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# Characterising longitudinal patterns of education, employment, and 'NEET' (Not in Education, Employment or Training) in young adulthood: an analysis of two UK longitudinal cohorts

**Zayn Rajan**
zayn.rajan@bristol.ac.uk
University of Bristol
**Gemma Hammerton**
University of Bristol
**Laura D Howe**
University of Bristol
**Esme Elden**
University of Edinburgh
**Ingrid Schoon**
University College London
**Annie Herbert**
University of Bristol

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## Abstract

# Background

Young people follow diverse pathways through education, employment and periods of being Not in Education, Employment or Training (NEET). However, relatively little research has examined longitudinal patterns of NEET while distinguishing between those actively seeking work and those economically inactive. This study aimed to identify distinct school-to-work transition patterns and examine their associations with socioeconomic, mental health, educational and behavioural characteristics during childhood and adolescence.

# Methods

Data were drawn from two prospective UK cohorts: the Avon Longitudinal Study of Parents and Children (ALSPAC; n = 5,999) and Next Steps (n = 11,709). Latent class analysis was used to identify patterns of education, employment, job-seeking NEET and inactive NEET between ages 17 and 30 in ALSPAC, and ages 17 and 32 in Next Steps. Associations between childhood and adolescent characteristics and class membership were examined using multinomial logistic regression with a bias-adjusted three-step approach, accounting for classification uncertainty.

# Results

Five distinct classes were identified in each cohort. Three broadly comparable patterns emerged across cohorts, characterised by early labour market entry, graduation and predominantly inactive NEET. ALSPAC additionally identified Late Graduates and Mixed Education/Employment classes, whereas Next Steps distinguished between Persistent Inactive NEET (2.7%) and Mixed NEET (8.5%), the latter characterised by greater job-seeking activity. Across both cohorts, socioeconomic disadvantage, mental health difficulties, attention-deficit hyperactivity disorder (ADHD), special educational needs, poor school engagement and disability were associated with increased odds of NEET class membership compared with the Graduate class. Associations were generally strongest for inactive NEET patterns, although most characteristics showed broadly similar associations across NEET subtypes.

# Conclusions

School-to-work transitions are heterogeneous, with a minority of young people experiencing persistent NEET, including distinct patterns of economic inactivity and job-seeking. Socioeconomic disadvantage, mental health and neurodevelopmental difficulties, and educational disengagement were consistently associated with NEET-related pathways. These findings highlight the importance of recognising the

diversity of NEET experiences and the potential value of earlier support for young people experiencing multiple vulnerabilities.

## Introduction

The school-to-work transition (STWT) is a complex life stage in which young people move from compulsory education into further or higher education, employment, training schemes, or periods of being Not in Education, Employment, or Training (NEET). NEET status is linked to worse mental health, substance use, and suicidality [1]. In the UK, 13.3% of 16–24-year-olds were NEET in late 2025, a rate that has trended upward since the coronavirus pandemic [2]. Beyond its economic costs in the form of welfare payments and lost productivity, it is estimated that a 5-percentage-point reduction in NEET could boost UK GDP by £38bn annually [3].

NEET is not a single, homogeneous state. Instead, young people move into and out of NEET over time, following diverse pathways between education, employment, and different contexts of NEET (e.g. being 'economically inactive' - i.e. of working age but neither working nor actively looking or available for work). An estimated 61% of young people who are NEET in the UK are economically inactive, while 39% are actively seeking work [4], and these subgroups likely differ in characteristics and needs. Although recent longitudinal studies have begun to examine the timing, recurrence and chronicity of NEET experiences [5, 6], relatively little research has characterised distinct longitudinal pathways while differentiating between job-seeking and economically inactive NEET experiences.

Sequence analysis (SA) and latent class analysis (LCA) are two approaches commonly used to identify typologies of school-to-work transitions [7, 8]. Although SA is well suited to describing complex transition sequences, particularly in data with many repeated observations, LCA offers a person-centred framework that identifies underlying subgroups within a heterogeneous population and assigns individuals to classes probabilistically [9]. LCA has been widely applied to longitudinal data to characterise patterns of adverse childhood experiences, mental health, and health behaviours [10, 11, 12]. LCA was also used to identify underlying patterns of social roles during the transition to adulthood, including a 'left behind' group characterised by a lack of qualifications and a high risk of unemployment [13]. In the context of education and employment trajectories, LCA can therefore be used to identify distinct pathways through education, employment, and NEET status, including subtypes that cannot be readily captured by cross-sectional analyses.

Known characteristics associated with NEET include poor physical, mental health, and socioeconomic disadvantage [14], alongside cannabis and drug use [1, 15]. However, existing evidence draws largely on cross-sectional data and rarely examines whether these characteristics differ by NEET subtype.

This study uses two large, prospective UK cohorts to identify longitudinal patterns of education, employment, and NEET status between ages 17 and 32 years, and examines associations between these patterns and various potential correlates including adolescent mental health, sociodemographic characteristics, substance use, and educational engagement. Specifically, we aim to identify distinct

STWT patterns, considering differences in the timing, duration, and type of NEET experiences, particularly whether these involve periods of job-seeking or economic inactivity. We then examine whether adolescent characteristics are associated with membership of different patterns, especially those characterised by persistent NEET, compared with patterns involving more sustained participation in education or employment. By examining these patterns across two UK cohorts, this study aims to provide a more detailed understanding of the heterogeneity of STWTs and the characteristics associated with different pathways.

## Methods

# Study populations

# Avon Longitudinal Study of Parents and Children (ALSPAC)

The first cohort study used in this analysis is ALSPAC [16, 17, 18, 19, 20], a population-based prospective birth cohort that recruited pregnant women living in Avon, UK, with expected delivery dates between April 1991 and December 1992. The study included 15,447 pregnancies. Further details are provided in Supplementary Section 1; the study website contains details of all the data that is available through a fully searchable data dictionary and variable search tool (http://www.bristol.ac.uk/alspac/researchers/our-data/).

## Next Steps

The second cohort study used for this analysis is Next Steps, a nationally representative longitudinal study of young people in England [21]. Participants were originally recruited at age 13–14 in 2004, with an original sample size of 15,770 participants.

## Measures

# Main Activity

In ALSPAC, main activity was derived at ages 17, 20, 21, 22, 23, 25, 27, and 30 from questionnaire items on education and employment; in Next Steps, participants directly reported their main activity at ages 17, 18, 19, 20, 25, and 32. At each timepoint, main activity was classified as employment, education, looking-for-work NEET, or inactive NEET and used as repeated categorical indicators in the latent class model. Inactive NEET included individuals who were not actively looking for work due to sickness or disability, caring responsibilities, travel or financial reasons, taking a break, a lack of skills or qualifications, or other reasons. Training, including apprenticeships and government schemes, was collapsed into employment due to its low prevalence and predominantly vocational nature, as suggested by previous literature [22].

