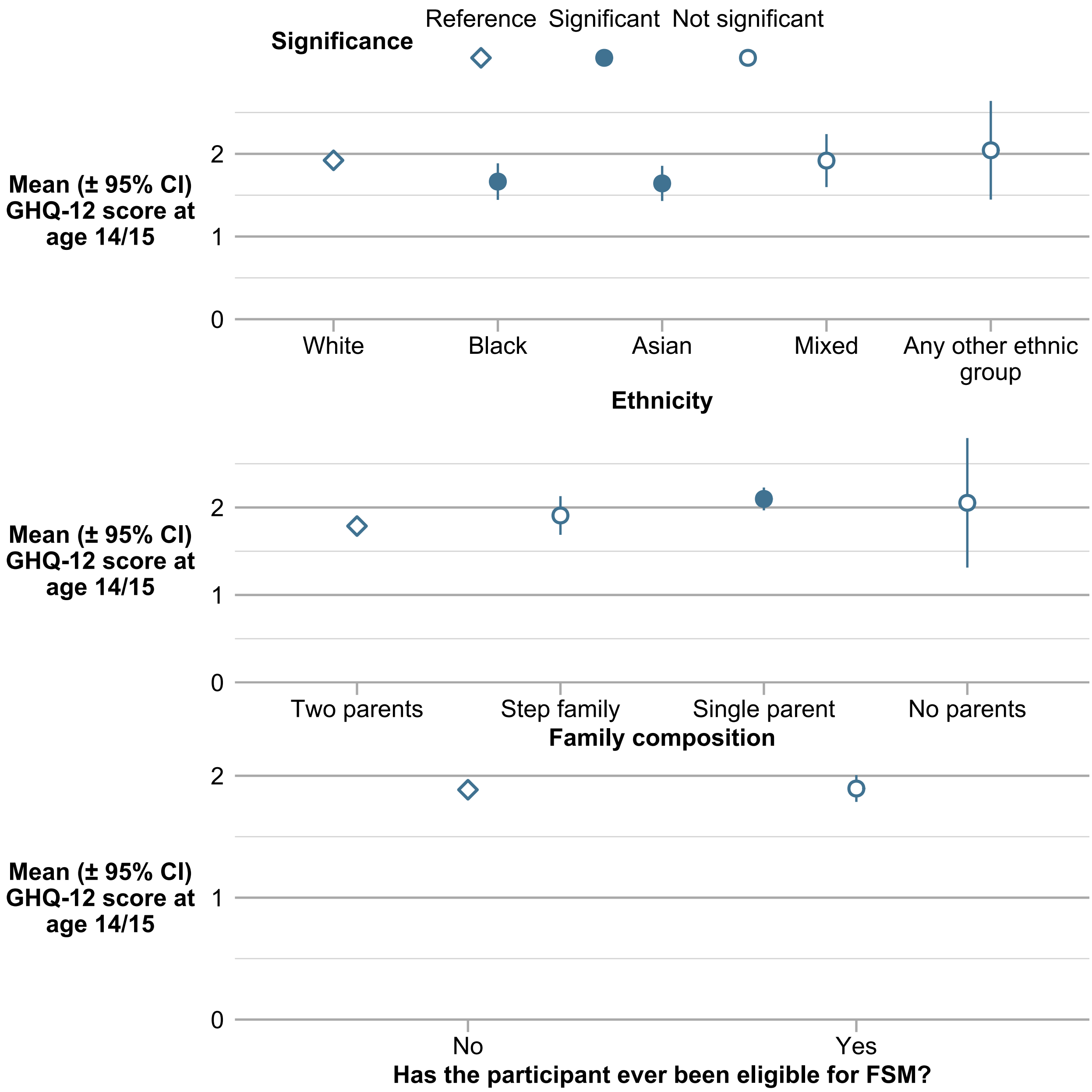
There was minimal difference in mental health between pupils with SEN (1.78, SD: 0.11) or a LSID (1.95, SD: 0.09) compared to those who did not have these classifications (pupils without SEN = 1.90, SD: 0.04; pupils without a LSID = 1.88, SD: 0.04). Similarly, no significant difference was found in mental health between students who had ever been eligible for FSM (1.90, SD: 0.06) and those who had not (1.89, SD: 0.04).

As can be seen in Figure 4.4, household composition was somewhat related to mental health. Students who lived with a single parent had a significantly higher GHQ-12 score (2.1, SD: 0.07) when compared with those who lived in a two-parent household, who had the lowest GHQ-12 score (1.79, SD: 0.04). Students who lived as part of a step-family and students who lived with neither biological parent also had slightly worse mental health than those living as part of a two-parent household. However, this difference was insignificant.

There was no significant difference in mental health depending on FSM eligibility. The average GHQ-12 score of those who have been eligible for FSM was 1.90 (SD: 0.06), which is only 0.01 point higher than those who have never been eligible for FSM (1.89, SD: 0.04) (Figure 4.4).

A significant difference in mental health was observed in relation to experiences of bullying and cannabis usage (Figure 4.5). Students who used cannabis had a GHQ-12 score of 3.71 (SD: 0.25), which was approximately double that of those who did not use cannabis (1.82, SD: 0.03). Further, students who had been bullied had a GHQ-12 score of 3.24 (SD: 0.07), almost three times that of students who had not been bullied (1.11, SD: 0.03).

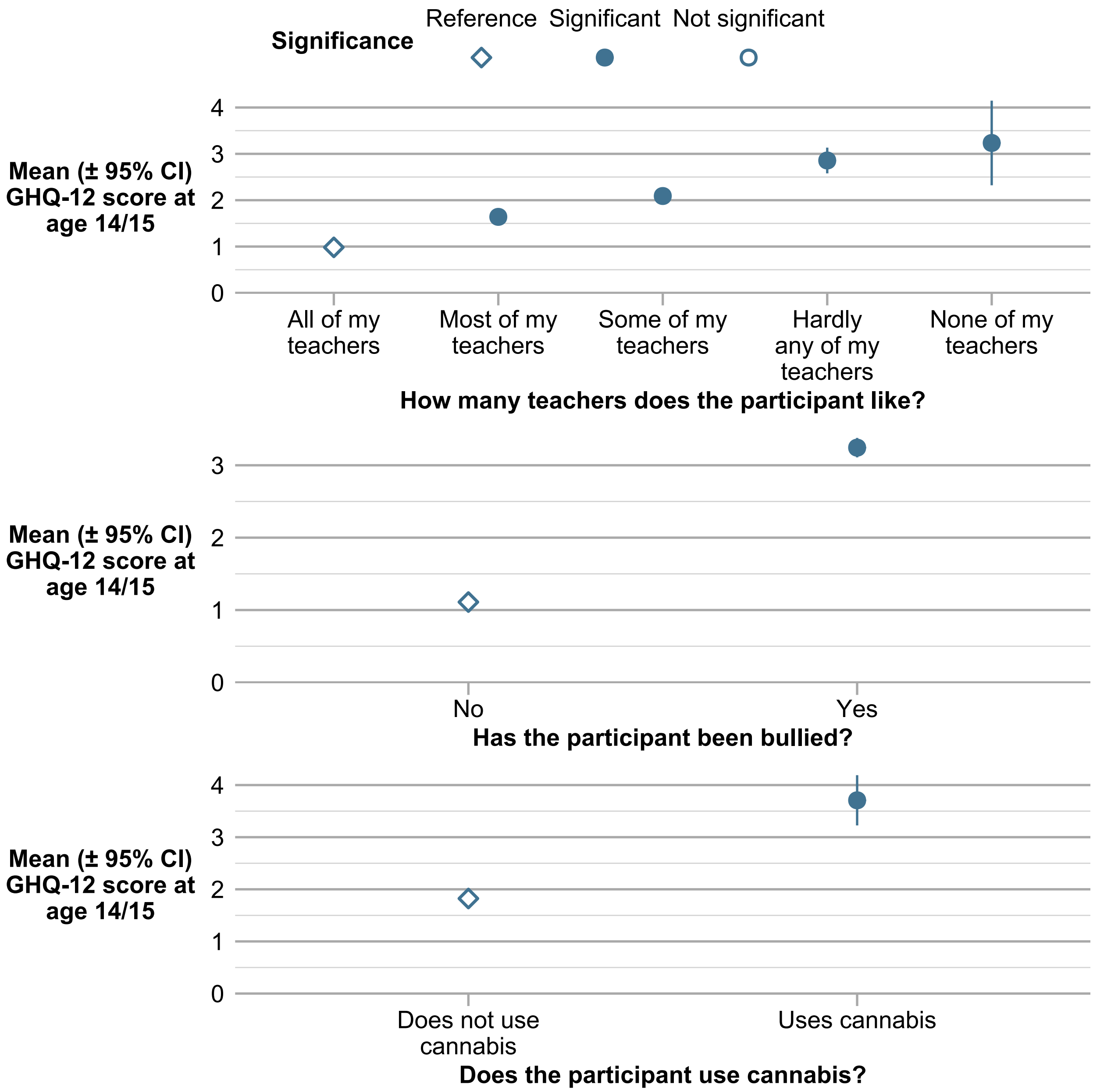
Figure 4.4. Average GHQ-12 score and 95% confidence interval by ethnicity, family composition, and free school meal (FSM) eligibility.



As presented in Figure 4.5, There was a near-linear relationship between the number of teachers a student liked and their mental health. Students who liked all their teachers had a very low GHQ-12 score, averaging 0.98 (SD: 0.09). As the number of liked teachers decreased, the GHQ-12 score increased by an average of 0.56 per level of the Likert item, reaching an average GHQ-12 score of 3.23 (SD: 0.47) in students who did not like any of their teachers. There was also a relationship between school enjoyment and GHQ-12, in which students who enjoyed school more reported a lower GHQ-12 score ($r = -0.28$, $p < 0.001$). However, the correlation between the two variables is weak.

There was little difference in GHQ-12 score based on parental aspirations. Students whose parents wished for them to continue in full-time education had the highest GHQ-12 score (1.95, SD: 0.04), with the best mental health being found in young people whose parents wanted them to do an apprenticeship. However, this group's mental health was only half a point lower than those in the group with the worst mental health (1.42, SD: 0.10).

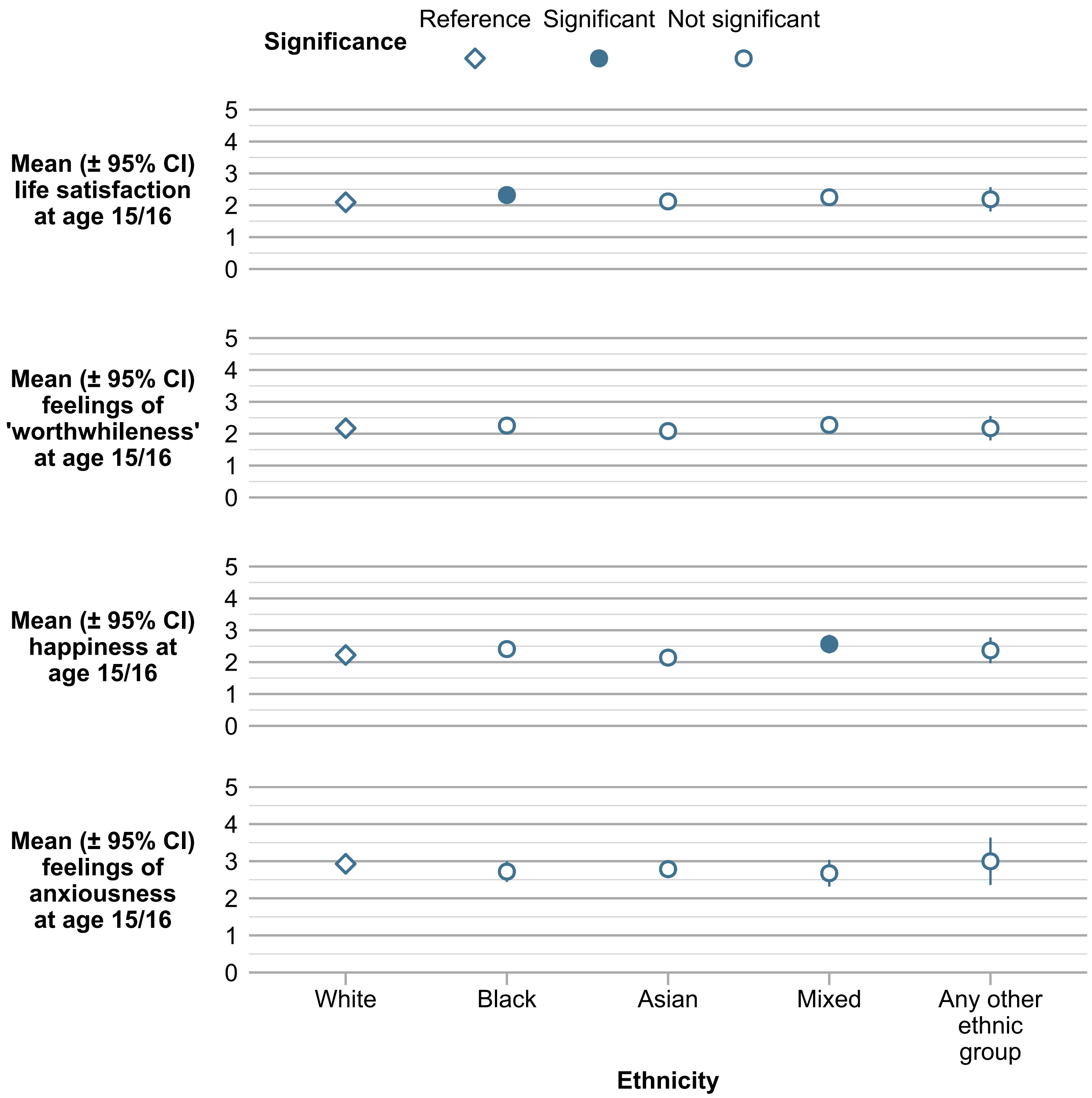
Figure 4.5. Average GHQ-12 score and 95% confidence interval by how many teachers the participant likes, whether the participant has been bullied, and whether the participant has used cannabis.



4.2.2 Personal wellbeing[3]

Almost all observed relationships between wellbeing measures and ethnicity were statistically insignificant (Figure 4.6). Similarly, there was no significant difference in

Figure 4.6. Average personal wellbeing measures and 95% confidence intervals by ethnicity.



[3] Across all wellbeing measures, a higher score indicates poorer personal wellbeing despite it not necessarily being semantically intuitive. For instance, a higher score in life satisfaction, feeling worthwhile, and happiness would indicate that the participant has a poorer score and therefore feels less satisfied, less worthwhile, and more unhappy.

mental wellbeing based on whether students had SEN or a LSID. Students with SEN or a LSID generally had slightly higher scores across most measures, suggesting poorer mental health, but these differences were extremely small and statistically insignificant. The only exception was anxiety, where students without SEN reported slightly higher levels (2.92, SD: 0.04) than those with SEN (2.73, SD: 0.11).

