Journal of Autism and Developmental Disorders
https://doi.org/10.1007/s10803-026-07481-3

ORIGINAL ARTICLE

Developmental Trajectories of Autistic Traits in Infants With Autism and/or ADHD Family History: Predictors and Mid-Childhood Outcomes

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Received: 10 April 2026 / Accepted: 30 July 2026
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Abstract

Purpose Autism is both a developmental and heterogeneous condition, with individual variation in the timing and shape of autistic symptom trajectories over time, as recognised by the concept of 'chronogeneity'. Prospective infant autism family history studies are well-suited to examining developmental trajectory variability, a key aspect of autism trait heterogeneity.

Methods We examined autistic trait trajectories in a large sample of infants with autism and/or ADHD family history (N=384) followed from infancy to mid-childhood. Using group-based multi-trajectory modelling, we identified classes with distinct trajectories across three autism trait measures taken at six, five, and four timepoints, respectively, between 5 months and 9 years.

Results A 5-class solution provided the best fit. Three classes included 50–75% children meeting autism diagnostic criteria at 3 years or mid-childhood, with distinct differences in timing, onset, and developmental patterns of autistic traits. Two classes were predominantly typically developing, with one characterised as 'slow starters'. Background characteristics including autism/ADHD family history, sex, maternal education, and household income (but not ethnicity) predicted class membership. Mid-childhood outcomes—IQ, adaptive function, autism and ADHD traits, anxiety and behavioural difficulties–differed across trajectory classes.

Conclusion The timing and developmental course of autistic traits—independent of trait level—relate meaningfully to infant and family characteristics, diagnostic timing, and mid-childhood outcomes. These findings support chronogeneity as a valuable framework for understanding autism heterogeneity in family history studies. The trajectory classes identified here are descriptive; future studies should examine their replicability, and explanatory and mechanistic value.

Keywords Developmental trajectories · Autism · ADHD · Family history infants · Predictors · Outcomes

Introduction

Autism has long been recognised as a developmental condition where presentation varies over time both within and between individuals (Rutter, 1978), with substantial heterogeneity at genetic, neural, cognitive, behavioural, and outcome levels (Lombardo et al., 2019; Lord et al., 2020; Mottron & Bzdok, 2020). Co-occurring conditions in autism—language disorder, ADHD, anxiety, and mood disorders—also vary considerably over time (Lai et al., 2019; Lord et al., 2020, 2022; Mandy et al., 2022). A more recent perspective, however, is that this variation in the timing and developmental course of autistic characteristics—termed 'chronogeneity' by Georgiades et al. (2017)—may represent a critical and clinically meaningful source of heterogeneity in autism. That is, differences in when and how autistic traits emerge and change over time may carry information about aetiology, prognosis, and intervention response that cross-sectional assessment does not capture. Thus, developmental approaches may provide novel insights into parsing the widely recognised but poorly understood aetiological and phenotypic heterogeneity in autism.

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Published online: 25 August 2026

Many studies have identified subgroups of autistic individuals showing distinct developmental trajectories in autism symptoms or traits (Fountain et al., 2023; Georgiades et al., 2022; Gotham et al., 2012; Kim et al., 2018; Szatmari et al., 2015). Whilst age, assessment intervals, and measures vary across studies, many find classes with stable high, medium or low symptoms and smaller classes showing increasing or decreasing levels of autistic symptoms over time (see Gentles et al., 2024; Hiralal et al., 2025; Pender et al., 2020; for reviews). Other studies have identified similar classes with different developmental trajectories on measures of IQ, adaptive behaviour, language ability and internalising and externalising behaviour (Anderson et al., 2007, 2009; Baribeau et al., 2021; Pickles et al., 2014; Szatmari et al., 2015; Vaillancourt et al., 2017). Another notable developmental pattern is regression or loss of skills, most commonly in the language and social domains, seen in between 20 and 35% of autistic children (Barger et al., 2013; Ozonoff & Iosif, 2019). These studies, however, have predominantly examined trajectories in children with established diagnoses, potentially missing early developmental heterogeneity.

Prospective infant family history studies (most commonly infants with an older diagnosed sibling) offer a unique opportunity to examine developmental trajectory variability across the full range of diagnostic outcomes (Dawson et al., 2023; Jones et al., 2014; Szatmari et al., 2016). They include children with heterogeneous outcomes—autism diagnosis at 3 years, autism diagnosis at mid-childhood, other atypical developmental outcomes, and typical development (Bazelmans et al., 2024; Brian et al., 2016; Charman et al., 2017, 2023, 2026; Messinger et al., 2013; Ozonoff et al., 2014, 2018, 2024). This range of outcomes, which provides greater trajectory variability than samples restricted to confirmed diagnoses, enables characterisation of which early characteristics and developmental patterns predict diagnostic outcomes and which do not. The prospective repeated-measures design also enables trajectory modelling from the earliest emergence of autistic characteristics through mid-childhood—developmental patterns not observable where diagnosis is already established.