For ALSPAC participants reporting multiple activities, full-time activities took priority over part-time, with education prioritised over employment among part-time activities. Next Steps participants were asked to report their main activity, and this was used as provided.

# Explanatory variables:

Associations with latent class membership were examined for a range of sociodemographic, mental health, educational, substance use, and health-related factors measured during childhood and adolescence. These included indicators of family socioeconomic position, emotional and behavioural difficulties, school experiences, educational aspirations, substance use, and disability. Variables were harmonised as closely as possible across ALSPAC and Next Steps; however, some differences in measurement and timing were unavoidable due to differences in cohort design and data collection. The measurement and timing of explanatory variables across ALSPAC and Next Steps are described in Supplementary Table 2.1.

## Missing data

Given the wide age range (17–32 years), analyses were restricted to participants with ≥ 2 observed main activity measures to improve class separation. Missing data on main activity was handled using Full Information Maximum Likelihood (FIML) [23]. Missing explanatory variable data was handled using multiple imputation by chained equations (MICE) [24] (Supplementary Section 3.1).

# Statistical Analysis:

# Longitudinal patterns of education, employment, and NEET status

Latent class analysis (LCA) was conducted in Mplus (version 9) to identify patterns of education and employment activity over follow-up, using main activity at each timepoint as categorical indicators. Separate models were fitted for ALSPAC and Next Steps, estimated sequentially from two to six classes. The optimal number of classes was determined using model fit indices, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), alongside interpretability and class size.

# Association between explanatory variables and longitudinal patterns of education, employment, training and NEET

Associations between explanatory variables and latent classes were examined using a manual bias-adjusted three-step approach [25], which estimates the latent class model separately from the regression model while accounting for classification uncertainty. This approach reduces bias arising from class misclassification compared with one-step models [26].

The procedure involved: (1) fitting and selecting the optimal latent class model as described above; (2) assigning participants to their most probable class based on posterior probabilities; and (3) estimating associations using multinomial logistic regression, with classification uncertainty incorporated through logits of class membership probabilities.

Explanatory variables were recoded as binary for interpretability. The Graduate class was used as the reference category in all analyses, as it was the largest class in the nationally representative Next Steps cohort and was also identified in ALSPAC. Associations between explanatory variables and latent class membership were estimated using multinomial logistic regression and pooled across multiply imputed datasets using Rubin's rules. Implemented through the MplusAutomation package in R [27]. Results are presented as odds ratios (ORs) with 95% confidence intervals (CIs).

## Sensitivity analysis

Latent class and association analyses were repeated in a less restricted sample that included participants with at least one observed main activity measure, rather than the minimum of two measures required for the primary analyses.

# Results

## Analytic samples

Figure 1 illustrates how the analytic samples were derived. The ALSPAC sample (n = 5,999) was predominantly female (62%) and White (96%); the Next Steps sample (n = 11,709) was more balanced according to sex (51% female), but also predominantly White (70%) (Table 1).

For analysis samples in both cohorts, imputed and observed sample characteristics were broadly similar, and participants in the analytic samples were more socioeconomically advantaged than excluded participants (ALSPAC to a greater degree than Next Steps) [Supplementary Tables 1.1–1.2].

Figure 2 provides the prevalence of NEET by subtype, in ALSPAC and Next Steps. In ALSPAC, the prevalence of NEET ranged from 2.5% at age 17 to 7.8% at age 21, while prevalence in Next Steps ranged from 4.0% at age 18 to 11.4% at age 32. In ALSPAC, the majority of young people who were NEET were economically inactive at most timepoints, whereas in Next Steps, looking-for-work NEET was more prevalent at younger ages, with economic inactivity becoming more common at ages 25 and 32. Age-specific prevalence estimates, stratified by subtype, are presented in Supplementary Table 4.1

Figure 1: Flow chart of analytic sample selection in ALSPAC and Next Steps. Initial cohort numbers represent all participants who were enrolled in the study and had not withdrawn their consent at the time of analysis.

Table 1
Characteristics of analysis sample across imputed datasets in ALSPAC and Next Steps

| **Sex** | **ALSPAC analysis sample [pooled percentages across 100 imputed datasets]** | **Next Steps analysis sample [pooled percentages across 100 imputed datasets]** |
|---|---|---|
| Male | 37.8 | 48.6 |
| Female | 62.2 | 51.4 |
| **Ethnicity** | | |
| White | 95.6 | 69.6 |
| Minoritised ethnic group* | 4.4 | 30.4 |
| **Housing status** | | |
| Owned/mortgage | 88.0 | 73.0 |
| Rented/other | 12.0 | 27.0 |
| **Household social class** | | |
| Manual | 16.0 | 55.0 |
| Professional/managerial | 84.0 | 45.0 |
| **Special educational needs** | | |
| No | 81.3 | 80.4 |
| Yes | 18.7 | 19.6 |
| **Depressive symptoms^** | | |
| No | 83.2 | 75.1 |
| Yes | 16.8 | 24.9 |

*Excluding White minorities (e.g. Gypsy, Roma and Traveller communities)

^ ALSPAC: Short Mood and Feelings Questionnaire (SMFQ) ≥ 12 at age 16

Next Steps: General Health Questionnaire-12 (GHQ-12) ≥ 13 at age 15

# Latent classes of education, employment and NEET status

5-class solutions were selected in both ALSPAC and Next Steps. In ALSPAC, AIC decreased as the number of classes increased, while BIC and SSA-BIC stopped decreasing after 4 and 5 classes, respectively (Supplementary Table 5.1). Visual inspection further indicated that the 5-class solution identified meaningful patterns not captured by solutions with fewer classes. The average posterior probability of assignment to the most likely class was adequate (> 0.70) for all 5-classes (Supplementary Table 5.2), with the smallest class size (based on model-estimated probabilities) being 5.5%. The entropy of the 5-class solution was 0.70 (Supplementary Table 5.1).

In Next Steps, AIC, BIC, and SSA-BIC continued to decrease up to 6 classes, while the LMR-LRT found no improvement beyond 4 classes (Supplementary Table 6.1). However, visual inspection showed the 5-class solution captured meaningful heterogeneity within NEET status: distinguishing persistently inactive NEET young adults from those NEET but more likely to be actively job-seeking. This distinction was central to our research aims, so we retained 5 classes. Its smallest class (2.7%) still represented ~ 300 people given our total sample of 11,709. The average posterior probability of being assigned to the most likely class was adequate (> 0.70) for all 5-classes (Supplementary Table 6.2) and the entropy of the 5-class solution was 0.79 (Supplementary Table 6.1)

The labels assigned to these classes and model-estimated percentages for each class are presented below, for both cohorts:

**ALSPAC – 5-class solution**:

# 1) Early labour market (45.3%)

Consistently high probability of being in employment from age 18 onwards, after some post-16 education.