Looking at family composition, it can be seen that pupils from a two-parent household had the best personal wellbeing (Figure 4.7). Pupils who either lived with one or no biological parents had the poorest levels of life satisfaction (single parent = 2.31, SD = 0.04; no parents = 2.32, SD: 0.29). Pupils who lived with neither biological parent were also less happy than other family compositions (2.75, SD: 0.3; two-parent household: 2.08, SD: 0.03). Finally, all household compositions that did not include two biological parents had higher levels of feeling anxious, but this was only a difference of ~0.1 point.

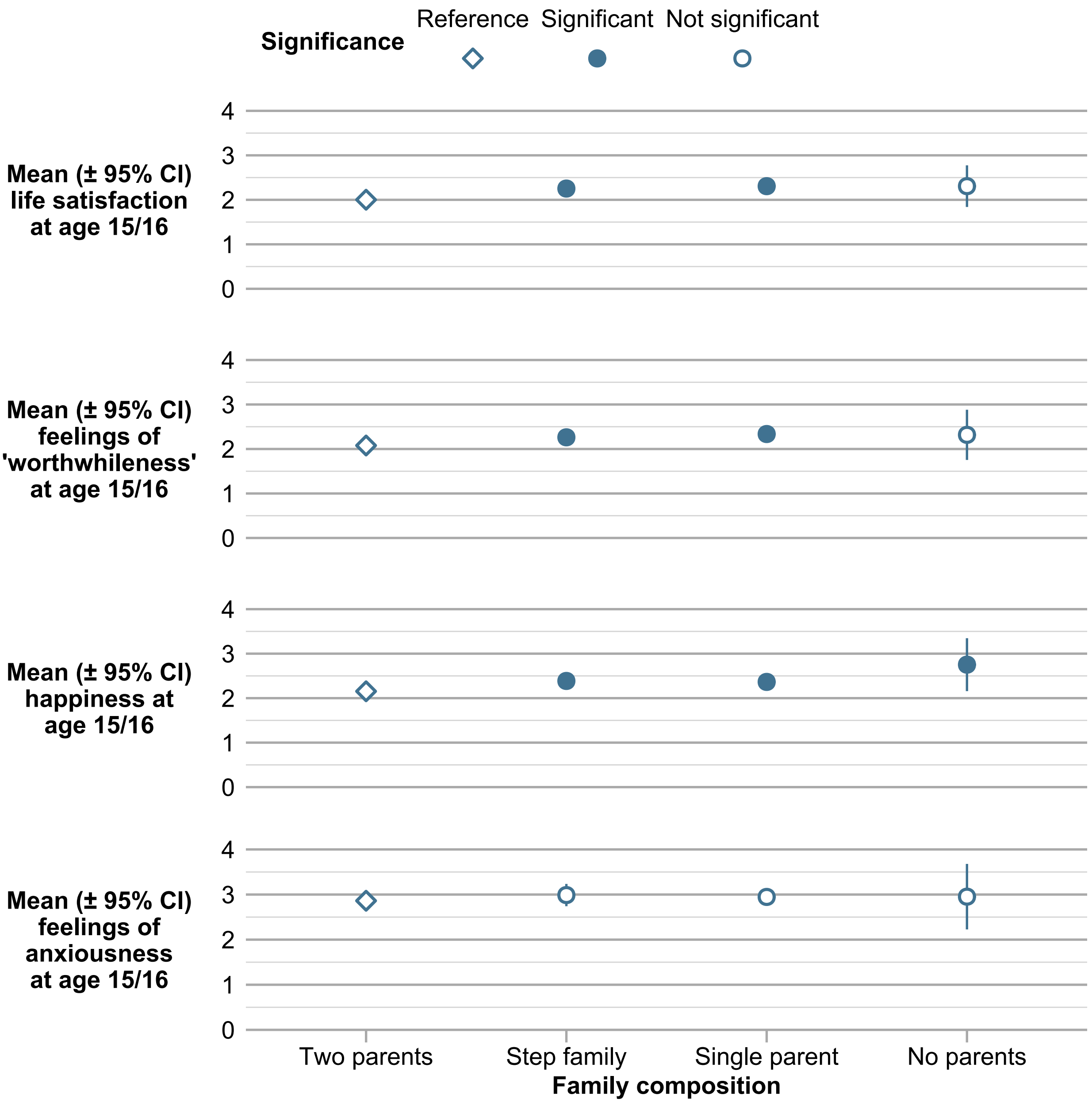
There were minimal differences in wellbeing between those eligible for FSM and those not. Students who were never eligible for FSM had slightly better life satisfaction (2.1, SD: 0.03), happiness (2.23, SD: 0.03), and feelings of worthwhileness (2.16, SD: 0.03) compared to those who were eligible (satisfaction = 2.16, SD: 0.04; happiness = 2.28, SD: 0.05; worthwhile = 2.21, SD: 0.04). Feelings of anxiety were slightly higher in students who were never eligible for FSM (2.94, SD: 0.05) compared to those eligible (2.8, SD: 0.06).

Cannabis usage had an impact on wellbeing measures. Students who used cannabis had poorer life satisfaction (2.85, SD: 0.1), feelings of worthwhileness (3.01, SD: 0.11), happiness (2.94, SD: 0.12), and higher levels of anxiousness (3.28, SD: 0.14) compared to non-users (satisfaction = 2.06, SD: 0.02; feeling worthwhile = 2.16, SD: 0.03; happiness = 2.19, SD: 0.03; anxiousness = 2.87, SD: 0.04).

There was not a significant relationship between parental aspirations and personal wellbeing, except when comparing the wellbeing of students whose parents wanted them to carry on into full-time education compared with students whose parents wanted them to do an apprenticeship. Here, across life satisfaction, happiness, and feelings of anxiety, the apprenticeship category had significantly more positive personal wellbeing than the full-time education group. There was not a significant relationship seen in the other categories.

Like with mental health, there is a clear linear relationship between the number of teachers a student likes and their personal wellbeing (Figure 4.8). Students who liked all of their teachers had the lowest feelings of anxiety (2.1, SD: 0.12) and most positive levels of life satisfaction (1.39, SD: 0.07), happiness (1.49, SD: 0.08), and feelings of worthwhileness (1.44, SD: 0.07). Across all the measures, the personal wellbeing of the students who did not like any of their teachers was approximately two times worse, with

Figure 4.7. Average personal wellbeing measures and 95% confidence intervals by family composition.

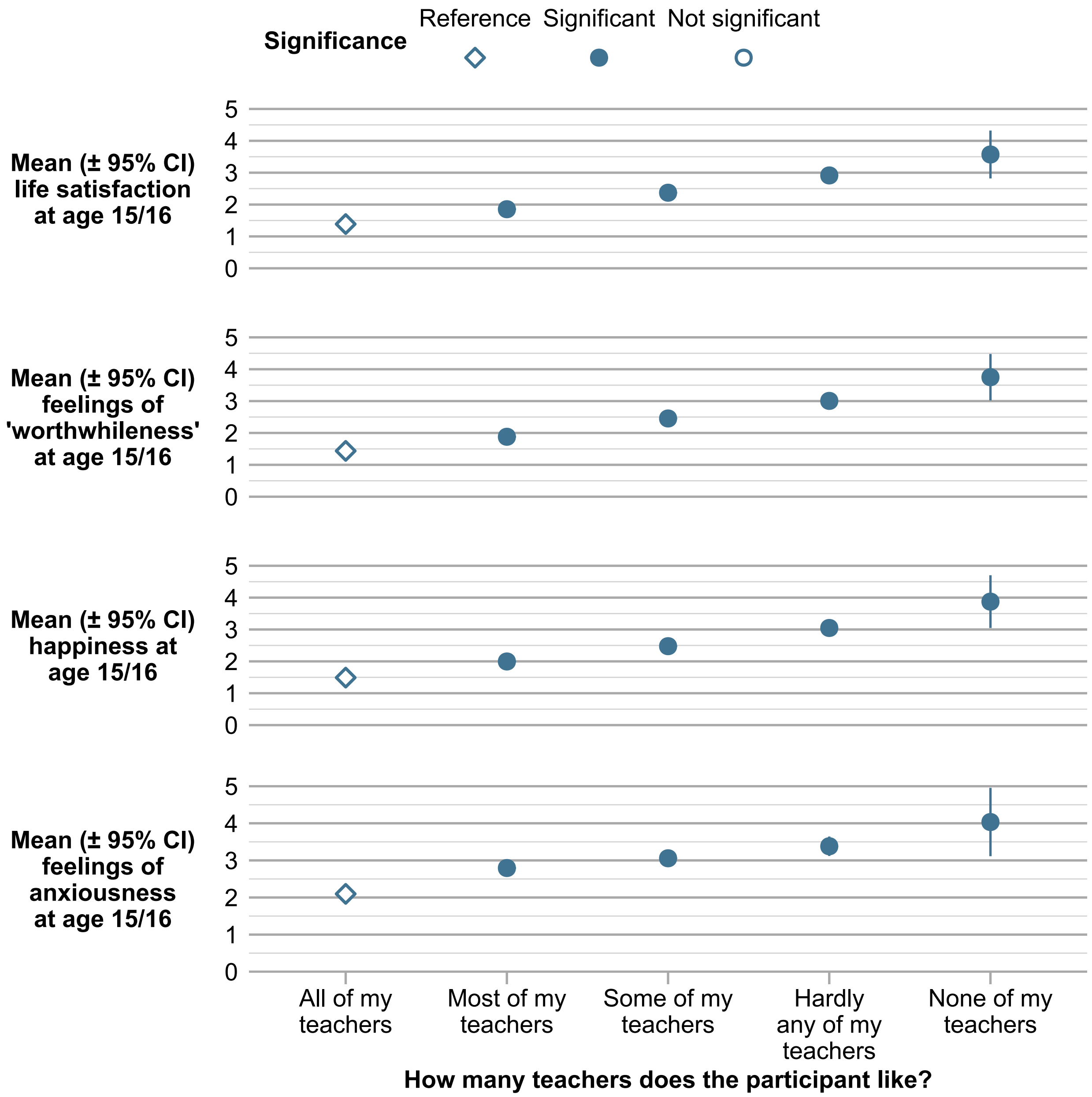


each additional level in the Likert item, resulting in the student's personal wellbeing becoming 0.5 points poorer (on average).

There was also a negative correlation between school enjoyment and the wellbeing measures, suggesting that those who enjoyed school more had better wellbeing. However, all the correlation coefficients were weak (life satisfaction: -0.35, worthwhile: -0.38, happiness: -0.28, anxiousness: -0.12), which suggests the relationship is not very strong.

Experiences of bullying significantly affected wellbeing. Students who had been bullied had much lower life satisfaction (2.85, SD: 0.05), felt things in their life were less worthwhile (3.04, SD: 0.06), were unhappier (3.04, SD: 0.06), and had higher feelings of anxiety (3.83, SD: 0.07) compared to those who had not been bullied (satisfaction: 1.81, SD: 0.02; feeling worthwhile: 1.88, SD: 0.03; happiness: 1.9, SD: 0.03; anxiousness: 2.51, SD: 0.04), indicating poorer mental health among bullied students.

Figure 4.8. Average personal wellbeing measures and 95% confidence intervals by how many teachers the student likes.



4.2.3 Summary

Across all measures of mental health and wellbeing, liking one's teachers, not experiencing bullying, abstaining from cannabis, and generally enjoying school were strong predictors of better mental health and wellbeing. These findings suggest that positive social environments and a sense of safety and satisfaction within the school setting are contributing to students' mental health and wellbeing. Liking teachers may indicate positive student-teacher relationships, which can foster a supportive learning environment and enhance students' enjoyment of school. Similarly, the absence of bullying likely contributes to a feeling of safety, reducing stress and feelings of anxiety, while abstaining from cannabis use may prevent the onset of substance-related mental health issues.

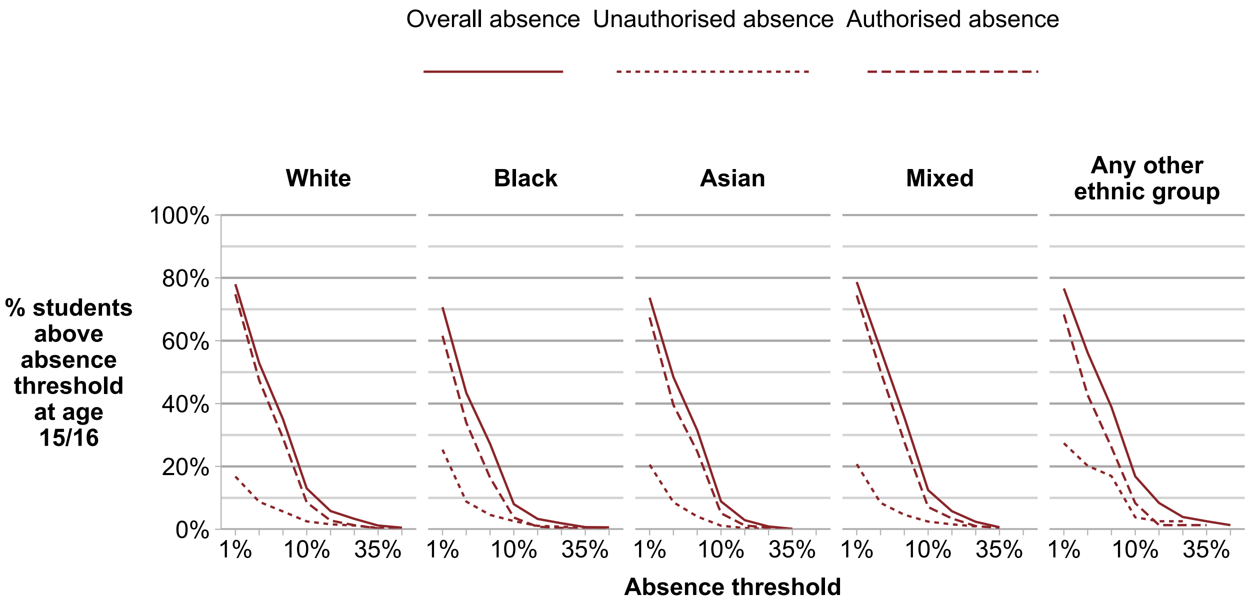
When looking at parental aspirations, a general trend emerged across the measures: students whose parents wanted them to pursue apprenticeships tended to have better mental health and wellbeing, whereas those whose parents encouraged them to continue into full-time education tended to have poorer mental health and wellbeing outcomes. This pattern could reflect differing levels of pressure. If the students are carrying on in higher education as a result of their parent's wishes, then there may be higher academic pressure – particularly when approaching their KS4 assessments – potentially contributing to stress and lower wellbeing. On the other hand, if their parents aspire for them to do an apprenticeship, then there may be less academic pressure as the grade requirements are typically lower for apprenticeships than entrance to sixth form and universities.