Infant sibling studies have tracked trajectories of social communication and repetitive/sensory traits, developmental ability, adaptive behaviour, and temperament, commonly comparing groups by family history and autism outcome (Del Rosario et al., 2014; Gunderson et al., 2021; McDonald et al., 2020; Ozonoff & Iosif, 2019; Ozonoff et al., 2010; Salomone et al., 2018; Wolff et al., 2014). Some studies have used person-centred modelling approaches to identify subgroups with distinct developmental patterns through to 3 years (Bussu et al., 2019; Franchini et al., 2023; Landa et al., 2012; Sacrey et al., 2019; Zwaigenbaum et al., 2021). Many find between two and four trajectory classes with patterns similar to those in diagnosed cohorts: classes showing stable high, medium, or low levels of autistic traits, developmental ability, or adaptive behaviour, alongside smaller classes showing increasing or decreasing levels over time. As expected, classes showing high or increasing autistic traits and low or declining developmental ability or adaptive function over time are more likely to receive an autism diagnosis at 3 years.[1] Whilst studies primarily focus on associations between trajectory class and autism diagnosis, some report class differences on symptom severity and developmental abilities at outcome (Bussu et al., 2019; Franchini et al., 2023; Zwaigenbaum et al., 2021). Predictors of class membership include child sex, early autism characteristics (Autism Observation Scale for Infants (AOSI); (Bryson et al., 2008) and developmental abilities (Franchini et al., 2023; Zwaigenbaum et al., 2021) at 6–12 months, though findings remain inconclusive.

The Current Study

Although post-hoc and exploratory, inspired by the chronogeneity framework (Georgiades et al., 2017), we exploited the repeated measurements from infancy through mid-childhood collected in our large prospective cohort of infants with autism and/or ADHD family history. Using group-based multi-trajectory modelling across three measures of autistic traits, we extended previous single-instrument trajectory studies by capturing the multidimensional phenotype. Group-based multi-trajectory modelling (GBTM)—also called Latent Class Growth Analysis—is a person-centred approach that identifies distinct developmental pathways (Nagin & Odgers, 2010; Nagin et al., 2024; Nguena Nguefack et al., 2020). Multi-trajectory modelling identifies clusters of individuals following similar patterns across multiple related outcomes (Nagin et al., 2018). We identify developmental trajectories of autistic traits from infancy through mid-childhood using multiple measures, then examine predictors of trajectory class membership and mid-childhood outcomes beyond autism diagnostic status.

Method

Participants

The study recruited 406 infants (213 male, 193 female) at 5 or 10 months of age based on family history criteria. Infants were eligible if they had a first-degree relative with either a

[1] In Franchini et al. (2023) to 5–7 years.

community clinical diagnosis of autism, a community clinical diagnosis of ADHD or elevated ADHD symptomatology, or both conditions. In many cases parents provided clinical reports for the research team to review that confirmed this. Most commonly, parents reported an existing clinical diagnosis of autism and/or ADHD in an older sibling, although some parents reported that they themselves had received a diagnosis of one or both conditions. When parents indicated suspected ADHD symptoms, a brief Conners screener confirmed eligibility (detailed in Appendix S1 and Table S1). A comparison group of infants without autism or ADHD family history and with a typically developing older sibling was also enrolled. Participants were recruited across three sequential phases: Phase 1 (n = 104), Phase 2 (n = 143), and Phase 3 (n = 159).

Participants completed research visits at 5, 10, 14, 24, 36 months and mid-childhood (6–12 years (M (SD) = 8.65 (1.27)). Retention from recruitment to mid-childhood by child and family demographics and 10 m child characteristics is shown in Tables S2 and S3). Infants from the Phase 1 and 2 cohorts were more likely to be retained than the Phase 3 cohort (χ^2 (1, N = 263) = 14.63, $p < .001$; χ^2 (1, N = 302) = 4.32, $p < .05$; respectively). Retention was lower in Asian/Black/Mixed compared to White children ($\chi 2$ (1, N = 390) = 8.72, $p < .01$) and those retained had a younger age at first visit compared to those non-retained ($t(400) = 2.73$, $p < .01$). However, there was no evidence of more or less affected infants being retained from 10 months of age. Mean age at initial assessment was 7.08 months ($SD = 2.21$), with infants entering the study by 12 months.[2] Of the 406 infants enrolled, 207 had a first-degree relative with autism only (FH-Autism), 30 had a first-degree relative with ADHD only (FH-ADHD), 67 had first-degree relatives with both autism and ADHD (FH-Autism + ADHD), and 102 had no first-degree relatives with either condition (No FH) (Table S1).

The study received ethical approval from the NHS RES London REC (14/LO/0170) and King's College London (RESCM-18/19-10556). Written informed consent was obtained from parents, and children provided written or verbal assent as appropriate for their age and developmental level.

[2] Six children's first research visit was between 13 and 15 months.

Measures

Family Demographic Characteristics

Ethnicity Infant sibling ethnicity was characterised as Asian/Black African/African Caribbean/Mixed vs. White/European/Irish.

Family Sociodemographic Information Annual household income was coded on a 5-point ordinal scale (< £20,000, £20,000–£40,000, £40,000–£60,000, £60,000–£80,000, > £80,000). Maternal highest education level was coded on a 4-point ordinal scale (16/GCSE, 18/School/College, Degree level, Postgraduate/Professional).

Participant demographic characteristics by family history sampling group are shown in Table 1.