1. **Graduates (35.7%)**

A high probability of being in education until their early 20s and then a consistently high probability of being in employment.

1. **Late graduates (7.9%)**

A high probability of being in education until their mid-20s, and then a high probability of being in employment.

1. **Mixed education & employment (5.5%)**

A high probability of being in either education or employment throughout young adulthood.

1. **Mixed inactive NEET (5.5%)**

High probability of being inactive NEET after leaving education at age 18, with a mixture of other statuses including being in employment and looking for work.

**Next Steps – 5-class solution**:

# 1) Graduates (52.5%)

A high probability of being in education until early 20s and then a high probability of being in employment after this. Low probabilities of other statuses throughout.

1. **Employment only (19.7%)**

A high probability of being in employment throughout young adulthood with low probabilities of being in any other statuses.

1. **Early labour market (16.6%)**

A high probability of being in employment from age 18 onwards, after some post-16 education. A moderate probability of being in education in early 20s, but low probability of other statuses throughout.

1. **Mixed NEET job seekers (8.5%)**

A high probability of being NEET but actively looking for work after leaving education at age 18. A moderate probability of being in employment, and an increasing probability of being inactive NEET later in young adulthood.

1. **Persistent inactive NEET (2.7%)**

A high probability of being inactive NEET throughout young adulthood after leaving education at age 18. A moderate probability of being in employment later in young adulthood.

Figure 3 presents the class-level probabilities of each status at each timepoint, in both the ALSPAC and Next Steps 5-class solutions.

Probability of each main activity status, at each timepoint, for all 5-classes in ALSPAC (top row) and Next Steps (bottom row).

# Sensitivity analysis - replication of latent classes in less restricted sample

5-class solutions with substantially similar class profiles and interpretations to the primary analyses were replicated in less restricted samples in both ALSPAC (n = 7,480) and Next Steps (n = 13,203) [Supplementary Figs. 5.1 and 6.1]. These samples included all participants with at least one observation of their main activity

# Associations between explanatory variables and latent classes

Prevalences of all explanatory variables reported in Supplementary Tables 7.1 and 8.1 for ALSPAC and Next Steps, respectively. Odds ratios and 95% CIs for associations between explanatory variables and latent classes are presented in Figs. 4 and 5, with exact values provided in Supplementary Tables 7.2 and 8.2. The **Graduates** latent class was used as the reference class for all association analyses.

# Sociodemographic factors

Women had higher odds than men of membership in the inactive NEET classes in both cohorts (ALSPAC mixed inactive NEET, OR [95% CI]: 1.70 [1.23–2.35]; Next Steps persistent inactive NEET: 6.49 [3.38–12.46]). However, in Next Steps, women had lower odds of membership in the Mixed NEET class (0.60 [0.49–0.73]). Socioeconomic disadvantage, including non-homeownership, manual household social class, parental unemployment and lower parental educational attainment, was consistently associated with higher odds of NEET class membership in both cohorts. Associations were particularly strong for inactive NEET classes (e.g., ALSPAC non-homeownership: 9.56 [6.11–14.95]; Next Steps parental education below degree level: 8.62 [2.92–25.64]). Having two or more siblings was also associated with higher odds of both NEET classes in Next Steps, but not ALSPAC. In ALSPAC, there was no clear overall association between ethnicity and class membership, although participants from minoritised ethnic groups had higher odds of belonging to the Late Graduates class (2.04 [1.11–3.76]). In contrast, minoritised ethnic group membership was associated with lower odds of belonging to all classes relative to the Graduates class in Next Steps.

# Mental health and neurodevelopmental conditions

Adolescent mental health difficulties and ADHD were strongly associated with NEET class membership in both cohorts, particularly the inactive NEET classes. In ALSPAC, ADHD at age 13 (11.17 [6.21–20.07]), elevated emotional difficulties at age 16 (7.48 [4.77–11.74]) and depressive symptoms at age 16 (3.95 [2.58–6.03]) were associated with higher odds of mixed inactive NEET membership. In Next Steps, ADHD was associated with substantially higher odds of membership in both the Mixed NEET (11.88 [5.80–24.34]) and persistent inactive NEET (5.64 [1.56–20.41]) classes. Psychological distress at age 15 was associated with higher odds of persistent inactive NEET membership (2.14 [1.41–3.24]), but there was weaker evidence of an association with Mixed NEET membership (1.18 [0.91–1.52]). Confidence intervals for some ADHD associations were wide, indicating considerable uncertainty in the magnitude of these estimates.

# School and educational engagement

Indicators of poorer school engagement and educational disadvantage, including special educational needs (SEN), school suspension, lower GCSE attainment (ALSPAC), and lower educational aspirations, were associated with increased odds of NEET class membership across both cohorts. Associations were generally strongest for the inactive NEET classes. For example, SEN was associated with higher odds of mixed inactive NEET membership in ALSPAC (5.13 [3.62–7.27]) and both persistent inactive NEET (2.57 [1.80–3.66]) and Mixed NEET (4.03 [3.28–4.94]) membership in Next Steps. Not enjoying

school was particularly strongly associated with inactive NEET membership in both cohorts (ALSPAC: 6.33 [4.18–9.52]; Next Steps: 10.53 [7.35–14.93]). Lower educational and occupational aspirations, including aspirations to leave full-time education and parental aspirations or expectations for manual occupations, also showed particularly strong associations with NEET class membership, although some estimates had wide confidence intervals.

# Substance use

In ALSPAC, having tried cannabis and high-risk alcohol or cannabis use at age 16 were associated with higher odds of mixed inactive NEET membership. High-risk cannabis use showed a particularly strong association (15.10 [2.82–80.77]), although the wide confidence interval indicated substantial uncertainty. In contrast, frequent alcohol consumption was not clearly associated with class membership overall (Wald test p = 0.166). In Next Steps, frequent alcohol consumption and having tried cannabis at age 16 were associated with higher odds of membership in all classes compared with the Graduates class, including persistent inactive NEET (alcohol: 1.94 [1.25–3.01]; cannabis: 1.92 [1.31–2.80]) and Mixed NEET (alcohol: 2.40 [1.86–3.09]; cannabis: 2.69 [2.17–3.34]).

# Disability/Caring responsibilities

Disability or long-term illness was associated with higher odds of inactive NEET class membership in both cohorts (ALSPAC mixed inactive NEET: 2.91 [1.79–4.72]; Next Steps persistent inactive NEET: 2.22 [1.52–3.25]). In Next Steps, disability or long-term illness was also associated with higher odds of Mixed NEET membership (1.76 [1.38–2.27]). In Next Steps, caring responsibilities was associated with membership of persistent inactive NEET (2.17 [1.30–3.64]) and Mixed NEET (1.49 [1.03–2.15]).