Students from two-parent households also had better mental health and wellbeing than those from other household compositions. The relatively worse outcomes observed among students living with a stepparent, a single parent, or neither biological parent could be attributed to various factors, such as economic instability or the challenges of adjusting to family transitions. For example, it has been observed that children of divorced parents fare worse than children living in biological nuclear families across multiple wellbeing indicators (Amato 2001).

4.3 Variation in absence by sociodemographic factors

There is not a large amount of difference in overall absence rates between the ethnic groups (Figure 4.9). At the 1% threshold, the difference between the highest rate of absence (mixed ethnicity: 79%, n = 253) and the lowest (black: 71%, n = 254) is just eight percentage points, with similarly small variations across the absence thresholds. This suggests a general consistency in absence rates across ethnicities. However, slight differences appear when looking at authorised vs. unauthorised absence. At the 1% threshold, 17% (n = 1056) of white students are absent for unauthorised reasons,

Figure 4.9. Percentage of students with absence rates above the binary absence threshold at age 15/16, stratified by absence type and ethnicity.

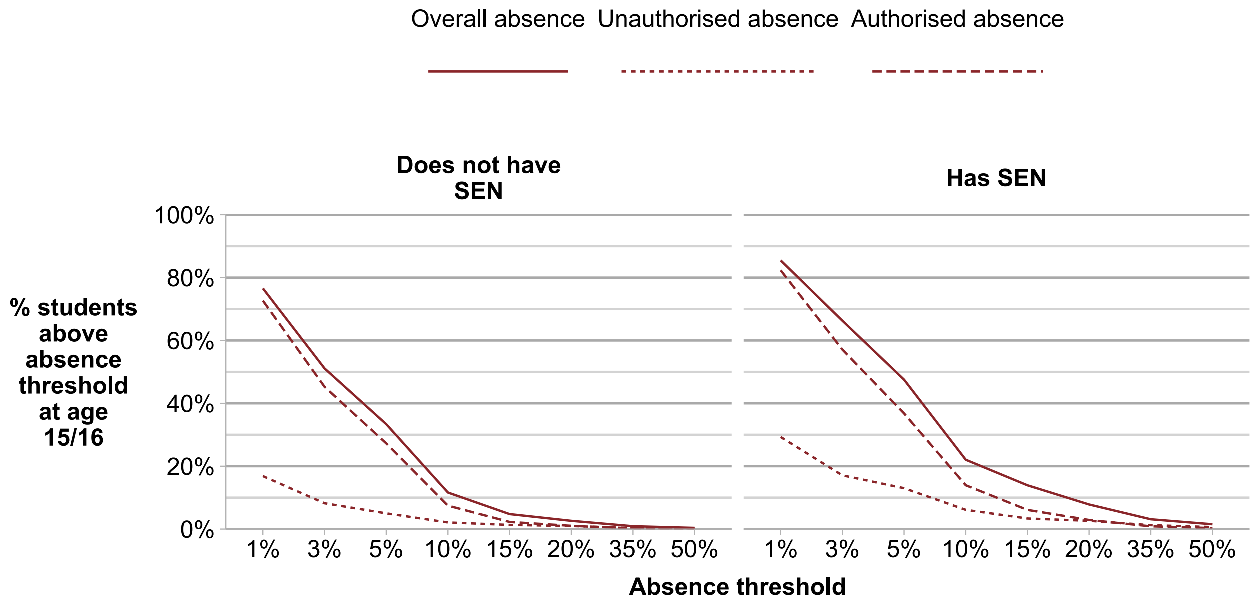


whereas other ethnic groups have rates that range from 21% to 27%. This highlights that unauthorised absences may be a more prevalent issue in these groups. In contrast, when considering authorised absences at the 1% threshold, 75% (n = 4700) of white students are classified as absent, compared to only 62% (n = 222) of black students. This indicates that for white students, authorised absences are a more significant contributor to their overall absence rates compared to their peers from other ethnic groups.

Students with a disability or SEN were more likely to be absent across all of the absence thresholds. 45% (n = 512) of students with a LSID missed at least 5% of sessions, compared to 33% (n = 2157) of students without a LSID. However, as the absence threshold narrowed, the differences between students with a LSID and those without became less stark. There was a 6-percentage point difference when looking at the 10% threshold (has a LSID: 18%, n = 201; does not have a LSID: 12%, n = 763), but only a 2-percentage point difference in the proportion of students who missed 20% of sessions (has a LSID: 5%, n = 60; does not have a LSID: 3%, n = 175). This suggests that having a LSID may be driving low levels of school absence but that there is little difference once absence levels become high. A very similar pattern is seen when looking at the student's SEN status (Figure 4.10).

Across all absence thresholds, students from two-parent households were least likely to fall into the 'absent' category (Figure 4.11). Three-quarters (n = 3569) of students from two-parent households missed at least 1% of sessions, compared to 79% (n = 563) of students from stepfamilies and 83% (n = 1801) of students from single-parent households. A low percentage of students who lived with neither biological parent missed

Figure 4.10. Percentage of students with absence rates above the absence threshold at age 15/16, stratified by absence type and SEN status.



1% of sessions (71%, n = 46) however, their representation in the narrower absence thresholds became larger, with 27% (n = 17) missing at least 10% of sessions (compared to 10% of students who lived with both parents, 13% of students who lived in a step-family, and 18% who lived with a single parent), and 1.2% being severely absent (compared to <1% of students who lived with both parents, one parent, or as part of a step-family). This appears to be driven by comparatively higher rates of authorised

Figure 4.11. Percentage of students with absence rates above the absence threshold at age 15/16, stratified by absence type and family composition.

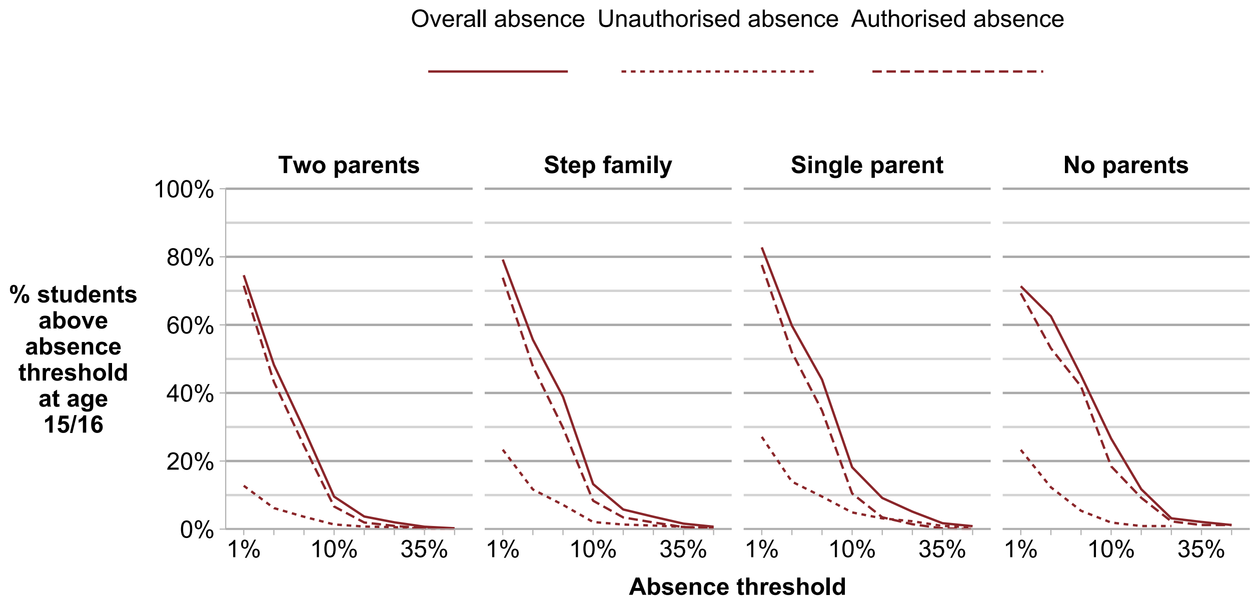
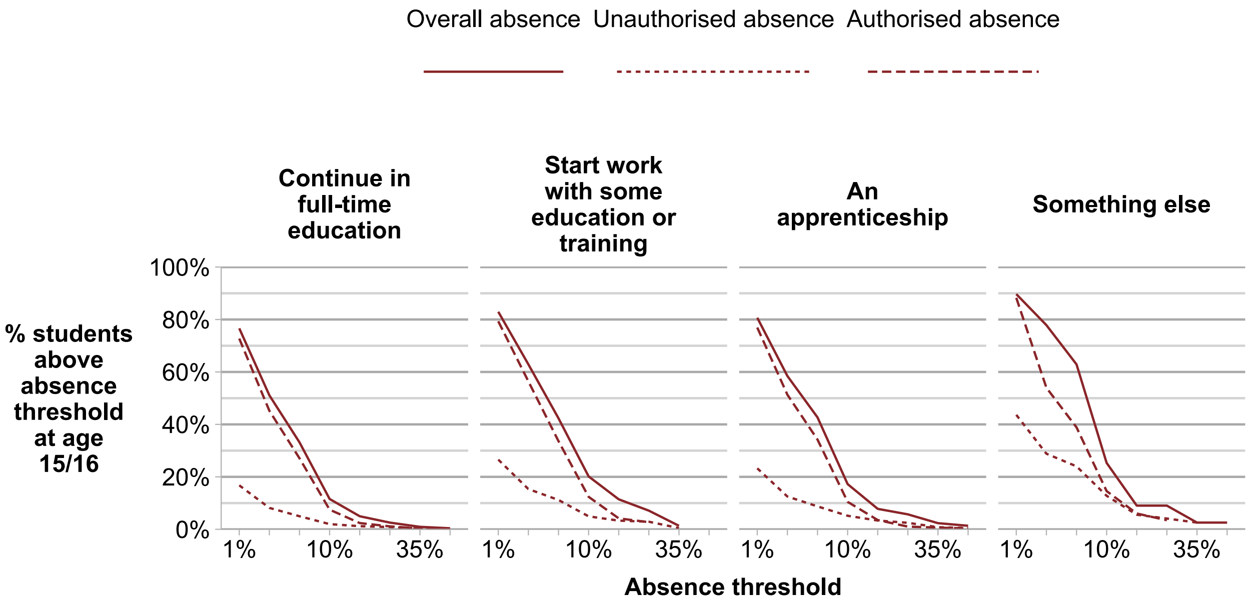


Figure 4.12. Percentage of students with absence rates above the absence threshold at age 15/16, stratified by absence type and parental aspirations.

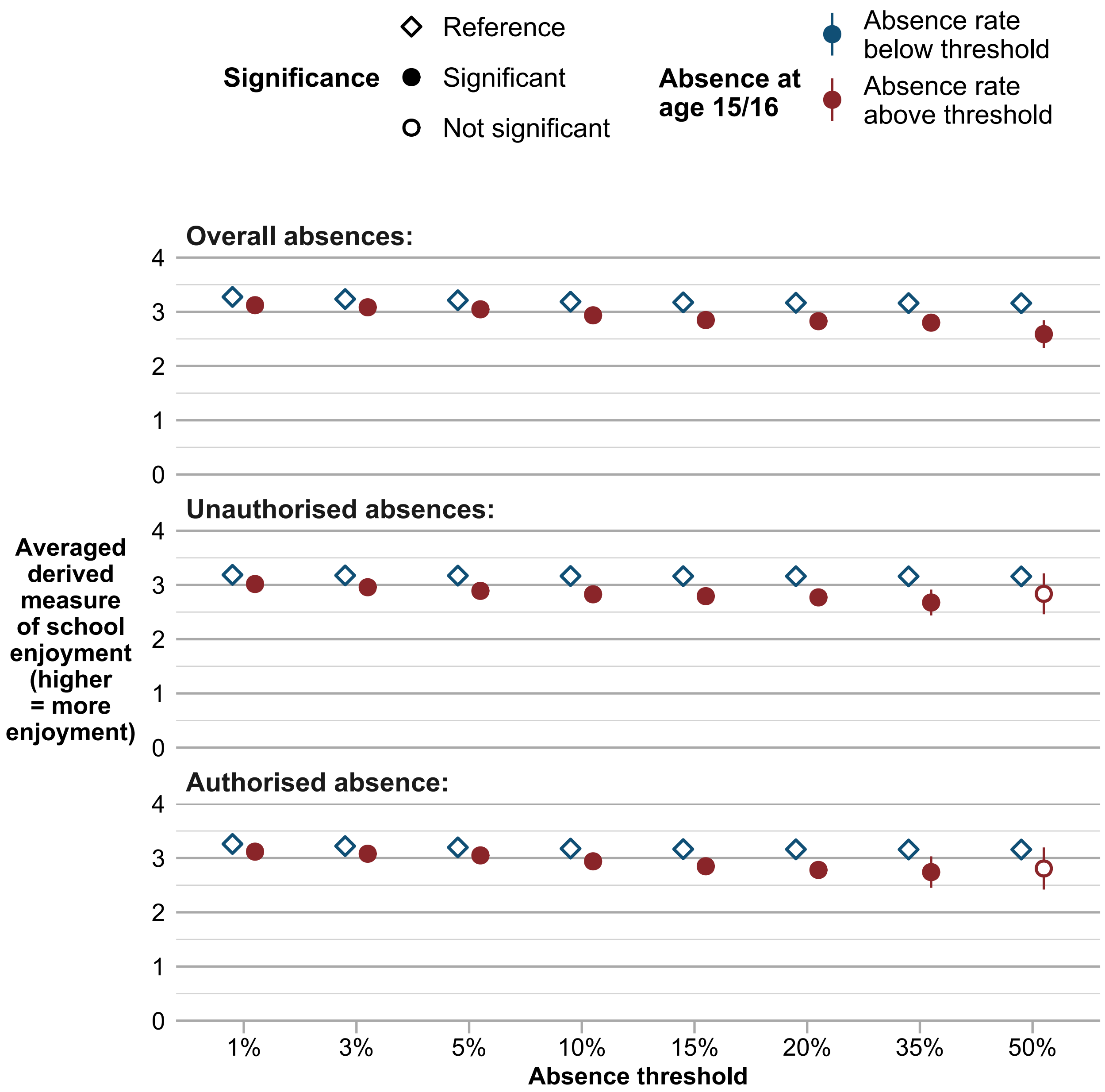


absences. At the 10% threshold, 19% (n = 12) of students living with neither biological parent fit into this category, compared to 11% (n = 228) of students living with one parent, 8% (n = 59) of students living as part of a stepfamily, and 7% (n = 318) of students living with both biological parents. Conversely, students from single-parent households were more common when looking at unauthorised absences. For example, 5% of students from single-parent households missed 10% of sessions for unauthorised reasons, compared to 2% of students from stepfamilies and no-parent households (n = 15 and 1, respectively) and 1% of students from two-parent households (n = 65).