Measures Used to Derive Trajectories of Autistic Traits

We selected measures that assessed core early autism traits (symptoms) using different methods across repeated timepoints from infancy to mid-childhood, providing partially independent assessments of the same developmental and behavioural domains. We use the term 'traits' rather than 'symptoms' because our family history sample includes many typically developing children alongside those with an autism diagnosis, and because measurements begin as early as 5–10 months of age, where characterising early behaviours as symptoms would be inappropriate. Table S4 shows participant numbers and mean scores for each measure at each timepoint.

Parent Report of Social Ability The Vineland Adaptive Behavior Scales Socialization Domain assessed parent-reported everyday social adaptive function at 5, 10, 14, 24, 36 months and mid-childhood (104 months).[3]

Questionnaire Measures of Autism Traits The Quantitative Checklist for Autism in Toddlers (Q-CHAT (Allison et al., 2008)) assessed parent-reported autism traits at 14 and 24 months. The Social Responsiveness Scale-2 (SRS-2 (Constantino & Gruber, 2012)) parent-report questionnaire was administered at 36 months and mid-childhood. Cross-

[3] Vineland-II (Sparrow et al., 2005) for all infant and toddler timepoints and mid-childhood timepoint for Phase 1 and Vineland-3 (Sparrow et al., 2016) for mid-childhood timepoint for Phase 2 and 3.

Table 1 Participant demographic characteristics by family history sampling frame

	FH-autism $N=207$	FH-autism+ADHD $N=67$	FH-ADHD $N=30$	No FH $N=102$
	N (%)	*N* (%)	*N* (%)	*N* (%)
Phase				
1	48 (23%)	6 (9%)	0 (0%)	50 (49%)
2	84 (41%)	32 (48%)	1 (3%)	26 (25%)
3	75 (36%)	29 (43%)	29 (97%)	26 (25%)
Child sex				
Male	107 (52%)	35 (52%)	18 (60%)	53 (52%)
Female	100 (48%)	32 (48%)	12 (40%)	49 (48%)
Age first visit (months)[a] Mean (SD)	7.17 (2.13)	7.34 (2.33)	8.37 (3.27)	6.39 (1.71)
Child ethnicity[b]				
Asian/African/African-Caribbean/Mixed	51 (25%)	11 (17%)	3 (11%)	17 (18%)
White/European/Irish	150 (75%)	54 (83%)	25 (89%)	79 (82%)
Maternal highest education[c]				
Up to 16/GCSE	18 (9%)	2 (3%)	0 (0%)	4 (4%)
Up to 18/school/college	53 (27%)	25 (40%)	14 (48%)	16 (17%)
Degree level	75 (38%)	21 (33%)	6 (21%)	30 (31%)
Postgraduate/professional	49 (25%)	15 (24%)	9 (31%)	46 (48%)
Annual household income[d]				
Up to £20,000	17 (9%)	5 (8%)	0 (0%)	6 (7%)
£20,000 to £40,000	52 (29%)	23 (39%)	2 (15%)	12 (13%)
£40,000 to £60,000	53 (29%)	13 (22%)	5 (38%)	18 (20%)
£60,000 to £80,000	25 (14%)	6 (10%)	1 (8%)	12 (13%)
Above £80,000	34 (19%)	12 (20%)	5 (38%)	41 (46%)

[a]Missing for $N=4$ participants

[b]Missing for $N=16$ participants

[c]Missing for $N=23$ participants

[d]Missing for $N=64$ participants

time correlations between Q-CHAT and SRS-2 scores are shown in Table S3.

Researcher Observations of Autism Traits The Autism Observation Scale for Infants (AOSI) (Bryson et al., 2008) and the Autism Diagnostic Observation Schedule-2 (ADOS-2) (Lord et al., 2012) are played-based researcher observational measures of autism characteristics. The AOSI was administered at 10 and 14 months and the ADOS-2 at 24 and 36 months and mid-childhood.

Cross-time correlations varied by measure type (Table S5). Parent-reported autism traits showed moderate-to-high stability (Q-CHAT/SRS-2: $r=.36–.76$). In contrast, both parent-reported social functioning (Vineland Socialization: $r=.14–.65$) and clinician-observed characteristics (AOSI/ADOS-2: $r=.12–.52$) showed lower, more variable correlations, likely reflecting genuine developmental change and differing assessment contexts from infancy through mid-childhood.

Mid-Childhood Outcome Measures

We examined cognitive ability and adaptive functioning as core functional indicators, and ADHD traits, anxiety, and emotional/behavioural difficulties as common co-occurring conditions, testing whether trajectory patterns relate to these outcomes beyond diagnostic status.

Cognitive and Language Ability The Mullen Scales of Early Learning (Mullen, 1995) Early Learning Composite (ELC) was used to characterise developmental ability at 5, 10, 14, 24 and 36 months. At mid-childhood, the Wechsler Abbreviated Scale of Intelligence—Second Edition (Wechsler, 2011)[4] assessed full-scale IQ (FSIQ).

Behaviour and Emotion In mid-childhood the parent-report Conners-3 (Conners, 2008) was used to assess attention deficit hyperactivity disorder (ADHD) characteristics (T-scores for the DSM-IV-TR Inattentive and Hyperactive/Impulsive scales) and the parent-report Spence Children's Anxiety Scale—Parent (SCAS) (Spence, 1999) was used to assess anxiety characteristics (Total T-scores). In mid-childhood the parent-report Strengths and Difficulties Questionnaire

[4] 4-subtest version (Block design, Vocabulary, Matrix Reasoning, Similarities) in Phase 1 and 2-subtest (Vocabulary, Matrix Reasoning) version in Phases 2 and 3.