# Sensitivity analysis

Findings in less-restricted samples (n = 7,480 in ALSPAC and n = 13,203 in Next Steps), which included participants with at least one observed main activity measure rather than the primary criterion of at least two, were broadly consistent with the primary analyses in direction, magnitude and strength of evidence (Supplementary Tables 7.3 and 8.3; Supplementary Figs. 7.1 and 8.1), particularly for the NEET classes.

## Declarations

# Abbreviations:

ADHD = Attention-Deficit Hyperactivity Disorder

GHQ-12 = General Health Questionnaire-12

**Discussion**

This study examined NEET status in a more nuanced way than previous research by considering subtypes of NEET experience, using data from two UK cohorts born in the early 1990s (ALSPAC and Next Steps) to assess whether findings replicated across samples. Latent class analysis identified a single, predominantly inactive NEET class in ALSPAC, whereas Next Steps identified two 'NEET' classes: a predominantly inactive NEET class, broadly comparable to that seen in ALSPAC, and a Mixed NEET class with a higher probability of job-seeking activity. We then estimated crude associations between a broad set of explanatory variables (26 in ALSPAC; 20 in Next Steps) and NEET class membership in an exploratory analysis to identify variables most strongly linked to NEET status.

Although broadly comparable Early Labour Market, Graduate and inactive NEET classes emerged across cohorts, some differences were observed. ALSPAC identified more varied education-to-employment patterns (Mixed Education/Employment and Late Graduates), whereas Next Steps showed greater heterogeneity in NEET experiences (Persistent inactive NEET and Mixed NEET). These differences may partly reflect differences in cohort composition. ALSPAC is a regional cohort and has experienced substantial attrition over time, resulting in a more socioeconomically advantaged analytical sample, which may help explain the identification of a Late Graduates class. In contrast, the greater socioeconomic and demographic diversity of Next Steps may partly explain the higher prevalence of NEET-related patterns, particularly when the Persistent inactive NEET and Mixed NEET classes are considered together (approximately 11%, compared with 6% in ALSPAC's inactive NEET class). Nevertheless, ALSPAC retained considerable heterogeneity, with a substantial proportion of participants experiencing periods of NEET. Differences in data collection may also have contributed, with the more detailed information on job-seeking behaviour in Next Steps potentially allowing greater differentiation of NEET subtypes.

Across both cohorts, indicators of socioeconomic disadvantage were generally more strongly associated with NEET-type class membership than with other classes, with large associations also consistently observed for mental health difficulties, ADHD, special educational needs and poor school engagement, several of which had odds ratios exceeding 5, albeit with wide confidence intervals. Within Next Steps, most variables showed similar associations across the two NEET subtypes, though female sex and psychological distress were more strongly linked to persistent inactive than Mixed NEET. Together, these findings point to identifiable vulnerabilities, particularly relating to economic deprivation, mental health, neurodevelopmental conditions, and educational disengagement, that may place young people at risk of difficult school-to-work transitions regardless of the specific trajectory they go on to follow. Further work is needed to establish whether and how these factors play a causal role in shaping later NEET experiences.

**Comparisons with other studies**

Our findings align with previous work suggesting that young people follow diverse school-to-work transitions (STWT), with socioeconomic disadvantage associated with more difficult and unstable pathways. Using sequence analysis, Anders and Dorsett [28] identified three broad pathways across four

English birth cohorts, including the Next Steps cohort also analysed in the present study: labour-market entry, human-capital accumulation, and potentially difficult transitions. These broadly correspond to our employment-focused, graduate-type, and NEET classes, and they similarly found that socioeconomic disadvantage predicted more difficult transitions. Likewise, Pelikh and Rowe [29] identified six education and employment trajectories between ages 16 and 26, including successful, education-linked, turbulent, and precarious pathways, and showed that socioeconomic disadvantage was associated with more turbulent transitions and poorer occupational outcomes. Extending this literature, our study focuses specifically on NEET experiences, distinguishing inactive and job-seeking NEET patterns that were not separated in either previous study. We also follow participants into their early thirties, capturing longer-term patterns of education, employment, and NEET status, and examine a broader range of correlates, including mental health, ADHD, educational engagement, and substance abuse. Finally, by using latent class analysis, we provide a complementary person-centred approach to the sequence analytic methods used in previous research.

In our study, mental health and neurodevelopmental conditions were strongly associated with NEET membership. ADHD showed particularly large associations (ORs 5.88–12.04), consistent with another ALSPAC study linking persistent ADHD to NEET status and benefit receipt at age 25 [30]. In Next Steps, ADHD was more strongly associated with mixed than inactive NEET patterns; previous research has emphasised the importance of suitable workplace accommodations for those with ADHD [31]. Recent evidence from the UK Household Longitudinal Study similarly found that adolescent emotional symptoms, conduct problems and hyperactivity were associated with both subsequent NEET status and greater NEET chronicity between ages 16 and 24 [5]. Previous ALSPAC research found that childhood-persistent and early-adult-onset depression, but not adolescent-onset depression, predicted NEET risk [32], highlighting the importance of timing and course of mental health problems.

Educational disengagement (SEN, suspension, and absence) and low attainment were strongly associated with NEET membership, consistent with their identification as leading risk factors in a scoping review [14]. Higher child and parental aspirations were protective against NEET, aligning with previous research [33], although their independent effects are difficult to disentangle given the influence of parental expectations on children's aspirations [34].

Cannabis abuse was strongly associated with inactive NEET membership in ALSPAC, consistent with evidence linking cannabis use to later NEET status [1, 35]. Alcohol associations varied by cohort: AUD was associated with NEET membership in ALSPAC, whereas consumption frequency was associated in Next Steps, consistent with broader evidence [36]. The relationship may also be bidirectional, as NEET status could increase vulnerability to harmful drinking through reduced social control [36]. Disability/long-term illness was associated with NEET membership in both cohorts, consistent with evidence linking chronic health conditions and functional limitations to economic inactivity [37, 38].

**Strengths**

By drawing on two rich, longitudinal cohorts, we were able to identify patterns of education, employment, and NEET status over time rather than at a single fixed timepoint, better reflecting the fluid, diverse nature of post-school transitions. We could also distinguish inactive from job-seeking NEET in Next Steps, where two distinct NEET classes emerged. Being established cohorts with over 30 years of follow-up resulted in data on a wide range of potential correlates – including adolescent mental health, socioeconomic status, school engagement, and substance use – which enabled examination of antecedents and associations with these patterns. Comparing patterns of association across cohorts allowed us to consider the generalisability while bearing in mind that the differences in timing and spacing of data collection may themselves contribute to some observed differences between cohorts Our use of a manual bias-adjusted three-step approach accounted for uncertainty in latent class assignment, reducing potential bias in explanatory variable associations.