Students whose parents expressed a desire for them to pursue "something else" after Year 11 displayed higher rates of absenteeism across all thresholds (Figure 4.12). For instance, at the 5% threshold, a quarter (n = 9) of students whose parents wanted them to do “something else” were absent, compared to 12% (n = 778) of students whose parents wanted them to continue in full-time education. When focusing solely on unauthorised absences, the discrepancy becomes even more pronounced. 13% (n = 5) of students whose parents wanted them to do "something else" missed 10% of sessions. This is more than double the 5% of students whose parents advocated for starting work with some education or training or beginning an apprenticeship (n = 14 and n = 35, respectively). Even larger is the gap with students whose parents wanted them to stay in full-time education, whereby 2% (n = 133) of these students missed 10% of sessions for unauthorised reasons.

School experiences are also associated with absence. Students who liked more of their teachers were less likely to fall into the ‘absent’ category. At the 10% threshold, students who liked none of their teachers were approximately two and a half times more likely to

Figure 4.13. Average levels of school enjoyment by absence threshold and type of absence.



be absent (29%, n = 18) than students who liked all their teachers (12%, n = 64). Further, students who were over the absence threshold were more likely to have been bullied. 40% of those who had been bullied reported missing at least 5% of sessions, compared to 31% of those who had not been bullied. This difference persists in the higher absence thresholds, whereby 1.7% of students who had been bullied missed 35% of sessions compared to <1% of those who had not been bullied.

Students who attended more school sessions consistently reported higher levels of school enjoyment, with the difference in enjoyment increasing as absence thresholds rose (Figure 4.13). Among students missing at least 10% of sessions, the average school enjoyment score was 2.94 (SD: 0.53), compared to 3.19 (SD: 0.43) for those attending 90% or more. At the 50% absence threshold, students who missed this proportion of sessions had an average enjoyment score of 2.59 (SD: 0.68), whereas those attending at least half of their sessions reported a higher average score of 3.16 (SD: 0.45).

4.4 Summary

Bivariate descriptive statistics show patterns in absence across various sociodemographic factors.

Overall absence rates appear relatively consistent across different ethnic groups, but small differences emerge when distinguishing between authorised and unauthorised absences. White students have higher rates of authorised absences, whereas other ethnic groups – particularly those from mixed and black ethnicities – exhibit higher rates of unauthorised absences. This highlighted that while the overall absence outcomes do not differ largely by ethnicity, the underlying reason is patterned by ethnicity.

Students with disabilities or an identified SEN are consistently more likely to be absent, particularly at the lower thresholds of absence. However, as the absence threshold becomes larger, the gap between students with and without a disability or SEN narrows, suggesting that these factors may contribute to low levels of absence rather than severe absenteeism.

Household composition is also related to absence. Students from two-parent households have the lowest rates of absence, while those from single-parent or no-parent households show higher rates. In particular, levels of unauthorised absences are higher in students who do not live with both biological parents. This may be due to fewer economic resources or social resources. For instance, single parents often experience difficulties in managing both work and family responsibilities, which can result in less supervision of their offspring's school attendance (Astone and McLanahan 1991; Mejías-Leiva and Moreno Mínguez 2024).

Parental aspirations are also associated with absenteeism, with students whose parents aspired for a non-academic post-16 pathway exhibiting higher rates of absence, particularly unauthorised absences. This may reflect a lack of alignment between parental expectations and the school system, potentially leading to less engagement and less encouragement from parents to attend school regularly.

Finally, school experiences are closely linked to attendance. Students who like more of their teachers are less likely to be absent across all absence types and all absence thresholds, and students who have been bullied are also more likely to be absent. Further, students who reported liking school more were less likely to be absent across all thresholds and types. This highlights the importance of a positive school experience in improving school attendance.

5 Is there a causal relationship between mental health/wellbeing and absence?

To understand whether there is a causal relationship between mental health/wellbeing and absence, logistic regression with inverse probability weighting was used to estimate the odds of being absent within each threshold and definition of absence (overall/unauthorised/authorised). All results presented here adjust for covariates described in previous sections (ethnicity, whether the participant has an LSID, whether the participant has SEN, family composition, FSM eligibility, cannabis usage, parental aspirations, student relationship with teachers, school enjoyment, whether the participant has ever been bullied, and previous absence). All models also include survey weights. For additional details about the model composition and statistical procedure, refer to Appendix B-C. The full results for all the models discussed below are presented in Appendix F.

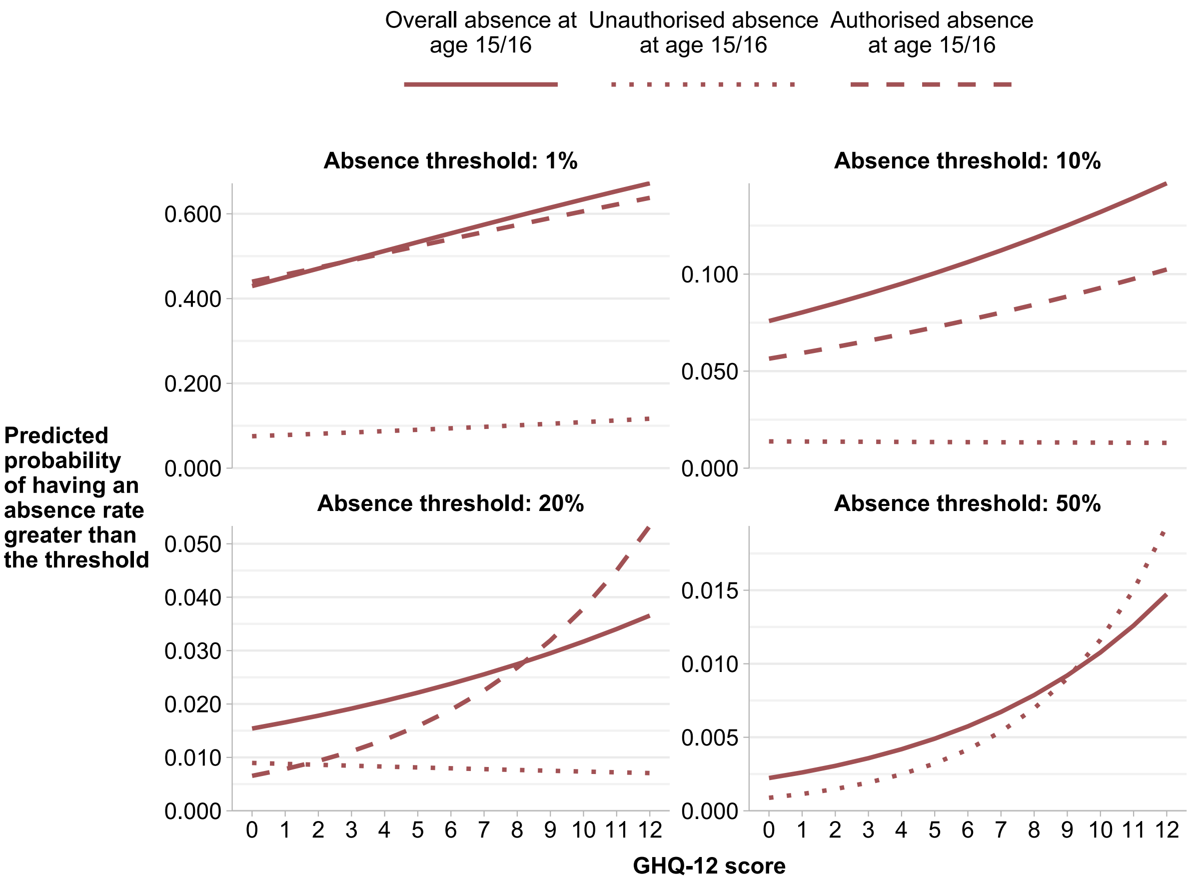
5.1 Mental health

A higher GHQ-12 score is associated with higher overall absence, regardless of which threshold is used. Here, as the threshold becomes larger, a one-unit increase in GHQ-12 score (i.e., worse mental health) more strongly predicts the odds of being in the absent category (Table 5.1).

When looking at the 1% absence threshold, the baseline odds of being absent are high (OR: 2.90, 95% CI: 1.27-6.31), meaning that it is relatively common to be absent at this low threshold, with each unit increase in GHQ-12 score being associated with a 9% increase in the odds of missing 1% of sessions or more (OR: 1.09, 95% CI: 1.05-1.13). When expanding the threshold to missing at least 5% of all possible sessions, the baseline odds of being absent are a lot lower (OR: 1.02, 95% CI: 0.51-2.04), and each unit increase in GHQ-12 score predicts a 4% increase in the odds of fitting into this absence threshold. As can be seen in Figure 5.1, as the absence threshold becomes larger, the baseline odds of being considered absent decrease. This means that at the more extreme definitions, it is relatively uncommon to fit into the ‘absent’ category.

It seems a great deal of the relationship between overall absence and GHQ-12 score is driven by authorised absences. Here, every unit increase in GHQ-12 score increases the odds of a student missing 1% or more sessions for authorised reasons by 7% (OR: 1.07, 95%: 0.53-0.85), 10% or more sessions by 6% (OR: 1.06, 95% CI: 1.01-1.10), 15% or more sessions by 11% (OR: 1.11, 95% CI: 1.05-1.19), 20% or more sessions by 20%

Figure 5.1. Predicted probabilities of being absent at thresholds of 1%, 10%, 20%, and 50%, calculated using marginal means from multivariate logistic regression models. Note that the y-axes have different ranges depending on the threshold.



Note: Estimates are adjusted for ethnicity = white; LSID = no; SEN = no; family composition = two parents; cannabis use = does not use cannabis; parental aspirations = continue in full-time education; number of teachers the student likes = all of their teachers; whether the student was bullied = not bullied; school enjoyment = 3.13; prior absence rate above threshold = not above threshold

(OR: 1.20, 95% CI: 1.11-1.29), and 35% or more sessions by 10%[4] (OR: 1.10, 95% CI: 0.97-1.25).

The relationship between the participant's GHQ-12 score and unauthorised absence is less clear, with most of the relationships not being statistically significant, meaning those with worst mental health are not significantly more likely to be absent from school for unauthorised reasons. In addition, the baseline odds of unauthorised absence are relatively low. At the 1% threshold, the baseline odds are 0.58 (95% CI: 0.24-1.39), and by the time we get to the 35% threshold, the baseline odds are 0.01 (95% CI, 0.00-0.70), indicating unauthorised absence – even at a low rate – is quite uncommon.

[4] When looking at authorised absences, the sample size in some of the covariates was too small to run a regression with severe absence (50% of sessions or more) as the outcome.

Table 5.1. Results from logistic regression, predicting odds of absence, showing the results for the variable GHQ-12. Odds of absence and 95% confidence intervals are shown for the various absence thresholds (%).

	1%	3%	5%	10%	15%	20%	35%	50%
Overall absence: Intercept	2.90 (1.27-6.61)	1.06 (0.47-2.39)	1.02 (0.51-2.04)	0.68 (0.26-1.76)	0.17 (0.05-0.57)	0.14 (0.03-0.71)	0.04 (0.00-0.34)	0.01 (0.00-0.09)
Overall absence: GHQ-12	1.09 (1.05-1.13)	1.05 (1.01-1.09)	1.04 (1.00-1.07)	1.06 (1.02-1.11)	1.06 (1.00-1.12)	1.08 (1.01-1.15)	1.07 (0.96-1.2)	1.17 (1.01-1.36)
Unauthorised absence: Intercept	0.58 (0.24-1.39)	0.24 (0.08-0.72)	0.12 (0.03-0.43)	0.16 (0.02-1.18)	0.09 (0.01-1.23)	0.14 (0.01-1.93)	0.01 (0.00-0.7)	0.00 (0.00-0.33)
Unauthorised absence: GHQ-12	1.04 (1.00-1.08)	1.03 (0.98-1.07)	1.06 (1.00-1.12)	1.00 (0.92-1.08)	0.99 (0.89-1.09)	0.98 (0.87-1.11)	1.10 (0.92-1.32)	1.30 (1.08-1.56)
Authorised absence: Intercept	2.84 (1.26-6.38)	0.88 (0.39-1.98)	0.75 (0.37-1.5)	0.47 (0.16-1.38)	0.08 (0.02-0.31)	0.05 (0.01-0.35)	0.00 (0.00-0.08)	-
Authorised absence: GHQ-12	1.07 (1.03-1.11)	1.04 (1.00-1.08)	1.04 (1.00-1.07)	1.06 (1.01-1.1)	1.11 (1.05-1.19)	1.20 (1.11-1.29)	1.10 (0.97-1.25)	-

Note: All models adjust for ethnicity, whether the participant has an LSID, whether the participant has a SEN diagnosis, family composition, FSM eligibility, cannabis usage, parental aspirations, how many teachers the student likes, school enjoyment, whether the participant has ever been bullied, previous absence

5.2 Personal wellbeing

5.2.1 Life satisfaction

Results suggest that life satisfaction does not predict absence well – regardless of the type of absence or threshold. As presented in Table 5.2, the results are largely statistically insignificant, and the confidence intervals are wide, which indicates there is little causal relationship between life satisfaction and absence.

When looking at overall absence, there is a slightly negative relationship between wellbeing and absence, whereby students who had good life satisfaction were more likely to miss at least 1% (OR: 0.99, 95% CI: 0.91-1.08) to 3% (OR: 0.96, 95% CI: 0.88-1.05) of possible sessions. However, as previously stated, this relationship is not significant. The only significant relationship when looking at overall absence is at the 10% threshold, whereby a unit decrease in life satisfaction is associated with 10% increased odds of missing this number of sessions (OR: 1.10, 95 CI: 1.02, 1.18).

There is also little relationship between unauthorised absences and life satisfaction. At most thresholds, the odds ratios are close to 1, indicating that life satisfaction has little to

Table 5.2. Results from logistic regression, predicting odds of absence, showing result for the variable "Overall, how satisfied are you with your life nowadays?". Odds of absence and 95% confidence intervals are shown for the various absence thresholds (%).