(SDQ) (Goodman, 1999) Total Difficulties Score and Impact Score assessed emotional and behavioural difficulties.

Research Diagnostic Assessments At both 3 years and mid-childhood, a best estimate clinical diagnosis of autism spectrum disorder was made based on DSM-5 criteria. The diagnostic process and outcomes are reported in Bazelmans et al. (2024) and Charman et al. (2026). In brief, DSM-5 diagnosis was informed by, but not dependent on, scores on the ADOS-2, Autism Diagnostic Interview-Revised (ADI-R) (Lord et al., 1994), Social Communication Questionnaire (SCQ) (Rutter et al., 2003) and Vineland; researcher observations on the visit; and additional parent-reported information by experienced researchers and overseen by a senior clinical psychologist. Children with autism diagnoses were classified as 'Earlier diagnosed' (diagnosed at 3 years) or 'Later diagnosed' (first diagnosed at mid-childhood) (see Bazelmans et al. (2024).

Statistical Analysis

Group-based multi-trajectory modelling (GBTM) is a person-centred finite mixture modelling approach designed to identify distinct developmental pathways across multiple related outcomes simultaneously (Nagin, 2005; Nagin & Odgers, 2010; Nagin et al., 2018). We used GBTM rather than growth mixture modelling (GMM) because our aim was to identify and describe distinct developmental patterns; GBTM's assumption of homogeneous classes without within-class variance provides a parsimonious approximation well-suited to this goal and to our multi-trajectory framework and sample size (Loughran & Nagin, 2006; Nagin, 2005; Nguena Nguefack et al., 2020). Parameters are estimated via maximum likelihood, accommodating missing data under a missing-at-random assumption.

We used the group-based multi-trajectory modelling extension (`multgroups`) developed by Nagin et al. (2018) of the Stata (StataCorp., 2025) `traj` plugin for GBTM developed by Jones and Nagin (2013). This simultaneously models multiple outcomes to identify subgroups with similar patterns across measures. The analysis included participants with at least one observation on each measure ($N=384$). Assessments were scheduled at 5, 10, 14, 24, 36, and 104 months of age, with these nominal ages used as the time metric. We used the study's nominal assessment ages (5, 10, 14, 24, 36, 104 months) as the common time metric, following standard practice in group-based trajectory modelling (Nagin, 2005; Nagin et al., 2018). In a sensitivity analysis, the five-class model was refitted using each participant's exact age at assessment[5]; classification was almost perfectly reproduced ($\kappa=0.87$).

The multi-trajectory model jointly estimated trajectories for Vineland Socialization (6 timepoints from 5 months), parent-reported autism traits using Q-CHAT and SRS-2 (4 timepoints from 14 months), and clinician-observed characteristics using AOSI and ADOS-2 (5 timepoints from 10 months). Participants contributed a mean of 11.5 of 15 possible assessments (SD = 2.6; 93% ≥ 8), uniformly across the five trajectory classes (range 11.2–11.8), so each case supplied substantial information to the full-information maximum likelihood estimation.

Standardised scores from the Vineland Socialization domain across all timepoints were used in the trajectory model. It was not possible to use raw scores for the Q-CHAT/SRS and AOSI/ADOS measures as these were assessed on different scales, with different ranges, different distribution, different skew and at non-identical timepoints. To account for the different scaling across other measures, within-timepoint, within-sample z-scores derived from total Q-CHAT and SRS-2 raw scores, and total AOSI and ADOS-2 raw scores, respectively, were used in the trajectory model. Within-wave standardisation provided a common metric (for Q-CHAT-SRS and AOSI-ADOS) without imposing an external reference population that is not available for our family-history sample.[6] Multi-trajectory modelling enables simultaneous modelling of multiple outcomes using appropriate probability distributions for each measure type (Nagin et al., 2018). Specifically, as outlined in the Statistical Analysis section we estimated censored normal distribution for z-scores (Q-CHAT and SRS; AOSI and ADOS) and standard scores (Vineland) for each measure type. Following established practice in trajectory modelling of psychometric scale data (Jones et al., 2014; Nagin et al., 2018), we modelled the autism trait measures using the censored normal distribution to account for the bounded nature of these scales.

Model fit. For each trajectory group, intercept, linear, and quadratic parameters were estimated using maximum likelihood with censored normal distributions. Model selection was guided by the Bayesian Information Criterion, which the `traj` plugin parameterises such that higher (less negative) values indicate better fit – the reverse of the conventional formulation that is minimised (Nagin, 2005). We formally evaluated model fit at each class number. For

[5] A small number of missing age-at-visit values (mean 4.1 [SD 3.2] per measure-wave; range 0–10; 62 observations in total) were imputed at the wave median so that both models were estimated on identical observations (n = 384).

[6] The trajectories on the raw scores for the Q-CHAT/SRS and AOSI/ADOS for the derived classes are shown in the Supplementary Materials (Fig. S1).