**Limitations**

Several limitations should be considered whilst interpreting findings. First, excluded participants in both cohorts were more likely to be socioeconomically disadvantaged (Supplementary Tables 1.1–1.2), suggesting potential for selection bias. However, sensitivity analyses using a less restrictive inclusion criterion (≥ 1 observed activity status rather than > = 2) produced highly consistent classes and associations (Supplementary Figs. 7.1, 8.1), suggesting that findings were not heavily influenced by this inclusion criterion. Nevertheless, selective attrition may have led to underrepresentation of the most disadvantaged young people, resulting in underestimation of the prevalence of persistent NEET membership and attenuation of associations with previous disadvantage [39]. Second, there was substantial missing data on main activity status, particularly in ALSPAC. We used FIML for activity status indicators and MICE for explanatory variables, incorporating extensive auxiliary information to strengthen plausibility of the Missing-at-Random (MAR) assumption.

Third, data collection and measurement timing differed substantially between cohorts: ALSPAC recorded activity more frequently, while Next Steps had gaps between ages 20–25 and 25–32, but had more detailed questionnaires on job-seeking behaviour. This may have influenced the classes identified, and limit direct comparability of the resulting patterns. Nevertheless, many similarities were observed across cohorts, with broadly comparable Early Labour Market, Graduate and inactive NEET classes emerging in both. Furthermore, the inactive NEET classes may encompass individuals who are inactive for different reasons, such as caring responsibilities or health-related difficulties, which may have distinct antecedent profiles. However, small sample sizes prevented us from examining these subgroups separately.

Fourth, LCA is limited by the local independence assumption [40], which would require that repeated measures of main activity are conditionally independent within classes. This assumption may not fully hold if activity status at an earlier age is associated with later activity status, even after accounting for class membership. However, LCA captures patterns of persistence and change over time through the identification of distinct trajectory classes, meaning that some of the dependence between repeated measures is accounted for. Another limitation of LCA is that the selection of a latent class model is a

subjective process, based on a combination of model fit statistics, class sizes and interpretability, rather than single definitive statistical criterion.

Fifth, given the wide range of characteristics examined, we adopted a descriptive approach using separate unadjusted models per explanatory variable rather than assessing causality. Even with confounder adjustment, estimates would remain susceptible to collider bias, since latent class comparisons implicitly condition on class membership by excluding participants in other classes [41]. Identifying causal determinants of difficult school-to-work transitions will require analytical approaches that explicitly address this selection process.

**Implications**

The recent government interim report on Young People and Work by Milburn describes NEET as comprising a multitude of overlapping cohorts rather than a homogeneous category [42]. Our findings support this perspective by identifying distinct subtypes of NEET experiences. However, when examining associations with potential antecedents, most characteristics did not distinguish between these subtypes. This suggests that, although some factors may be associated with NEET status, they may have limited utility for identifying more specific high-risk groups beyond the broad classification of NEET. Nevertheless, understanding the wide range of characteristics associated with NEET remains important for policymakers, particularly given Milburn's suggestion that risk factors may accumulate and compound across the life course.

The Milburn report also highlights the increasing contribution of mental health and neurodevelopmental conditions to health-related economic inactivity. These were among the characteristics most strongly associated with NEET classes in our study, further highlighting the relevance of health-related factors to young people's transitions into NEET. The report also argues that NEET is rooted in social disadvantage, which aligns with our strong findings associating deprivation with NEET patterns. These findings suggest that policy responses may need to address both the health and socioeconomic circumstances associated with disengagement from education and employment.

Improving school engagement may represent another important policy goal: indicators of educational disengagement were among the characteristics most strongly associated with NEET-class membership, including school suspension, low GCSE attainment, and lower educational aspirations. A report by the Education policy Institute identifies school suspensions, particularly multiple suspensions, as an early indicator of later disengagement and unmet support needs, potentially mediated through their effects on GCSE attainment [43]. The report argues that suspension may be an indicator of wider vulnerability requiring earlier intervention, with a need to focus on underlying mental health or behavioural difficulties which could contribute to exclusionary patterns.

Although NEET subtypes showed broadly similar associations with the retrospective characteristics we examined, they may differ in their prospective associations with subsequent health and social outcomes. Recent ALSPAC evidence suggests that repeated NEET experiences are associated with poorer

subsequent mental health, with accumulating NEET occasions associated with progressively higher odds of depression, lower life satisfaction and a recent suicide attempt [6]. Future research should therefore examine whether distinct NEET patterns or subtypes should be met with different forms of support, rather than assuming a single approach is appropriate for all young people experiencing NEET.

## Conclusion

While most young people followed relatively linear pathways into employment, a minority have a high probability of NEET status; our study findings suggest this group of young adults who are NEET may further differentiate into persistently inactive and actively job-seeking. Across a range of recognisable adolescent vulnerabilities, persistent NEET status is particularly associated with worse mental health, socioeconomic deprivation, ADHD, special educational needs and disability, and lower educational engagement, suggesting they may be important markers for identifying young people at risk of long-term labour market disengagement. Policymakers should consider the diversity of NEET experiences, while research is needed to establish the causal relationship between the strongest risk factors and persistent NEET.

## List of abbreviations

ADHD – Attention-Deficit Hyperactivity Disorder

AIC – Akaike Information Criterion

ALSPAC – Avon Longitudinal Study of Parents and Children

AUD – Alcohol Use Disorder

AUDIT – Alcohol Use Disorders Identification Test

BIC – Bayesian Information Criterion

CAST – Cannabis Abuse Screening Test

CI – Confidence Interval

CSE – Certificate of Secondary Education

FIML – Full Information Maximum Likelihood

GCSE – General Certificate of Secondary Education

GHQ-12–12-item General Health Questionnaire

LCA – Latent Class Analysis

LMR-LRT – Lo–Mendell–Rubin Likelihood Ratio Test

MAR – Missing at Random

MICE – Multiple Imputation by Chained Equations

NEET – Not in Education, Employment or Training

OR – Odds Ratio

SA – Sequence Analysis

SDQ – Strengths and Difficulties Questionnaire

SEN – Special Educational Needs

SMFQ – Short Mood and Feelings Questionnaire

SSA-BIC – Sample-Size Adjusted Bayesian Information Criterion

STWT – School-to-Work Transition

# Declarations

**Ethics approval and consent to participate**

Ethical approval for the study was obtained from the ALSPAC Ethics and Law Committee and the

# Consent for publication

Not applicable

# Competing Interests

The authors declare that they have no competing interests

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# Author Contribution

ZR, AH, LH, GH all involved in study design and methodology ZR conducted data analysis ZR, AH, LH, GH, EE, IS all involved in interpretation of findings and communication of results

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# Data Availability

The informed consent obtained from ALSPAC (Avon Longitudinal Study of Parents and Children) participants does not allow the data to be made available through any third party maintained public repository. Supporting data are available from ALSPAC on request under the approved proposal number, B5178. Full instructions for applying for data access can be found here: http://www.bristol.ac.uk/alspac/researchers/access/. The ALSPAC study website contains details of all available data (http://www.bristol.ac.uk/alspac/researchers/our-data/). The Next Steps data analysed in this study are available from the UK Data Service (https://ukdataservice.ac.uk/), study number 5545. Access to the data is subject to registration and applicable licensing conditions. Further information about the Next Steps cohort and data access procedures is available from the Centre for Longitudinal Studies (https://cls.ucl.ac.uk/cls-studies/next-steps/).