	1%	3%	5%	10%	15%	20%	35%	50%
Overall absence: Intercept	3.45 (1.39-8.54)	2.05 (0.45-9.34)	1.67 (0.41-6.75)	0.43 (0.13-1.41)	0.27 (0.06-1.31)	0.17 (0.03-1.08)	0.01 (0.00-0.08)	0.06 (0.00-1.92)
Overall absence: Life satisfaction	0.99 (0.91-1.08)	0.96 (0.88-1.05)	1.01 (0.93-1.09)	1.10 (1.02-1.18)	1.03 (0.95-1.11)	1.05 (0.95-1.16)	1.06 (0.91-1.25)	1.10 (0.89-1.36)
Unauthorised absence: Intercept	0.27 (0.09-0.81)	0.33 (0.08-1.41)	0.22 (0.03-1.5)	0.11 (0.01-1.09)	0.02 (0.00-0.24)	0.03 (0.00-0.57)	0.06 (0.00-1.89)	0.00 (0.00-0.2)
Unauthorised absence: Life satisfaction	0.97 (0.9-1.04)	0.99 (0.91-1.09)	0.99 (0.88-1.11)	1.04 (0.93-1.16)	1.01 (0.91-1.12)	0.99 (0.87-1.11)	0.8 (0.63-1.03)	0.72 (0.48-1.06)
Authorised absence: Intercept	3.28 (1.43-7.53)	1.82 (0.48-6.91)	1.45 (0.41-5.12)	0.33 (0.09-1.2)	0.1 (0.01-0.68)	0.23 (0.02-2.56)	0.00 (0.00-0.13)	-
Authorised absence: Life satisfaction	1 (0.92-1.08)	0.97 (0.9-1.05)	1.02 (0.96-1.09)	1.18 (1.08-1.29)	1.06 (0.96-1.17)	1.07 (0.93-1.22)	1.11 (0.88-1.41)	-

Note: All models adjust for ethnicity, whether the participant has an LSID, whether the participant has a SEN diagnosis, family composition, FSM eligibility, cannabis usage, parental aspirations, how many teachers the student likes, school enjoyment, whether the participant has ever been bullied, previous absence

no significant impact on the odds of unauthorised absences. At higher thresholds (e.g., 35% and 50%), the odds of being absent are greater in those with more positive life satisfaction scores, but these relationships are not significant.

As with the other definitions, life satisfaction has little effect on authorised absences. At the lower thresholds (1%-5%), the odds ratios are extremely close to 1, which indicates no effect. Life satisfaction does significantly predict authorised absences at the 10% threshold, where for every one-unit decrease in life satisfaction, the odds of absence increase by 18% (OR: 1.18, 95% CI: 1.08-1.29). At the higher thresholds, the impact of poor life satisfaction on odds of absence remains positive but not statistically significant.

5.2.2 Feeling things in life are worthwhile

Results indicate there is a minimal relationship between the perception of life not being worthwhile and absence across various thresholds and types of absence. In Table 5.3, it can be seen that most odds ratios are not statistically significant, with wide confidence intervals pointing towards a negligible or non-existent causal link between this measure of personal wellbeing and absence.

Table 5.3. Results from logistic regression, predicting odds of absence, showing result for the variable "Overall, to what extent do you feel that the things you do in your life are worthwhile?". Odds of absence and 95% confidence intervals are shown for the various absence thresholds (%).

	1%	3%	5%	10%	15%	20%	35%	50%
Overall absence: Intercept	3.8 (1.51-9.6)	0.89 (0.31-2.62)	0.73 (0.24-2.24)	0.22 (0.05-0.88)	0.15 (0.03-0.7)	0.12 (0.02-0.92)	0.00 (0.00-0.16)	0.03 (0.00-0.61)
Overall absence: Worthwhile	0.96 (0.9-1.02)	0.99 (0.93-1.05)	1.04 (0.99-1.09)	1.02 (0.96-1.09)	0.97 (0.9-1.05)	1.01 (0.91-1.12)	1.15 (0.96-1.37)	1.06 (0.83-1.37)
Unauthorised absence: Intercept	0.14 (0.04-0.46)	0.15 (0.04-0.62)	0.06 (0.01-0.4)	0.09 (0.01-0.98)	0.01 (0.00-0.12)	0.03 (0.00-0.55)	0.06 (0.00-1.3)	0.00 (0.00-0.15)
Unauthorised absence: Worthwhile	1.06 (0.99-1.14)	1.02 (0.94-1.1)	1.1 (0.99-1.21)	0.96 (0.86-1.06)	0.92 (0.83-1.03)	0.97 (0.86-1.08)	0.88 (0.72-1.09)	0.72 (0.47-1.09)
Authorised absence: Intercept	3.49 (1.51-8.04)	0.81 (0.29-2.26)	0.84 (0.29-2.42)	0.21 (0.06-0.73)	0.08 (0.01-0.63)	0.13 (0.01-2.25)	0.00 (0.00-0.17)	-
Authorised absence: Worthwhile	0.98 (0.92-1.04)	0.97 (0.92-1.03)	1.01 (0.96-1.07)	1.06 (0.96-1.17)	1.04 (0.94-1.15)	1.1 (0.96-1.25)	1.14 (0.90-1.43)	-

Note: All models adjust for ethnicity, whether the participant has an LSID, whether the participant has an SEN diagnosis, family composition, FSM eligibility, cannabis usage, parental aspirations, how many teachers the student likes, school enjoyment, whether the participant has ever been bullied, previous absence

When looking at the relationship between overall absence and feelings that life is worthwhile, the association is inconsistent and generally insignificant. Specifically, individuals who felt like their life was less worthwhile exhibited a slight decrease in the odds of being absent at the 1% (OR: 0.98, 95% CI: 0.90-1.06) and 3% (OR: 0.99, 95% CI: 0.98-1.08) thresholds. As the threshold increases to 10%, a significant pattern emerges, in which students who feel more worthwhile have lower odds of absence (OR: 1.14, 95% CI: 1.04-1.25). Beyond this threshold, however, the significance dissipates, suggesting a negligible effect of this measure of wellbeing on overall absence.

In the context of unauthorised absences, the impact of feelings of life not being worthwhile is generally minimal. Across all thresholds, the odds ratios remain close to 1. For instance, at the 1% threshold, the OR is 0.97 (95% CI: 0.89-1.05), and at the 5% threshold it is 1.02 (95% CI: 0.90-1.16).

When exploring authorised absences, the relationship with feelings of life not being worthwhile remains weak. At the lower thresholds, the odds ratios are very close to 1, indicating a negligible effect. One exception is the 10% threshold, where those who feel like their life is less worthwhile have increased odds of fitting within the 'absent' category (OR: 1.21, 95% CI: 1.10-1.32).

5.2.3 Happiness

Model results suggest that the relationship between happiness and absence is weak and inconsistent. As shown in Table 5.4, many of the odd ratios are not significant, suggesting that happiness has minimal effect on the likelihood of absence across all thresholds and types.

When looking at overall absence rates, models show mixed results. At the lower thresholds of 1% and 3%, there is a slight and non-significant increase in the odds of being absent as happiness decreases (1% = OR: 1.02, 95% CI: 0.98-1.07; 3% = OR: 1.04, 95% CI: 1.00-1.08). Like the previous wellbeing measures, there is a significant relationship when the absence threshold is missing 10% of sessions or more, whereby a one-unit decrease in happiness increases the odds of being absent by 11% (OR: 1.11, 95% CI: 1.04-1.19). At the severe absence threshold (50% of sessions), the results

Table 5.4. Results from logistic regression, predicting odds of absence, showing result for the variable "Overall, how happy did you feel yesterday?". Odds of absence and 95% confidence intervals are shown for the various absence thresholds (%).

	1%	3%	5%	10%	15%	20%	35%	50%
Overall absence: Intercept	2.58 (1.26-5.31)	1.33 (0.67-2.64)	0.61 (0.28-1.34)	0.2 (0.06-0.7)	0.16 (0.05-0.52)	0.14 (0.03-0.72)	0.17 (0.00-5.67)	0.56 (0.03-10.46)
Overall absence: Happiness	1.02 (0.98-1.06)	1.04 (1-1.08)	1.06 (1.01-1.11)	1.11 (1.04-1.19)	1.06 (1.00-1.12)	1.06 (0.98-1.16)	1.05 (0.88-1.26)	1.13 (0.9-1.41)
Unauthorised absence: Intercept	0.12 (0.05-0.29)	0.13 (0.04-0.46)	0.31 (0.08-1.14)	0.15 (0.02-1.02)	0.05 (0.00-0.63)	0.1 (0.01-1.25)	0.79 (0.03-22.45)	0.13 (0.00-6.88)
Unauthorised absence: Happiness	1.06 (1.01-1.12)	1.06 (0.99-1.13)	1.01 (0.94-1.07)	0.97 (0.88-1.06)	0.99 (0.88-1.11)	1.02 (0.9-1.15)	0.97 (0.79-1.19)	0.81 (0.57-1.16)
Authorised absence: Intercept	2.62 (1.33-5.15)	0.88 (0.45-1.72)	0.41 (0.18-0.94)	0.09 (0.02-0.39)	0.04 (0.01-0.24)	0.11 (0.01-1.16)	0.03 (0.00-0.61)	-
Authorised absence: Happiness	1.01 (0.97-1.05)	1.04 (1.00-1.08)	1.06 (1.01-1.11)	1.12 (1.05-1.21)	1.08 (1.00-1.16)	1.16 (1.03-1.3)	1.08 (0.82-1.42)	-

Note: All models adjust for ethnicity, whether the participant has an LSID, whether the participant has a SEN diagnosis, family composition, FSM eligibility, cannabis usage, parental aspirations, how many teachers the student likes, school enjoyment, whether the participant has ever been bullied, previous absence indicate that for every one-unit decrease in happiness, the odds of being absent increase by 13% (OR: 1.13, 95% CI: 0.90-1.41), however, this relationship is again not significant.

Again, there is little relationship between happiness and unauthorised absence. At the 1% threshold, the results indicate a small but significant increase in the odds of unauthorised absence in response to lower happiness (OR:1.06, 95% CI: 1.01-1.12). However, this relationship does not persist across the other thresholds, with all other odds ratios being insignificant and inconsistent in their relationship, whereby at the 10%, 15%, 35% and 50% thresholds, happier students are more likely to be absent (albeit not to a significant degree).

Authorised absences show a similar weak relationship; however, the direction of the association is more consistent. At the 3% threshold, a one-unit decrease in happiness is associated with 4% increased odds of being absent (OR: 1.04, 95% CI: 1.00-1.08), with the odds increasing to 12% at the 10% absence threshold (OR: 1.12, 95% CI: 1.01-1.11), and 16% at the 20% absence threshold (OR: 1.16, 95% CI: 1.03-1.30).

5.2.4 Feelings of anxiety

For overall absence, the results indicate a weak but mostly positive, association between feelings of anxiety and the odds of absence across the different thresholds. At the 1% threshold, there was a negligible increase in the odds of absence with increased anxiousness (OR: 1.01, 95% CI: 0.99-1.03). As the threshold increased to 5%, the association strengthened slightly, indicating a statistically significant increase in the odds of absence as feelings of anxiety increased. However, the effect size was still small, with a one-unit increase in anxiousness resulting in only a 4% increase in the odds of absence (OR: 1.04, 95%: 1.02-1.06). For the 5% threshold, the OR was 1.02 (95% CI: 1.00-1.04), again suggesting a minimal association between the two variables. A similar trend was seen across the higher thresholds, whereby a one-unit increase in feelings of anxiety was associated with 1-2% increased odds of absence across all thresholds (Table 5.5).

A similar trend was seen when just looking at unauthorised absences. At all thresholds, the relationship was not statistically significant. Further, the direction of the association was inconsistent. At the 1%, 3%, 5%, 15%, 20% and 35% thresholds, for every one-unit increase in anxiousness, the odds of falling into the ‘absent’ category increased by 1-5%. However, for the 10% and 50% thresholds, a one-unit increase in anxiousness decreased the odds of fitting within the absent threshold by 1% (OR: 0.99, 95% CI: 0.93-1.05) and 14% (OR: 0.86, 95% CI: 0.68-1.10), respectively.

There is a slightly clearer relationship between authorised absence and feelings of anxiety, in which the odds of being absent are greater in the larger thresholds; however,

Table 5.5. Results from logistic regression, predicting odds of absence, showing result for the variable "Overall, how anxious did you feel yesterday?". Odds of absence and 95% confidence intervals are shown for the various absence thresholds (%).

	1%	3%	5%	10%	15%	20%	35%	50%
Overall absence: Intercept	2.77 (1.41-5.43)	1.11 (0.62-1.99)	0.89 (0.49-1.64)	0.32 (0.13-0.76)	0.1 (0.03-0.33)	0.03 (0.01-0.17)	0.02 (0.00-0.36)	0.2 (0.01-6.88)
Overall absence: Anxiousness	1.01 (0.99-1.03)	1.04 (1.02-1.06)	1.02 (1.00-1.04)	1.02 (0.99-1.05)	1.02 (0.97-1.06)	1.03 (0.97-1.09)	1.03 (0.93-1.13)	1.01 (0.86-1.2)
Unauthorised absence: Intercept	0.22 (0.11-0.44)	0.28 (0.11-0.7)	0.27 (0.08-0.89)	0.06 (0.01-0.42)	0.03 (0.00-0.33)	0.03 (0.00-0.51)	0.17 (0.00-11.98)	0.00 (0.00-14.98)
Unauthorised absence: Anxiousness	1.02 (1.00-1.05)	1.02 (0.99-1.06)	1.01 (0.97-1.05)	0.99 (0.93-1.05)	1.00 (0.93-1.08)	1.05 (0.96-1.14)	1.05 (0.91-1.21)	0.86 (0.68-1.10)
Authorised absence: Intercept	2.48 (1.33-4.61)	0.8 (0.45-1.42)	0.56 (0.3-1.05)	0.15 (0.05-0.44)	0.03 (0.01-0.16)	0.04 (0.01-0.31)	0.00 (0.00-0.19)	-
Authorised absence: Anxiousness	1.00 (0.98-1.03)	1.03 (1.01-1.05)	1.01 (0.99-1.03)	1.02 (0.98-1.05)	1.05 (1.00-1.12)	1.11 (1.02-1.22)	1.14 (0.98-1.32)	-

Note: All models adjust for ethnicity, whether the participant has an LSID, whether the participant has a SEN diagnosis, family composition, FSM eligibility, cannabis usage, parental aspirations, how many teachers the student likes, school enjoyment, whether the participant has ever been bullied, previous absence