GBTM the appropriate selection criterion is BIC with Bayes Factor approximation via 2 × ΔBIC (Jones & Nagin, 2013; Kass & Raftery, 1995; Nagin, 2005), with a threshold of 10 designated as 'very strong evidence' (Kass & Raftery, 1995). For GBTM this is similar to the Lo–Mendell–Rubin (LMR) test and the bootstrap likelihood-ratio test (BLRT) for growth mixture models (GMM) as implemented in Mplus but are not applicable to GBTM, which uses a different likelihood structure with no continuous random effects. We then compared the best fitting quadratic model—theoretically motivated by the 5–104 month observation window, across which non-linear developmental change may be expected—with its linear counterpart.

We used multinomial logistic regression to examine baseline predictors of trajectory class membership for the best-fitting solution. Predictors included Phase, child sex, ethnicity, maternal education, family income, and family history of autism and ADHD. The percentage of missing values ranged from zero to 44 (11%) and 330 from 384 participants (86%) had full data under listwise deletion. We used multiple imputation by chained equations (MICE) with auxiliary variables (paternal education, number of siblings). The Stata `mi impute chained` command generated 50 imputed datasets with 10 burn-in iterations. Imputed values were similar to observed values and results using listwise deletion similar to those using multiple imputation, so imputed results are presented (using the Stata `mi estimate: mlogit` command). For both binary and ordinal predictor variables relative risk ratios (RRR) and 95% confidence intervals (CIs) are reported.

Mid-childhood outcomes compared across classes included: autism diagnosis (earlier vs. later), FSIQ, Vineland ABC, autism traits (ADI-R current algorithm domain scores), ADHD traits (Conners-3 Inattentive and Hyperactive/Impulsive T-scores), anxiety (Spence Total T-score) and SDQ Total Difficulties and SDQ Impact score. We used ANOVA with post-hoc Tukey–Kramer corrections to account for unequal cell sizes for continuous measures and chi-square tests followed by the `tabchi` command to estimate adjusted standardised residuals for binary measures.

Results

Model Fit

Model fit across the 2- to 5-class linear and quadratic solutions (see Table S6) was compared using the Bayes Factor approximation based on BIC differences (2 × ΔBIC; Kass & Raftery, 1995). AIC favoured the quadratic specification consistently across all group solutions, with differences ranging from + 10.1 to + 51.0. BIC results were more nuanced: at the 2- and 3-class solutions, BIC marginally favoured the linear specification (ΔBIC = − 0.67 and − 7.71 respectively), while at the 4- and 5-class solutions BIC favoured quadratic (ΔBIC = + 8.90 and + 21.38). The BIC advantage of quadratic increased monotonically with group number, suggesting that as the model captured greater heterogeneity across groups, the non-linear shape of individual trajectories became increasingly distinct and better recovered by the quadratic term. A quadratic solution is also theoretically motivated by the 5–104 month observation window, across which non-linear developmental change in autism related traits may be expected.

Critically, at the selected 5-class solution, both BIC (+ 21.38) and AIC (+ 51.01) favoured the quadratic specification, and the Bayes Factor approximation (2 × ΔBIC = 42.8; Kass & Raftery, 1995) exceeded the threshold of 10 that Kass and Raftery (1995) designate as very strong evidence in favour of the quadratic over linear solution. The 5-class solution also met all established classification quality criteria (Nagin & Odgers, 2010): AvePP > 0.70 for all groups (range: 0.84–0.97), OCC > 5.0 for all groups (range: 10.99–588.89), and entropy = 0.85 (see Table S7). The quadratic specification was retained on both empirical and theoretical grounds, and the 5-class solution represents the most parsimonious well-fitting solution the data support and the only one that captures the full heterogeneity in developmental profiles.

Description of Trajectory Classes

Figure 1 shows trajectory plots for the multi-trajectory classes on the three autism trait measures modelled. Table 2 shows scores on each measure at each timepoint and Table S6 the estimated model parameters. *Class 1 (Infant Low to High Autism Traits with Amelioration)*, *N* = 18 (14 boys, 4 girls), 4.7%)) showed high Vineland Socialization scores and low autism traits early infancy (5–10 months), then high autism traits and low Vineland scores by toddlerhood (24–36 months), with partial amelioration by mid-childhood.[7] *Class 2 ((High Early Persistent Autism Traits)*, *N* = 23 (15 boys, 8 girls), 6.0%) had low (and decreasing) Vineland scores and high (and increasing) autism traits from infancy onwards. *Class 3 ((Typical (Slow Starters))*, *N* = 87 (53 boys, 34 girls), 22.7%)) had slightly low Vineland scores and slightly elevated autism traits in infancy which increased and decreased, respectively, through the toddler assessments to mid-childhood. *Class 4 ((Later Emerging*

[7] We also tested models including cubic terms. A 6-class solution was the best fit but inferior to our best-fitting model, only 2 cubic terms were significant at $p < .05$ (for Q-CHAT + SRS-2 and AOSI + ADOS-2 in Class 1), and the inclusion of an additional 18 parameters led to a less parsimonious model.