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# Figures

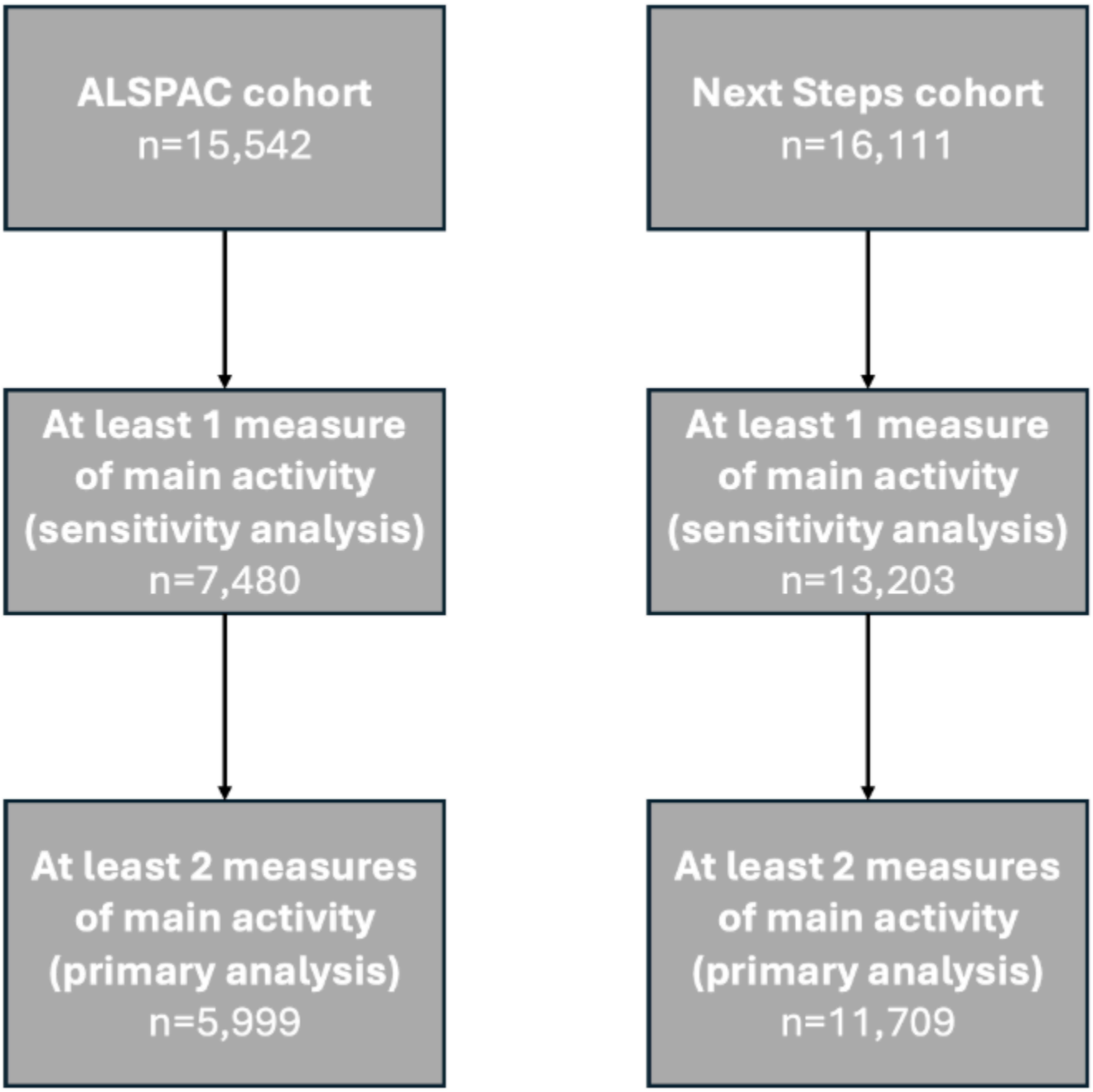
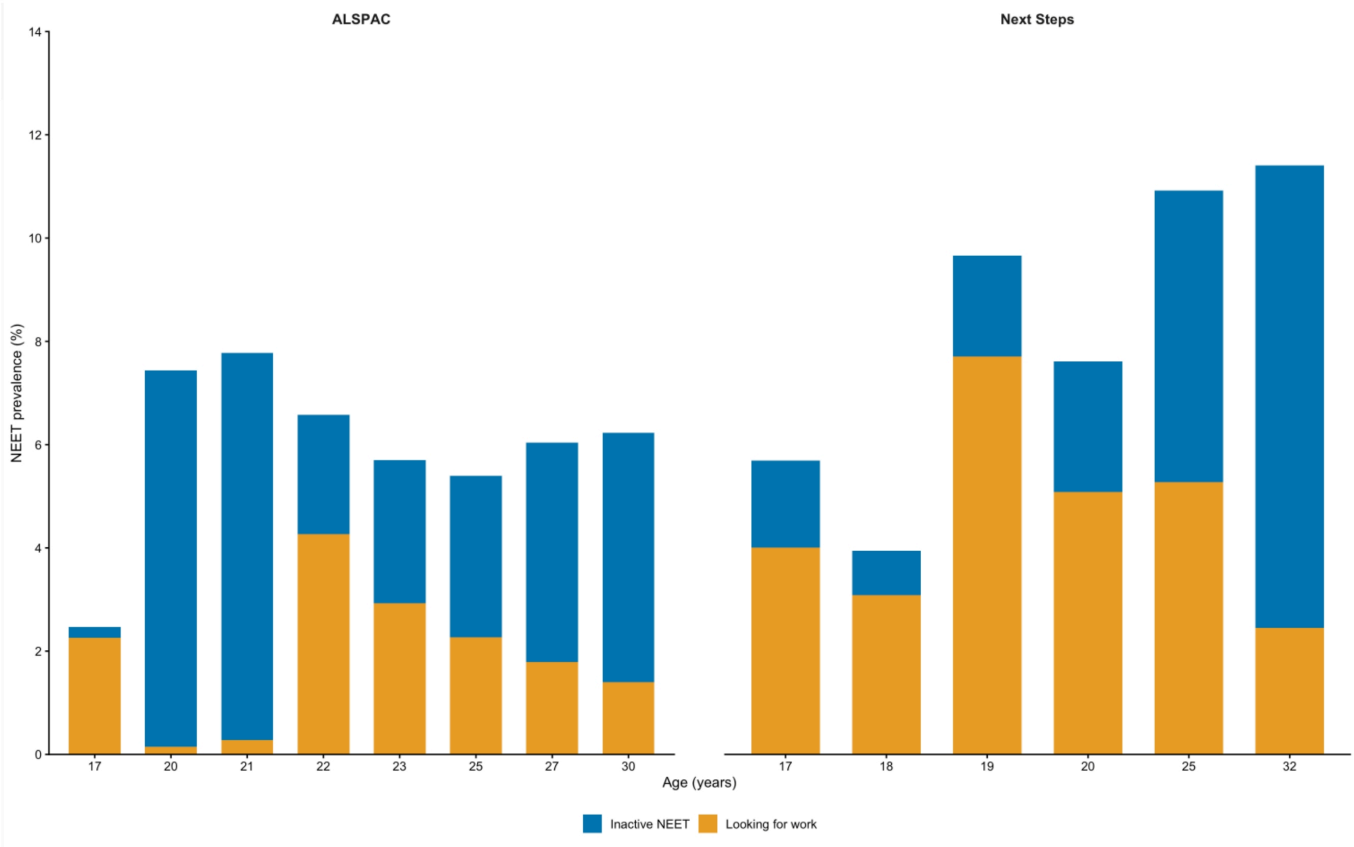