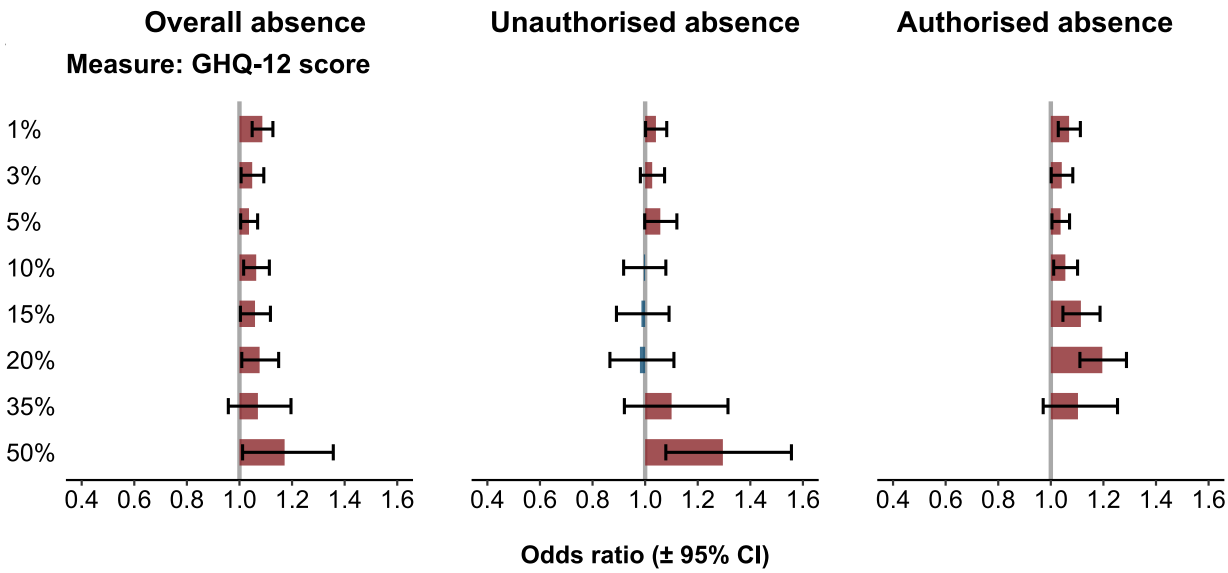
this relationship is not always significant. At the 1% threshold, the OR was 1.00 (95% CI: 0.98-1.03), indicating no significant difference. At the 3% threshold, there was a significant effect, with a one-unit increase in anxiousness increasing the odds of being above the absence threshold increasing by 3% (OR: 1.03, 95% CI: 1.01-1.05). However, with the exception of the 20% threshold (OR: 1.11, 95% CI: 1.02-1.22), the rest of the associations were not significant.

5.3 Summary

The results from the mental health and personal wellbeing variables are summarised in Figure 5.2 and Figure 5.3

The findings suggest that mental ill health – as measured by GHQ-12 scores – is a contributing factor in school absences, as poorer mental health is consistently linked to higher odds of being absent across all absence thresholds. This relationship strengthens as the absence threshold increases, indicating that students with more severe mental health challenges are disproportionately likely to miss a significant number of school sessions. Importantly, this pattern appears to be largely driven by authorised absences

Figure 5.2. Odds ratios (and 95% confidence intervals) for the association between GHQ-12 scores and different absence thresholds. Results are derived from logistic regression models, where the outcome is whether a student's absence rate exceeds the specified threshold. An odds ratio of above 1 (red bars) indicates increased odds of exceeding the absence threshold as GHQ-12 scores increase, whereas an odds ratio of below 1 (blue bars) indicates a decreased odds of exceeding the absence threshold.

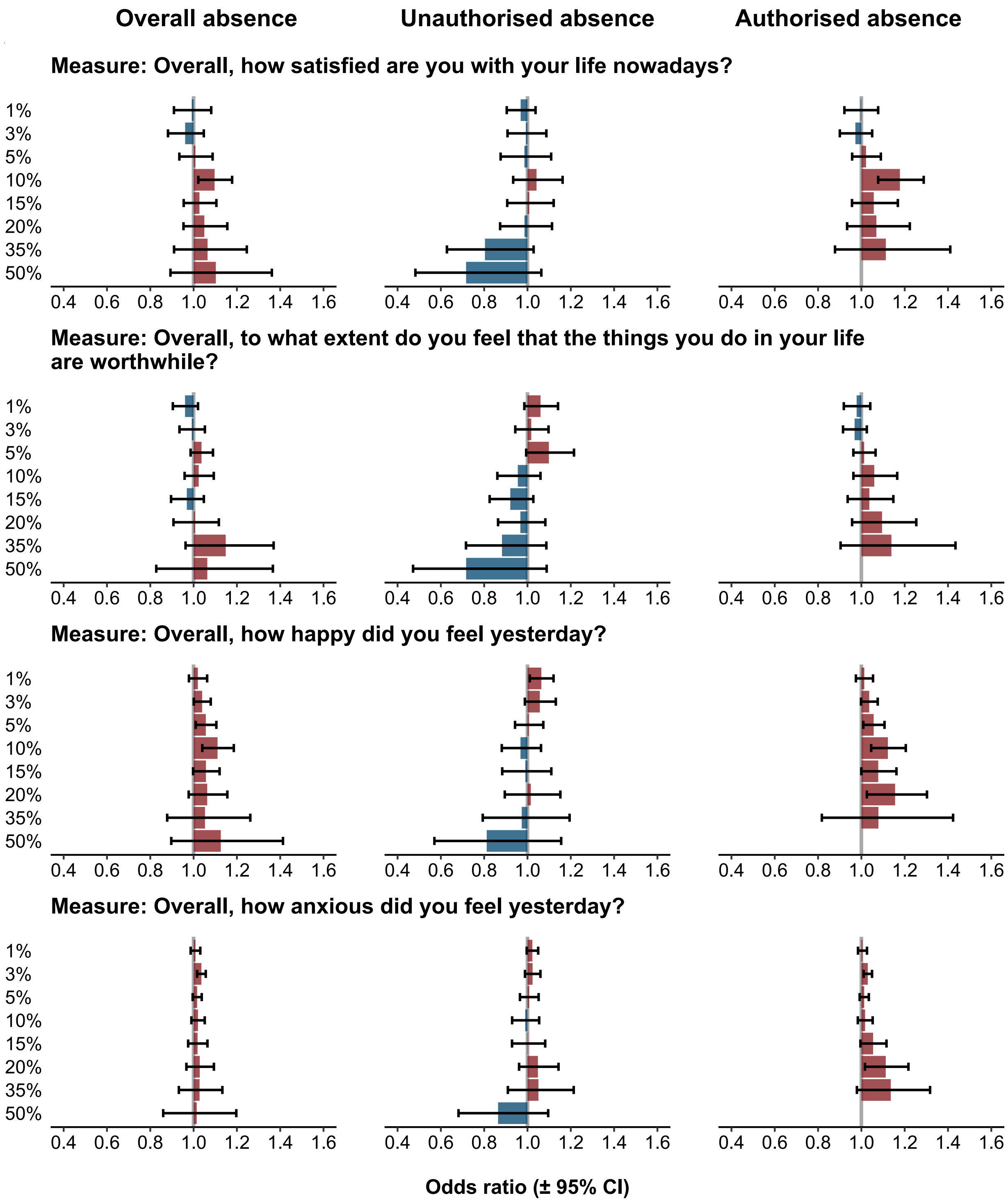


rather than unauthorised ones. This suggests that mental health issues may lead to absences that are sanctioned by schools, often as a result of parents notifying the school about their child being unwell. This highlights the potential role of parental involvement and school systems in acknowledging and accommodating absences related to mental health challenges.

In contrast, the relationships between life satisfaction, feelings of worth, happiness and school absences were minimal. Across all thresholds and definitions of absence, the effect sizes were weak, inconsistent, and statistically insignificant. These findings suggest that general aspects of personal wellbeing, such as overall life satisfaction or feelings of happiness, may not have a direct or substantial influence on school attendance.

However, when examining feelings of anxiety, a slight positive association with school absences was found, particularly at higher absence thresholds. This finding implies that students experiencing elevated levels of anxiety may be somewhat more likely to miss school, especially when absences accumulate to more significant levels. Even so, the effect sizes for anxiety were relatively small and not consistently statistically significant across all thresholds.

Figure 5.3. Odds ratios (and 95% confidence intervals) for the association between personal wellbeing measures and different absence thresholds. Results are derived from logistic regression models, where the outcome is whether a student's absence rate exceeds the specified threshold. An odds ratio of above 1 (red bars) indicates increased odds of exceeding the absence threshold as GHQ-12 scores increase, whereas an odds ratio of below 1 (blue bars) indicates a decreased odds of exceeding the absence threshold.



6 Discussion

When looking at GHQ-12, it can be seen that a higher score is associated with higher levels of overall absence, regardless of the threshold. Even when the threshold is missing 1% of sessions, every one-unit increase in the GHQ-12 score was associated with a 9% increase in the odds of absence. By the time we get to severe absence (missing 50% of possible sessions), a one-unit increase in GHQ-12 score increases the odds of absence by 17%. However, it should be noted that the overall odds of missing a large number of sessions are relatively low.

It seems that a great deal of the relationship between overall absence and GHQ-12 score is driven by authorised absence. Here, every unit increase in GHQ-12 score increased the odds of a student missing 1% or more sessions by 6.7%, 10% of sessions by 6%, 15% of sessions by 11%, 20% of sessions by 20%, and 35% of sessions by 10% (for authorised reasons). As this analysis uses causal methods, we can conclude that poor mental health is a contributing factor to authorised absences in this dataset. Currently, the reasons for authorised absences held in the NPD do not differentiate feeling mentally unwell from feeling physically unwell, and therefore, it is not possible to confirm that these students with a higher GHQ-12 score are citing mental health as their reason for absence. Further, research shows that people with mental health issues often experience poorer physical health than the general population, suggesting that mental health challenges may co-occur with physical health issues (Ohrnberger et al. 2017). Nonetheless, the results here suggest that poor mental health is a cause of authorised absence (at all levels) in the LSYPE2 cohort.

It may be that unauthorised absence is driven more by socioeconomic factors rather than poor mental health. Covariate results are presented in Appendix F, where it can be seen that unauthorised absences are elevated in groups such as those who live as part of a single-parent or stepparent household and are eligible for FSM.

The story becomes less clear when looking at measures of wellbeing. Most relationships were not statistically significant, and there was often no consistent direction of association. This may stem from differences in the nature and wording of the questions used in the GHQ-12 and the ONS4 wellbeing measures. The GHQ-12 is a diagnostic tool designed to detect persistent psychological distress and mental health challenges, whereas the ONS4 focuses on capturing current, immediate wellbeing. The wording of the ONS4 questions (e.g., "… how happy did you feel yesterday?") emphasises short-term states, which may reflect temporary distress or fluctuations in mood rather than sustained mental health difficulties. This difference highlights that these tools capture distinct dimensions of mental health and personal wellbeing. While the GHQ-12 reflects longer-term psychological patterns, the ONS4 captures momentary wellbeing. As a result, ONS4 responses may vary depending on whether they were collected during a particularly challenging period (e.g., following a recent hardship) or a more stable time.

This variability could obscure meaningful patterns, especially if the responses were collected very close to or far from a period of absence. For example, a pupil's recent wellbeing struggles might not align temporally with their absence data, making it harder to identify a consistent relationship.

Timing further complicates the interpretation. Mental health data from the GHQ-12 were drawn from Wave 2, a year before the attendance outcome, while personal wellbeing data from the ONS4 were collected in Wave 3, the same year as the outcome. The overlap in timing, combined with the immediate framing of the ONS4 questions, might limit their ability to capture broader patterns that persist over time.

In contrast, the GHQ-12's focus on longer-term distress aligns more closely with the types of mental health challenges likely to influence attendance. Together, these differences in timing, question design, and conceptual focus underscore why the GHQ-12 may be more sensitive to capturing the relationship between mental health and absenteeism than the ONS4 wellbeing measures.

6.1 Future directions

This research shows that poor mental health is causally related to absence; therefore, the upward trend in poor mental health over recent years could be a contributing factor to the increase in absence over the same period, although we cannot be sure to what extent. This analysis also shows that previous absence strongly predicts future absence. Therefore, it may be that there is a self-reinforcing cycle occurring. For this reason, it is important to equip parents, teachers, and students with the resources they need to identify if a student is struggling with mental health and – once someone has been identified – provide them with the resources they need to be supported or seek help. Since 2020, it has been mandatory to teach students about mental health and wellbeing in relationship and sex education classes[5]. In primary school, pupils are taught about personal wellbeing and the importance of self-care, and in secondary school, pupils learn about how to spot symptoms of mental illnesses in themselves and others and how to access professional help (Department for Education 2021). However, it is currently unclear at what age mental health starts affecting absences, and therefore, future research should focus on understanding the temporal patterns in mental health and absence to ensure students are being taught about mental health in an effective way relative to its risks.

It would also be beneficial to understand what the implications of sending students with poor mental health to school are. While we know that poor school attendance has long-reaching socioeconomic consequences, we need to examine how attending school might

[5] Schools were given an extension to 2021 to incorporate it into the curriculum as a result of disruption from the pandemic.

impact students struggling with mental health issues and also how schools can better support those struggling with poor mental health to attend where appropriate. Although negative experiences at school, such as bullying and exam pressure, have been found to worsen students' mental health (Abdinasir 2019), schools also serve as a protective environment that can foster resilience and support. Further, the results show that students who enjoy school more have better mental health and lower absence rates. Hence, this analysis underscores the importance of creating a school environment where students with mental health challenges thrive and that developing effective interventions that both encourage school attendance and improve the students' mental health are critical.

6.2 Limitations

The primary limitation of this research lies in the timing of the data used. Data used in this analysis was collected between 2012 and 2015, and since then, there have been a number of large societal changes that affect both mental health/wellbeing and school attendance, such as the incorporation of mental health and wellbeing into the school curriculum, the widespread usage of smartphones and social media, and the Covid-19 pandemic.

The data used in this study were collected prior to curriculum changes. As previously stated, since 2020/21, schools have been required to educate students about the benefits of personal wellbeing and how to spot common mental health problems. Because the data precede these changes, the findings may not reflect the current landscape in schools where mental health and wellbeing are more actively supported. Students in school today might benefit from earlier identification and more robust support systems. As a result, the relationship between mental health and absence might differ under the current conditions.