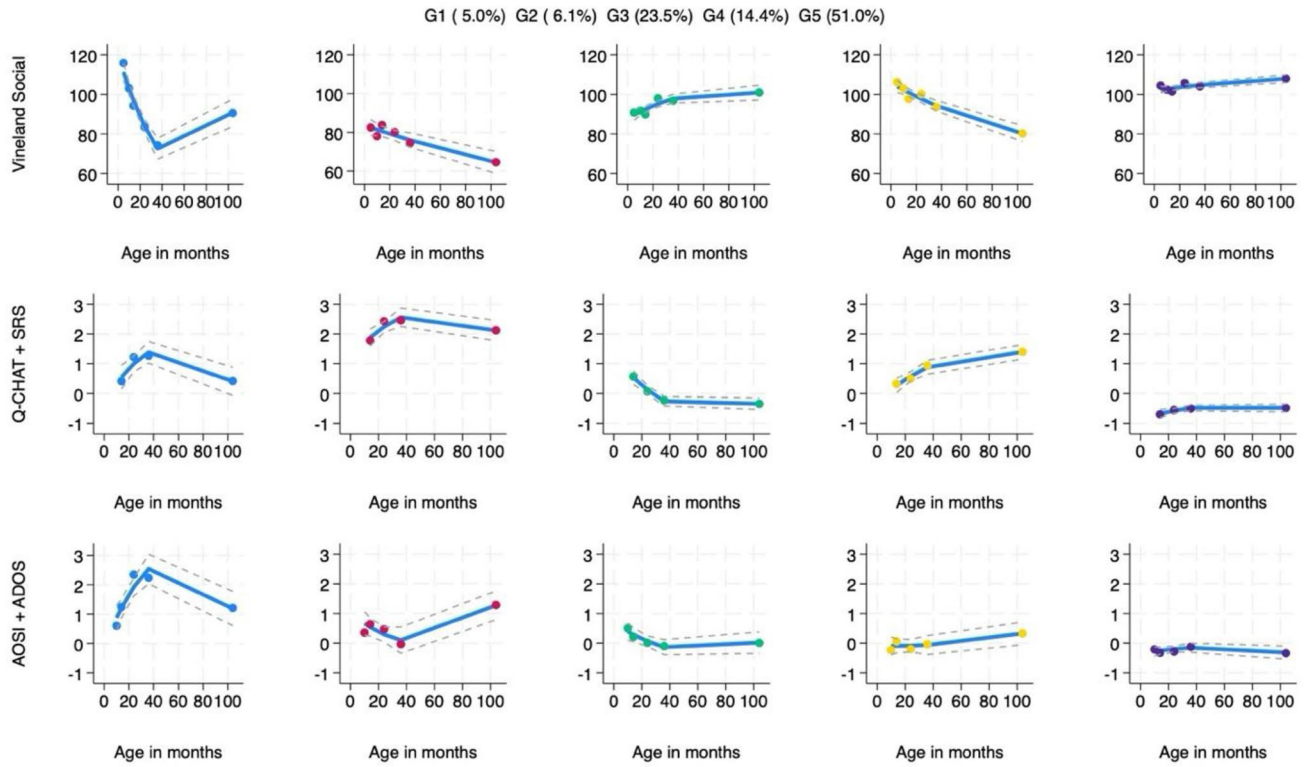

Fig. 1 Joint developmental trajectories of autistic traits. Vineland Social: Vineland Socialization domain score; Q-CHAT: Quantitative Checklist for Autism in Toddlers; SRS-2: Social Responsiveness Scale-2; AOSI: Autism Observation Scale for Infants; ADOS-2: Autism Diagnostic Observation Schedule-2

Autism Traits), $N = 53$ (28 boys, 25 girls), 13.8%)) had average Vineland scores and low autism trait scores in infancy but these declined and increased, respectively, through toddlerhood to mid-childhood. *Class 5 ((Typical Class)*, $N = 203$ (89 boys, 114 girls), 52.9%)) was the dominant class comprising more than half the sample and had average Vineland scores and low autism trait scores across all timepoints. The distribution of joint trajectory classes across family history groups is shown in Table S9.

Because Classes 1, 2 and 4 showed increasing autistic traits during infancy, we examined parent-reported regression using ADI-R items at the 3 year assessment (N = 314). Regression was reported in 10–20% of children in these classes, most commonly language loss, with rates not differing significantly between classes (see Appendix S2 for details).

Predictors of Joint Trajectory Class Membership

Multinomial logistic regression was conducted to examine baseline predictors of trajectory class membership. Class 1 showed complete separation for FH-Autism (all members had family history), which prevented model convergence so was excluded from the multivariate analysis (see below). Class 5 (Typical, 53%) was selected as the reference category. Using a joint Wald test across all trajectory class comparisons following multiple imputation neither Phase ($F(6, 2.7 \times 10^7) = 1.98$, $p = .065$) nor the interaction between FH-Autism and FH-ADHD ($F(3, 2.9 \times 10^7) = 2.10$, $p = .097$) significantly predicted trajectory class membership and were excluded from further analyses. Table S10 shows multinomial logistic regression results examining predictors of trajectory class membership, with relative risk ratios (RRR) and 95% confidence intervals (CI) for each comparison. Overall model fit was adequate ($F = 3.23$ (18, 1.2×10^6), $p < .0001$). Compared to Class 5 (Typical), autism family history predicted membership in Class 2 (High Persistent: RRR = 10.89, 95%CI [1.39, 85.50]) and Class 4 (Later Emerging: RRR = 2.24, 95%CI [1.02, 4.92]). Male sex predicted membership in Class 2 (High Persistent: RRR = 3.13, 95%CI [1.19, 8.19]) and Class 3 (Slow Starters: RRR = 2.16, 95%CI [1.28, 3.65]), compared to the reference category (Class 5). ADHD family history predicted Class 4 membership (Later Emerging: RRR = 3.07, 95%CI [1.56, 6.06]), compared Class 5. Lower maternal education predicted Class 2 membership (High Persistent: RRR = 0.71, 95%CI [0.52, 0.96]), and lower household income predicted Class 2 (High Persistent: RRR = 0.50, 95%CI [0.31, 0.80]) and Class 4 membership (Later Emerging: RRR = 0.72, 95%CI