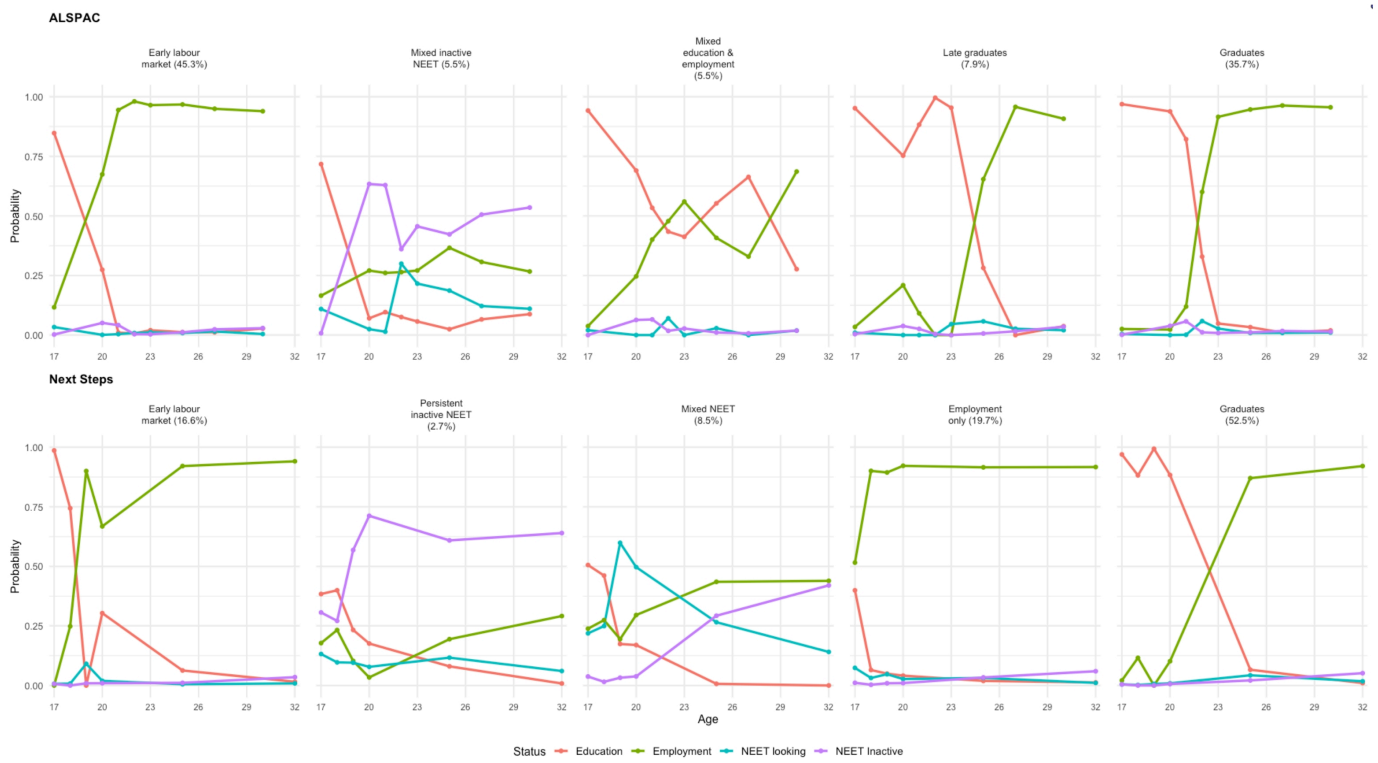

**Figure 1**

Flow chart of analytic sample selection in ALSPAC and Next Steps. Initial cohort numbers represent all participants who were enrolled in the study and had not withdrawn their consent at the time of analysis.




## Figure 2

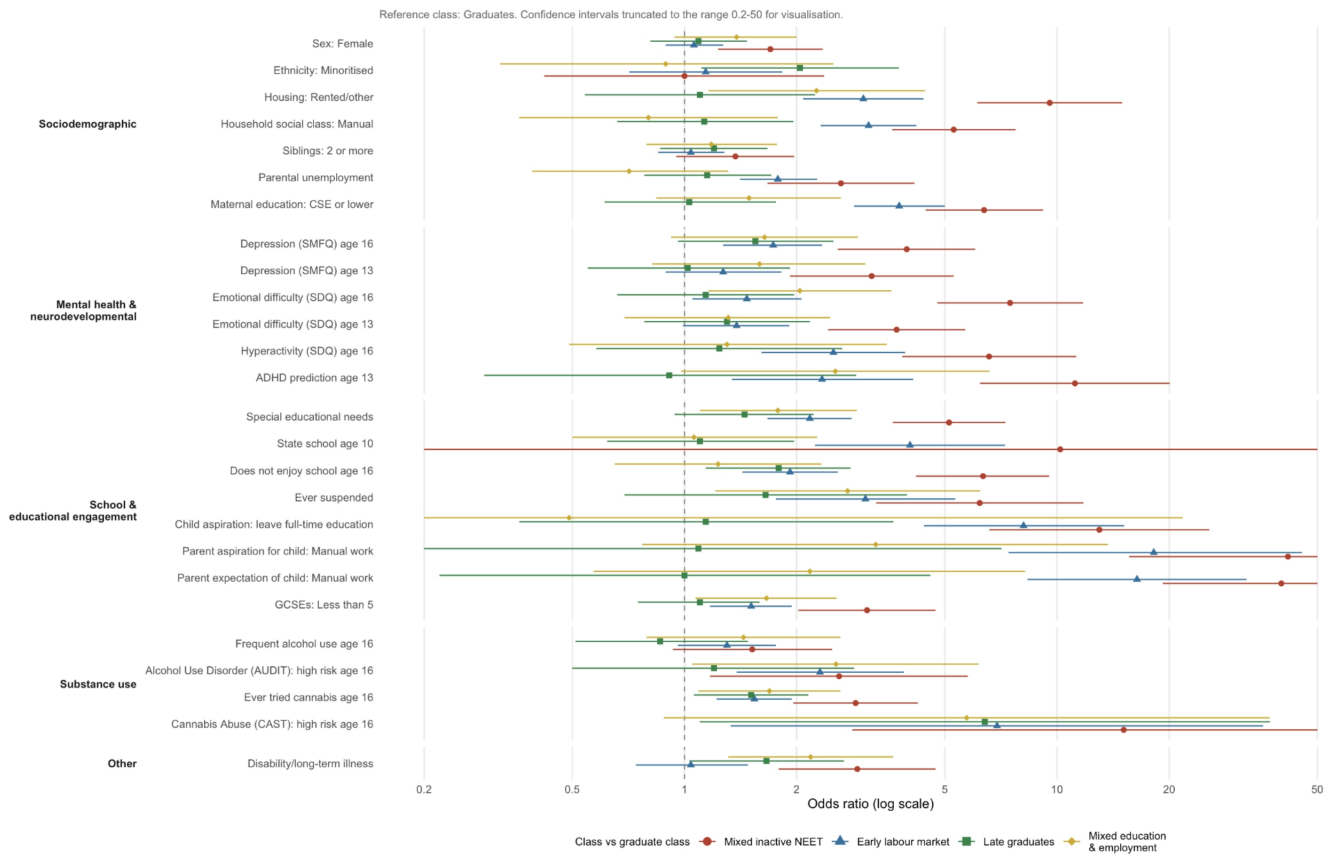
Prevalence of NEET by subtype in observed data for ALSPAC (n=5,999) and Next Step (n=11,709)