Perhaps most significantly, the data were collected before the Covid-19 pandemic. The pandemic introduced a number of unprecedented challenges for young people, including prolonged school closures and remote learning, social isolation, and increased levels of uncertainty. The mental health impact of these factors has been substantial, with a large number of studies reporting a rise in anxiety, depression, and other mental health issues among young people both during and after the pandemic (Panchal et al., 2023). Given the data used do not capture the pandemic's impact, the findings may not fully represent the current state of the mental health of students or its current relationship with school absences. It is likely that the pandemic has intensified the link between mental health and school attendance, with evidence for this coming from the correlational association between the two presented in Figure 1.1 and Figure 1.2. Therefore, it may be that the patterns of absence presented in this analysis are the same as today, with the only exception being that the odds of being absent are now greater.

6.3 Concluding thoughts

This analysis highlights the complexity of mental health and wellbeing's relationship to attendance, and demonstrates that varying definitions and measures can lead to different results. Therefore, research going forward should ensure that appropriate measures are used. Despite the variation in results, the results suggest that poorer mental health may be contributing to the rise in school absences. Given the growing prevalence of mental health challenges among young people, it is essential to clarify whether interventions aim to promote positive mental health for all students or to treat those experiencing specific mental health issues. While both approaches are valuable, addressing risk and protective factors for mental ill-health – particularly through fostering strong relationships and creating a sense of thriving and belonging within schools – can play a significant role in prevention. It is particularly important to notice early signs of attendance deterioration, understand the underlying causes for each individual child, and explore how best to address these issues within the school and wider support systems.

Appendices

Appendix A. Measures of mental health and personal wellbeing

To measure mental health, a GHQ-12 score was used, which is derived from the following 12 questions (Goldberg 1972):

1. Have you recently been able to concentrate on whatever you are doing?
2. Have you recently lost much sleep due to some worry?
3. Have you recently felt constantly under strain?
4. Have you recently felt that you could not overcome your difficulties?
5. Have you recently been feeling unhappy and depressed?
6. Have you recently been losing confidence in yourself?
7. Have you recently been thinking of yourself as a worthless person?
8. Have you recently felt that you are playing a useful role in life?
9. Have you recently felt capable of making decisions about things?
10. Have you recently been able to enjoy your normal day-to-day activities?
11. Have you recently been able to face up to your problems?
12. Have you recently been feeling reasonably happy, all things considered?

Participants respond to each item on a 4-point scale (e.g., Better than usual, Same as usual; Less than usual; Much less than usual). From this, the bimodal scoring method is then used to calculate a GHQ-12 score that ranges from 0 to 12. Here, the two more “positive” responses within the 4-point Likert item are scored 0, and the two more “negative” responses that indicate poorer mental health are scored 1 (e.g., (Better than usual = 0; Same as usual = 0; Less than usual = 1; Much less than usual = 1).

To measure personal wellbeing, the ONS4 is used (Office for National Statistics 2024):

1. Overall, how satisfied are you with your life nowadays?
2. Overall, to what extent do you feel that the things you do in your life are worthwhile?
3. Overall, how happy did you feel yesterday?
4. Overall, how anxious did you feel yesterday?

For each of these questions, a 0 to 10 scale is used to collect responses, where 0 = “not at all” and 10 = “completely”. To make the measures comparable to GHQ-12 in terms of meaning (i.e., a higher score indicates poorer mental health) and to ease interpretation, items 1 to 3 were reversed so that 10 indicates poorer life satisfaction, not feeling worthwhile, and unhappiness.

Therefore, across all the mental health and wellbeing measures, a high score is indicative of poorer mental health and personal wellbeing.

Appendix B. Statistical methods

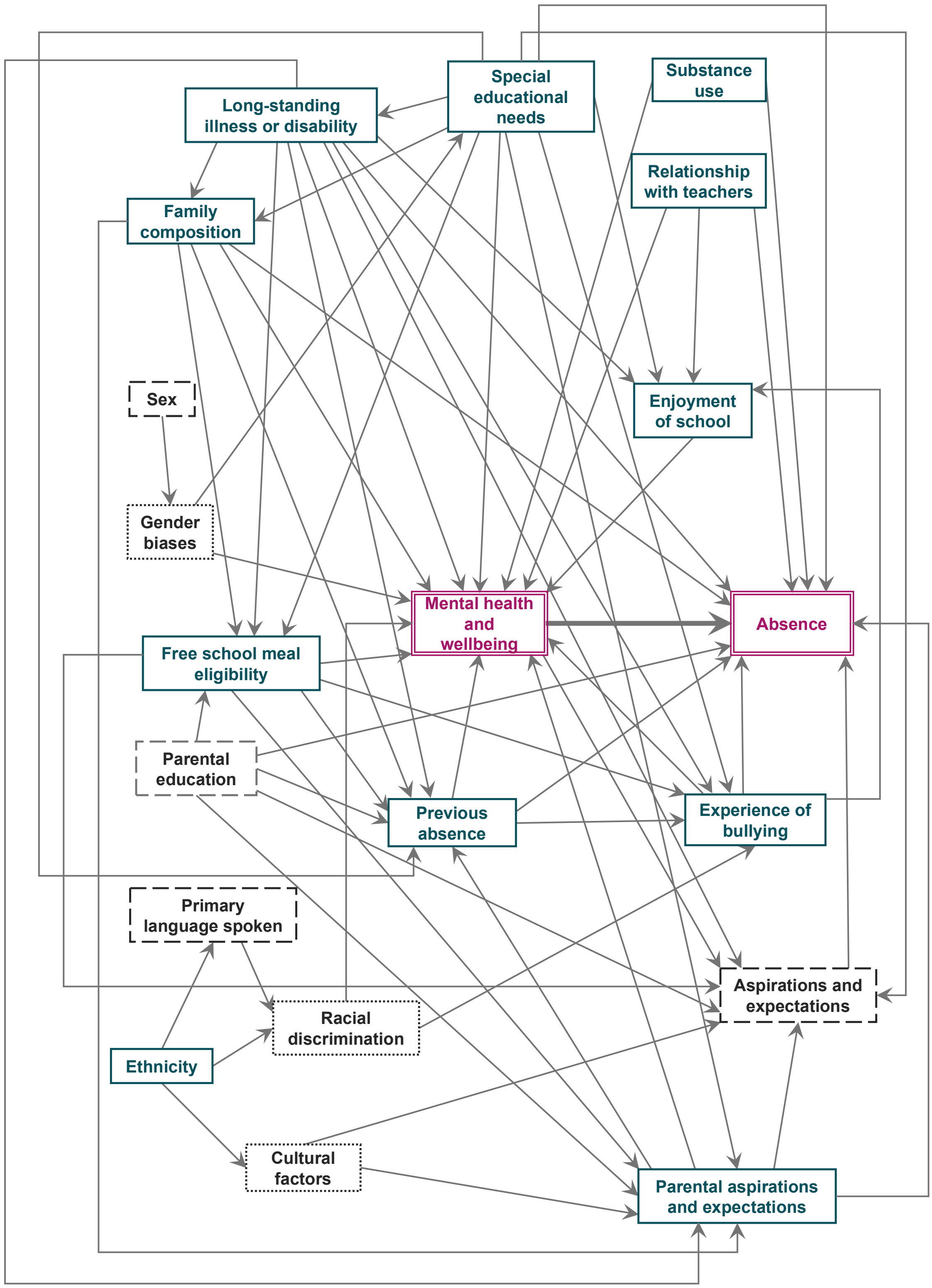
The aim of this piece of research is to understand whether mental health/wellbeing and absence are causally related. In the absence of randomised control trials, the combination of longitudinal data and causal methods can help us unpick the relationship between the variables.

Firstly, a DAG was used for variable selection. DAGs are useful firstly because they allow us to visually represent causal relationships and structures. Directed edges (arrows) in DAGs indicate the assumed causal relationship between two variables, and this helps us to distinguish between cause and effect. Because the edges are directed, there are no feedback loops in the causal relationships represented. Therefore, this allows us to identify confounding variables that might bias estimates of causal effects, with confounding variables being those that are associated with both the exposure of interest (mental health/wellbeing) and the outcome (absence) (Pearl 1995).

A DAG was initially made based on variables hypothesised to be related to both the exposure and the outcome by the authors (Appendix B Figure 1). From this DAG, a minimally sufficient adjustment set6 of variables can be identified. This allows us to estimate the causal relationship between mental health/wellbeing and absence without controlling for variables that mask any causal relationship. DAGs also allow for the inclusion of latent or unobserved variables. Latent variables are those that were not measured, but are thought to be related to the exposure or outcome. Often, we want to introduce latent variables to DAGs because they simplify the model. For instance, in the case of the DAG shown in Appendix B Figure 1, there is the latent variable “gender expectations” between “sex” and “SEN”. This is because boys are more likely to be identified with an SEN, with girls only making up between 34% and 36% of all students accessing SEN support across UK regions. However, rather than this being solely driven by biological differences, it is thought that it is largely the result of gender biases that result in the under-identification of females across different SEN and disabilities categories (Daniel and Wang, 2023). For instance, the diagnostic criteria for many SEN

[6] A minimally sufficient adjustment set is a list of variables that require adjustment in order to estimate the magnitude of the relationship between an exposure and outcome (Pearl, 1995).

Appendix B Figure 1. The assumed causal relationship between the variables included in the directed acyclic graph. The pink text with double lined box indicates that the variable is the key exposure or outcome; dark blue text with solid lined box indicates proposed covariates that are included in the final model; grey text with dashed box indicates proposed covariates that are not included in the final model; grey text with dotted box indicates that the variable is latent.



categories are often based on male characteristics, and girls are often able to "camouflage" certain challenges better than boys (Rynkiewicz et al. 2016; Tillmann et al. 2018). It has also been thought that in a school setting, boys are more commanding of teachers' attention, resulting in them having a larger number of referrals for social, emotional and mental health difficulties, while girls may go under the radar (Derks et al. 2007). Hence, within a DAG, while there is a relationship between sex and SEN, sex itself is not the causal factor; it is a factors related to gender biases/expectations, and therefore a latent variable is included in the DAG.

After removing variables from the DAG that are colliders, mediators, or not confounders, the remaining variables are:

- Exposure: mental health/wellbeing
- Outcome: absence (binary value based on threshold)
- Covariates: Family composition, whether the participant has a LSID, whether the participant has SEN, whether the student has ever been eligible for FSM, ethnicity, substance use, relationship with teachers, enjoyment of school, experience of bullying, parental aspirations and expectations, previous absence

Causality was then also estimated using inverse probability weighting (IPW) as part of the modelling procedure (Rosenbaum and Rubin 1983). This is a statistical technique that can be used in causal inference to estimate a causal effect of an exposure on an outcome in an observational study (such as the LSYPE2). The underlying logic of IPW is that we can re-weight the data such that it resembles a hypothetical randomised control trial, where the treatment (exposure) assigned is independent of the observed covariates. In observational studies, the participant's experience of the exposure is influenced by confounding variables that are associated with both the treatment and the outcome. This can bias the estimates of the causal effect. IPW helps address this by reweighting the data such that all participants are balanced with respect to the covariates, effectively mimicking randomisation. These weights are then assigned to each observation in the dataset based on the inverse of the probability of the exposure level given the covariates. This weighting ensures that observations with rare or extreme exposure levels are appropriately accounted for. The goal of IPW is to achieve a covariate balance across different levels of exposure as a means of reducing the bias in the estimated causal effect. Once the data are reweighted, causal effects can be estimated by using regression. The calculation of the IPW is as follows:

$$\mathrm{IPW} = \frac{f_X\,(X;\;\mu_1,\sigma_1^2)}{f_{X|C}(X|C = c;\mu_2,\sigma_2^2)}$$

Where:

- X is the exposure

- C is the other covariates
- $f(.)$ in both the numerator and denominator is the probability density function, with a mean of μ and a variance of σ^2
- $f_X\,(X;\ \mu_1, \sigma_1^2)$ is the probability distribution of the exposure
- $f_{X|C}(X|C = c; \mu_2, \sigma_2^2)$ is the probability distribution of the exposure variable explained by the covariates

In addition to IPW, survey weights are also included in the data weighting process. The calculation of survey weights is outlined in the LSYPE2 technical information (Kantar Public 2016). Here, the data are weighted based on a value that includes both the IPW and the survey weights, whereby the IPW and survey weights are multiplied together, and then this survey design is applied to the data (DuGoff et al. 2014). As a note, for descriptive statistics, only the survey weights are applied.

The final causal method used is the inclusion of previous measures of the outcome. As shown in Appendix B Figure 1, a previous measure of attendance is adjusted to mitigate the possibility of a bidirectional relationship between mental health and absence. This is important because frequent absenteeism can negatively impact mental health and wellbeing, potentially leading to increased absence levels. The timing of the variables included in the DAG for the different outcomes can be found in Appendix C Table 1.

Logistic regression was used to estimate the odds of a student being absent based on mental health and wellbeing, after adjusting for the aforementioned covariates, accounting for the IPW and survey weights. A total of 115 models were made for this analysis, as there were three types of absence (overall, unauthorised, authorised), eight definitions of absence (greater than 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%[7] of sessions), and five exposures (GHQ-12, life satisfaction, worthwhile, happiness, anxiety). Appendix C Table 3 illustrates the different model combinations.

All analyses were carried out in R version 4.3.3 (R Core Team 2024). The package *ipw* (Wal and Geskus 2011) is used to calculate IPW, and *srvyr* (Freedman Ellis and Schneider 2023) and *survey* (Lumley 2004) to weight the data and create weighted general linear models. *ggplot2* (Wickham, 2016) was used to create data visualisations.

Appendix C. Data and variable information

Data used in this analysis are derived both from the LSYPE2 and the NPD.

[7] Note: Where authorised absence was the outcome, the 50% threshold was not used due to sample size constraints.

From the LSYPE2, participants were only included if they were present in Wave 3 (from when the outcome variable was drawn) and consented for their data to be linked to the NPD[8]. Participants from independent schools were dropped from the analysis as their data were not in the NPD[9]. Participants with missing data were also dropped from the analysis. Given IPW is already being used for causal reasons, data were not imputed as IPW has been shown to be an effective method of mitigating the effects of missing data (Seaman and White 2013). This left us with a sample of 7,737 participants in the mental health dataset and 7,374 in the personal wellbeing dataset.

When mental health was used as the exposure of interest, covariates from Wave 2 were used, and when personal wellbeing was the exposure of interest, covariates from Wave 3 were used (with the exception of ethnicity, relationship with teachers, and previous absence). The timing of all the variables can be found in Appendix C Table 1.