Table 2 Joint trajectory class scores on trajectory measures

	Infant low to high autism traits (with amelioration)			High early persistent autism traits			Typical (slow starters)			Later emerging autism traits			Typical class		
	Mean	SD	*N*	Mean	SD	*N*	Mean	SD	*N*	Mean	SD	*N*	Mean	SD	*N*
Parent report of social ability[a]															
Vineland social 5 m	117.00	(11.75)	7	82.50	(13.33)	10	89.58	(13.89)	33	106.20	(15.33)	20	104.54	(10.77)	74
Vineland social 10 m	102.56	(9.59)	18	77.00	(14.82)	20	91.49	(10.63)	77	103.17	(9.76)	48	102.35	(11.80)	190
Vineland social 14 m	93.69	(7.37)	16	83.38	(8.81)	21	88.67	(8.06)	79	98.26	(12.31)	50	101.64	(9.46)	183
Vineland social 24 m	82.88	(9.75)	17	79.86	(7.84)	21	97.81	(7.52)	77	100.52	(8.53)	50	105.59	(8.89)	187
Vineland social 36 m	73.80	(9.23)	15	74.23	(9.41)	22	96.60	(9.07)	78	93.61	(10.56)	46	103.87	(8.25)	179
Vineland social 104 m	89.67	(12.21)	9	64.54	(11.64)	13	100.07	(10.50)	44	79.94	(13.14)	31	108.04	(8.15)	125
Questionnaire measure of autism traits[b]															
Q-CHAT 14 m	0.48	(0.85)	12	1.79	(0.75)	16	0.62	(0.68)	62	0.35	(0.77)	43	− 0.71	(0.59)	122
Q-CHAT 24 m	1.29	(0.85)	16	2.41	(0.89)	19	0.13	(0.73)	76	0.47	(0.69)	48	− 0.55	(0.51)	179
SRS-2 36 m	1.27	(1.13)	16	2.49	(1.00)	17	− 0.21	(0.39)	70	1.02	(0.96)	42	− 0.50	(0.33)	181
SRS-2 104 m	0.48	(0.73)	9	2.11	(0.47)	13	− 0.35	(0.46)	55	1.44	(0.77)	35	− 0.49	(0.51)	130
Researcher observation of autism traits[b]															
AOSI 10 m	0.58	(1.07)	12	0.42	(1.20)	10	0.55	(1.12)	52	− 0.30	(0.81)	33	− 0.21	(0.87)	137
AOSI 14 m	1.26	(1.26)	18	0.64	(0.86)	23	0.22	(0.99)	77	0.05	(1.00)	51	− 0.30	(0.83)	187
ADOS-2 24 m	2.42	(0.94)	17	0.40	(0.82)	22	0.01	(0.94)	73	− 0.20	(0.72)	50	− 0.28	(0.71)	145
ADOS-2 36 m	2.20	(1.40)	15	− 0.06	(1.03)	22	− 0.12	(0.93)	79	0.01	(0.85)	49	− 0.12	(0.82)	190
ADOS-2 104 m	1.26	(1.31)	10	1.29	(1.49)	13	− 0.02	(0.90)	45	0.34	(0.85)	32	− 0.32	(0.74)	123

Q-CHAT quantitative checklist for autism in toddlers, *SRS-2* social responsiveness scale-2, *AOSI* autism observation scale for infants, *ADOS-2* autism diagnostic observation schedule-2

[a]Standard score

[b]Z-score

[0.53, 0.96]), compared Class 5. Child ethnicity was not associated with class membership.

The multivariate model compared Classes 2, 3, and 4 to reference Class 5 only (excluding Class 1), so we conducted a non-planned series of univariate tests to examine all class associations (Table 3). Chi-square tests with `tabchi` post-hocs examined binary variables; ANOVAs with post-hoc Tukey–Kramer corrections examined ordinal variables.

Child sex was associated with class (χ^2 (4, N = 384) = 14.59, p < .01): Class 1 (Low to High with Amelioration) had more boys (z = 2.26, p < .05) and Class 5 (Typical) more girls (z = 3.32, p < .01) than expected. Child ethnicity showed no association (χ2 (4, N = 377) = 5.89, p = .21).

Autism family history was associated with class (χ^2 (4, N = 384) = 27.61, p < .001): Classes 1 (Low to High with Amelioration) (z = 2.93, p < .01), 2 (High Persistent) (z = 2.87, p < .01), and 4 (Later Emerging) (z = 2.10, p < .05) had more children with autism family history than expected; Class 5 (Typical) had fewer (z = 4.09, p < .001). ADHD family history was associated with class (χ^2 (4, N = 384) = 15.31, p < .01): Class 4 (Later Emerging) had more children with ADHD family history than expected (z = 3.82, p < .001); Class 5 (Typical) had fewer (z = 2.07, p < .05).