## Figure 3

**Class-level probabilities for 5-class solutions in ALSPAC and Next Steps**

Probability of each main activity status, at each timepoint, for all 5-classes in ALSPAC (top row) and Next Steps (bottom row).




## Figure 4

**Associations between explanatory variables and latent class membership in ALSPAC (n=5,999): Odds ratios and 95% confidence intervals.**

**Abbreviations:**

ADHD = Attention-Deficit Hyperactivity Disorder

AUDIT= Alcohol Use Disorder Identification Test
CAST = Cannabis Abuse Screening Test

CSE = Certificate of Secondary Education

GCSE = General Certificate of Secondary Education

SDQ = Strengths and Difficulties Questionnaire

SMFQ = Short Mood and Feelings Questionnaire

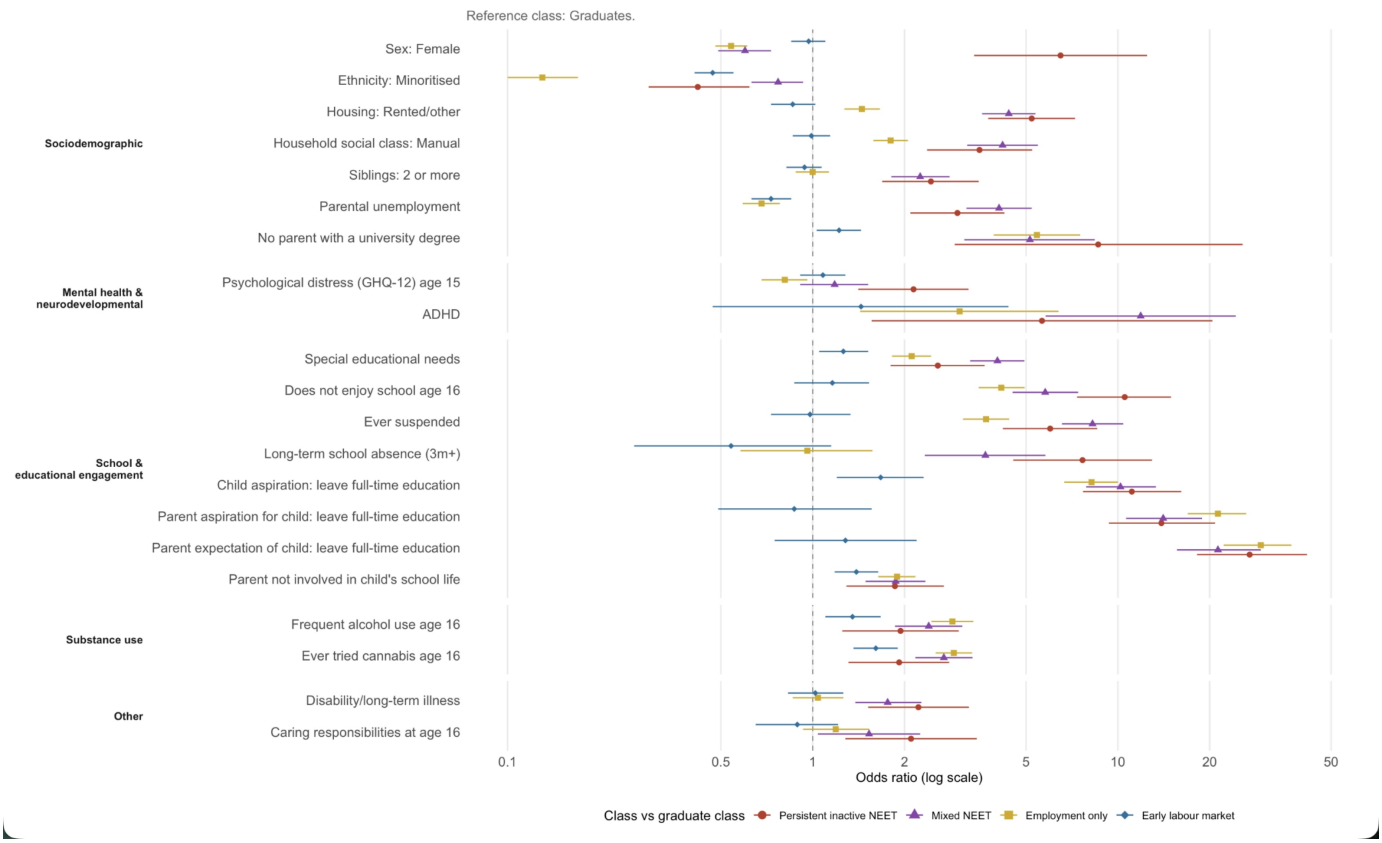



**Figure 5**

**Associations between explanatory variables and latent class membership in Next Steps (n=11,709): Odds ratios and 95% confidence intervals.**

**Abbreviations:**
ADHD = Attention-Deficit Hyperactivity Disorder
GHQ-12 = General Health Questionnaire-12

# Supplementary Files

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- SupplementSTWTBMC.docx