Given the mental health/wellbeing variables were measured at different waves, the covariates included in the datasets were measured at waves that corresponded with the timing of the exposure, with the exception of ethnicity, the student's relationship with their teachers, and previous absence. By definition, ethnicity is a time-invariant variable. However, there is some movement within-person across different time points, likely due to social factors that influence ethnic identity (Simpson et al. 2015). Therefore, in all datasets, ethnicity is drawn from the 2012/13 academic year of the NPD, which Given the mental health/wellbeing variables were measured at different waves, the covariates included in the datasets were measured at waves that corresponded with the timing of the exposure, with the exception of ethnicity, the student's relationship with their teachers, and previous absence. By definition, ethnicity is a time-invariant variable. However, there is some movement within-person across different time points, likely due to social factors that influence ethnic identity (Simpson et al. 2015). Therefore, in all datasets, ethnicity is drawn from the 2012/13 academic year of the NPD, which corresponds to Wave 1 of LSYPE2. The participants' relationship with their teachers was only measured in Wave 1 and 2, meaning it could not be included in Wave 3. This variable was, therefore, included as a time-lagged variable (i.e., when all the Wave 2 variables are being measured, this variable will be drawn from Wave 1). Though this means it is not necessarily comparable to the other variables, there was little switching between the categories between Waves 1 and 2, so it can be seen as a relatively stable variable across waves (Appendix C Table 2). Finally, the previous absence was measured in the wave before all the other covariates as a means of controlling for bidirectionality.

[8] Wave 3 had a total of 10010 participants, of which 9531 (95%) consented to data linkage with the NPD.
[9] There was a total of 11 students from independent schools in the Wave 3 sample.

Appendix C Table 1. Timing and levels of variables used in the analysis.

Variable name	Variable levels	Mental health dataset wave	Personal well-being dataset wave
GHQ-12	Likert score ranging from 0-12, where 12 = poorer mental health	Wave 2	-
Life satisfaction	Likert item ranging from 0-10, where 10 = lower life satisfaction	-	Wave 3
Worthwhile	Likert item ranging from 0-10, where 10 = higher feelings of un-worthwhileness	-	Wave 3
Happiness	Likert item ranging from 0-10, where 10 = feeling less happy	-	Wave 3
Anxiousness	Likert item ranging from 0-10, where 10 = higher feelings of anxi-ety	-	Wave 3
Absence threshold (overall – 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%)	Absence rate above threshold; Ab-sence rate below threshold	Wave 3	Wave 3
Absence threshold (unauthorised – 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%)	Absence rate above threshold; Ab-sence rate below threshold	Wave 3	Wave 3
Absence threshold (authorised – 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%)	Absence rate above threshold; Ab-sence rate below threshold	Wave 3	Wave 3
Ethnicity	White; Black; Asian; Mixed; Any other ethnic group	Wave 1	Wave 1
Does the participant have a LSID?	Yes; No	Wave 2	Wave 3
Does the participant have SEN?	Yes; No	Wave 2	Wave 3
Family composition	Two parents; Step-family; Single parent; No parents	Wave 2	Wave 3
Has the participant ever been eligible for FSM?	Yes; No	Wave 2	Wave 3
Does the participant use cannabis?	Uses cannabis; Does not use can-nabis	Wave 2	Wave 3
What the main par-ent would like the participant to do once they finish Year 11	Continue in full-time education; Start work with some education or training; An apprenticeship; Some-thing else	Wave 2	Wave 3

How many teachers does the participant like?	All of their teachers; Most of their teachers; Some of their teachers; Hardly any of their teachers; None of their teachers	Wave 1	Wave 2
School enjoyment	Continuous measure ranging from 1 to 4, where a higher score = more school enjoyment	Wave 2	Wave 3
Has the participant ever been bullied?	Yes; No	Wave 2	Wave 3
Previous absence (overall – 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%)	Absence rate above threshold; Absence rate below threshold	Wave 1	Wave 2
Previous absence (unauthorised – 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%)	Absence rate above threshold; Absence rate below threshold	Wave 1	Wave 2
Previous absence (authorised – 1%, 3%, 5%, 10%, 15%, 20%, 35%, 50%)	Absence rate above threshold; Absence rate below threshold	Wave 1	Wave 2

Appendix C Table 2. The frequency of responses to “How many of your teachers do you like?” in Waves 1 and 2.

How many teachers does the participant like?	Wave 1 n = 9362	Wave 2 n = 9362
None of my teachers	108 (1.2%)	127 (1.4%)
Hardly any of my teachers	889 (9.7%)	928 (10%)
Some of my teachers	3,545 (39%)	3,471 (38%)
Most of my teachers	3,957 (43%)	3,908 (43%)
All of my teachers	659 (7.2%)	733 (8.0%)

Most of the variables are taken straight from LSYPE2 with limited processing. Where that is the case, the corresponding variable name is presented in Appendix C Table 4. In some cases, the variable was derived as a composite of multiple other existing variables. In Appendix C Table 4, it is indicated where this is the case, and the method of derivation is outlined.

Appendix C Table 3 and Table 4 can be found in the supplementary file.

Appendix D. Univariate descriptive statistics

For Appendix D Table 1, see the supplementary file.

Appendix E. Bivariate descriptive statistics

For Appendix E Table 1–10, see the supplementary file.

Appendix F. Multivariate logistic regression results

For Appendix F Table 1–15, see the supplementary file.

References

Abdinasir, K., 2019. *Making the grade* [online]. Centre for Mental Health: The Health Foundation. Available from: https://cypmhc.org.uk/wp-content/uploads/2019/11/MakingTheGrade.pdf.

Amato, P. R., 2001. Children of divorce in the 1990s: an update of the Amato and Keith (1991) meta-analysis. *Journal of Family Psychology*, 15 (3), 355–370.

Anjara, S. G., Bonetto, C., Van Bortel, T. and Brayne, C., 2020. Using the GHQ-12 to screen for mental health problems among primary care patients: psychometrics and practical considerations. *International Journal of Mental Health Systems*, 14 (1), 62.

Ansari, A. and Gottfried, M. A., 2021. The Grade-Level and Cumulative Outcomes of Absenteeism. *Child Development*, 92 (4), e548–e564.

Astone, N. M. and McLanahan, S. S., 1991. Family Structure, Parental Practices and High School Completion. *American Sociological Review*, 56 (3), 309–320.

Baker, C., Dawson, D., Thair, T. and Youngs, R., 2014. *Longitudinal study of young people in England: cohort 2, wave*. Department for Education.

Brooks, J. E., 2006. Strengthening Resilience in Children and Youths: Maximizing Opportunities through the Schools. *Children & Schools*, 28 (2), 69–76.

Department for Education, 2011a. *A profile of pupil absence in England*. Education Standards Analysis and Research Division: Department for Education.

Department for Education, 2011b. *Persistent absence: government changes definition to deal with reality of pupil absenteeism in schools* [online]. Available from: https://www.gov.uk/government/news/persistent-absence-government-changes-definition-to-deal-with-reality-of-pupil-absenteeism-in-schools [Accessed 4 Sep 2024].

Department for Education, 2020. *Pupil absence in schools in England, Academic year 2018/19* [online]. Explore Education Statistics. Available from: https://explore-education-statistics.service.gov.uk/find-statistics/pupil-absence-in-schools-in-england/2018-19 [Accessed 19 Aug 2024].

Department for Education, 2021. *Five things you didn’t know about mental health support in schools* [online]. The Education Hub. Available from: https://educationhub.blog.gov.uk/2021/05/10/five-things-you-didnt-know-about-mental-health-support-in-schools/ [Accessed 19 Aug 2024].

Department for Education, 2023. *Pupil absence in schools in England, Academic year 2022/23* [online]. Explore Education Statistics. Available from: https://explore-education-statistics.service.gov.uk/find-statistics/pupil-absence-in-schools-in-england/2022-23 [Accessed 25 Jun 2024].

Department for Education, 2024a. *The link between absence and attainment at KS2 and KS4, Academic year 2018/19* [online]. Explore Education Statistics. Available from: https://explore-education-statistics.service.gov.uk/find-statistics/the-link-between-absence-and-attainment-at-ks2-and-ks4 [Accessed 25 Jun 2024].

Department for Education, 2024b. The Second Longitudinal Study of Young People in England. [online]. Available from: https://ons.metadata.works/browser/dataset/1405106/0 [Accessed 5 Aug 2024].

Department for Education, 2024c. *Pupil absence statistics: methodology* [online]. Methodologies. Available from: https://explore-education-statistics.service.gov.uk/methodology/pupil-absence-statistics-methodology [Accessed 5 Aug 2024].

Derks, E. M., Hudziak, J. J. and Boomsma, D. I., 2007. Why more boys than girls with ADHD receive treatment: a study of Dutch twins. *Twin Research and Human Genetics: The Official Journal of the International Society for Twin Studies*, 10 (5), 765–770.

Dräger, J., Klein, M. and Sosu, E., 2024. The long-term consequences of early school absences for educational attainment and labour market outcomes. *British Educational Research Journal* [online]. Available from: https://onlinelibrary.wiley.com/doi/abs/10.1002/berj.3992 [Accessed 25 Jun 2024].

DuGoff, E. H., Schuler, M. and Stuart, E. A., 2014. Generalizing Observational Study Results: Applying Propensity Score Methods to Complex Surveys. *Health Services Research*, 49 (1), 284–303.

Freedman Ellis, G. and Schneider, B., 2023. srvyr: 'dplyr'-Like Syntax for Summary Statistics of Survey Data. [online]. Available from: https://CRAN.R-project.org/package=srvyr.

Goldberg, D. P., 1972. The Detection of Psychiatric Illness by Questionnaire. *Maudsley Monograph*, 21.

Goldberg, D. P., Oldehinkel, T. and Ormel, J., 1998. Why GHQ threshold varies from one place to another. *Psychological Medicine*, 28 (4), 915–921.

Gottfried, M. A. and Ansari, A., 2021. Detailing New Dangers: Linking Kindergarten Chronic Absenteeism to Long-Term Declines in Executive Functioning. *The Elementary School Journal*, 121 (3), 484–503.

Hodge, L., Little, A. and Weldon, M., 2021. *GCSE attainment and lifetime earnings*. Department for Education. Research Report.

Jay, M. A., Grath-Lone, L. M. and Gilbert, R., 2019. Data Resource: the National Pupil Database (NPD). *International Journal of Population Data Science* [online], 4 (1). Available from: https://ijpds.org/article/view/1101 [Accessed 25 Jun 2024].

Kantar Public, 2016. Technical report for the 2nd cohort of the Longitudinal Study of Young People in England (LSYPE2): Wave 1. [online]. Available from: https://doc.ukdataservice.ac.uk/doc/7813/mrdoc/pdf/7813technical_report_wave_1.pdf.

Lumley, T., 2004. Analysis of Complex Survey Samples. *Journal of Statistical Software*, 9, 1–19.

McElreath, R., 2020. *Statistical Rethinking*. 2nd ed. Boca Raton, FL: CRC Press.

Mejías-Leiva, M. and Moreno Mínguez, A., 2024. School absence of adolescents from single-parent families in Andalusia (Spain): exploring the mediating and moderating role of economic and social resources. *Genus*, 80 (1), 4.

Ministry of Justice and Department for Education, 2019. *Understanding the educational background of young offenders: summary report* [online]. GOV.UK. Available from: https://www.gov.uk/government/statistics/understanding-the-educational-background-of-young-offenders-summary-report [Accessed 25 Jun 2024].

NHS England (2024) *Mental Health of Children and Young People in England 2022 - wave 3 follow up to the 2017 survey*, *NHS England Digital* [online]. Available from: https://digital.nhs.uk/data-and-information/publications/statistical/mental-health-of-children-and-young-people-in-england/2022-follow-up-to-the-2017-survey [Accessed: 25 June 2024].

Office for National Statistics, 2024. *Personal well-being user guidance* [online]. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/methodologies/personalwellbeingsurveyuserguide [Accessed 25 Jun 2024].

Ohrnberger, J., Fichera, E. and Sutton, M., 2017. The relationship between physical and mental health: A mediation analysis. *Social Science & Medicine*, 195, 42–49.

O’Shea, N., 2021. *Covid-19 and the nation’s mental health*.

Panchal, U., Salazar de Pablo, G., Franco, M., Moreno, C., Parellada, M., Arango, C. and Fusar-Poli, P., 2023. The impact of COVID-19 lockdown on child and adolescent mental health: systematic review. *European Child & Adolescent Psychiatry*, 32 (7), 1151–1177.

Pearl, J., 1995. Causal diagrams for empirical research. *Biometrika*, 82 (4), 669–688.

R Core Team, 2024. R: A Language and Environment for Statistical Computing. [online]. Available from: https://www.R-project.org/.

Rosenbaum, P. R. and Rubin, D. B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70 (1), 41–55.

Rynkiewicz, A., Schuller, B., Marchi, E., Piana, S., Camurri, A., Lassalle, A. and Baron-Cohen, S., 2016. An investigation of the 'female camouflage effect' in autism using a computerized ADOS-2 and a test of sex/gender differences. *Molecular Autism*, 7 (1), 10.

Santibañez, L. and Guarino, C. M., 2021. The Effects of Absenteeism on Academic and Social-Emotional Outcomes: Lessons for COVID-19. *Educational Researcher*, 50 (6), 392–400.

Seaman, S. R. and White, I. R., 2013. Review of inverse probability weighting for dealing with missing data. *Statistical Methods in Medical Research*, 22 (3), 278–295.

Simpson, L., Warren, J. and Jivraj, S., 2015. Do people change their ethnicity over time? *In*: Simpson, L. and Jivraj, S., eds. *Ethnic Identity and Inequalities in Britain: The Dynamics of Diversity* [online]. Bristol University Press, 79–92. Available from: https://www.cambridge.org/core/books/ethnic-identity-and-inequalities-in-britain/do-people-change-their-ethnicity-over-time/E5B110A230428DDECA4275C226CE9F78 [Accessed 26 Jun 2024].

Tillmann, J., Ashwood, K., Absoud, M., Bölte, S., Bonnet-Brilhault, F., Buitelaar, J. K., Calderoni, S., Calvo, R., Canal-Bedia, R., Canitano, R., De Bildt, A., Gomot, M., Hoekstra, P. J., Kaale, A., McConachie, H., Murphy, D. G., Narzisi, A., Oosterling, I., Pejovic-Milovancevic, M., Persico, A. M., Puig, O., Roeyers, H., Rommelse, N., Sacco, R., Scandurra, V., Stanfield, A. C., Zander, E. and Charman, T., 2018. Evaluating Sex and Age Differences in ADI-R and ADOS Scores in a Large European Multi-site Sample of Individuals with Autism Spectrum Disorder. *Journal of Autism and Developmental Disorders*, 48 (7), 2490–2505.

Wal, W. M. van der and Geskus, R. B., 2011. ipw: An R Package for Inverse Probability Weighting. *Journal of Statistical Software*, 43, 1–23.

Wickham, H., 2016. *ggplot2: Elegant Graphics for Data Analysis* [online]. Springer-Verlag New York. Available from: https://ggplot2.tidyverse.org.

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