Maternal education was associated with class (F(4, 364) = 4.77, p < .001): Class 5 (Typical) had higher maternal education than Classes 2 (High Persistent) and 3 (Slow Starters) (both p < .05). Household income was associated with class (F(4, 335) = 8.09, p < .001): Class 5 (Typical) had higher income than Classes 2 (High Persistent) and 4 (Later Emerging) (both p < .001), and Class 3 (Slow Starters) had higher income than Class 2 (High Persistent) (p < .05).

Association Between Trajectory Classes and Autism Diagnosis

Table 4 shows autism diagnosis rates and timing by trajectory class. Classes showing elevated traits had high diagnosis rates but different patterns: Class 1 (Low to High with Amelioration) 72% diagnosed, all at 3 years; Class 2 (High Persistent) 78% diagnosed, mostly at 3 years; Class 4 (Later Emerging) 51% diagnosed, two-thirds at mid-childhood. The typical trajectory classes had low diagnosis rates: Class 3 (Slow Starters) 12% and Class 5 (Typical) 7%.

Outcomes Associated With Trajectory Class Membership

Of the 384 participants, 260 (68%) provided mid-childhood data (228 in-person, 32 questionnaire-only), with variable completion across measures. Table 5 shows scores and post-hoc comparisons for IQ, adaptive function, autism trait severity, ADHD, anxiety, and SDQ difficulties and impact; ANOVAs are in Appendix S3 and profiles of classes on a common z-score metric in Fig. 2. We focus on ADI-R current algorithm scores for autism trait severity as these are

Table 3 Joint trajectory class by predictors

	Infant low to high autism traits (with amelioration)	High early persistent autism traits	Typical (slow starters)	Later emerging autism traits	Typical class
	N (%)	*N* (%)	*N* (%)	*N* (%)	*N* (%)
Child sex					
Male	14 (78%)	15 (65%)	53 (61%)	28 (53%)	89 (44%)
Female	4 (22%)	8 (35%)	34 (39%)	25 (47%)	114 (56%)
Child ethnicity[a]					
Asian/African/African Caribbean/ Mixed	6 (33%)	2 (9%)	21 (25%)	12 (23%)	36 (18%)
White/European/Irish	12 (67%)	21 (91%)	62 (75%)	41 (77%)	164 (82%)
FH-autism					
No FH autism	0 (0%)	1 (4%)	27 (31%)	10 (19%)	82 (40%)
FH autism	18 (100%)	22 (96%)	60 (69%)	43 (81%)	121 (60%)
FH-ADHD					
No FH ADHD	14 (78%)	17 (74%)	70 (80%)	30 (57%)	165 (81%)
FH ADHD	4 (22%)	6 (26%)	17 (20%)	23 (43%)	38 (19%)
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Maternal highest education[b]	3.06 (0.77)	2.43 (0.90)	2.75 (0.97)	2.68 (0.91)	3.07 (0.88)
Annual household income[c]	3.00 (1.00)	2.27 (0.98)	3.25 (1.38)	2.67 (1.06)	3.53 (1.31)

[a]Missing for N = 7 participants

[b]Missing for N = 15 participants

[c]Missing for N = 44 participants

Table 4 Association between trajectory class and autism diagnosis

Class	Research autism diagnosis			
	Not autism $N=303$	Earlier diagnosed $N=46$	Later diagnosed $N=35$	Total $N=384$
	N (%)	*N* (%)	*N* (%)	
Class 1: infant low to high autism traits (with amelioration)	5 (28%)	13 (72%)	0 (0%)	$N=18$
Class 2: high early persistent	5 (22%)	16 (70%)	2 (9%)	$N=23$
Class 3: typical (slow starters)	77 (89%)	5 (6%)	5 (6%)	$N=87$
Class 4: later emerging autism traits	26 (49%)	9 (17%)	18 (34%)	$N=53$
Class 5: typical class	190 (94%)	3 (2%)	10 (5%)	$N=203$

From $N=384$ children with sufficient data on trajectory measures to be included in this analysis 3 year diagnostic assessments were completed on $N=359$ and mid-childhood diagnostic assessments on $N=225$ children. The Not Autism classification includes all children not given an autism diagnosis at either the 3 year or mid-childhood assessment, including those not seen

independent of trajectory variables, though ADOS-2 CSS and SRS-2 Total T-scores are also shown.

Mid-childhood outcomes differed significantly across trajectory classes on all measures. Class 1 (Low to High with Amelioration) showed average cognitive ability but low average adaptive functioning, high autism traits (ADI-R), slightly elevated ADHD traits, average anxiety, and average SDQ difficulties with elevated impact. Class 2 (High Persistent) showed low average cognitive ability, well below average adaptive functioning, and very high autism traits, ADHD traits, anxiety, and behavioural difficulties. Class 3 (Slow Starters) showed average cognitive ability and adaptive functioning, with very low autism traits and all other measures in the average range. Class 4 (Later Emerging) showed average cognitive ability but below average adaptive functioning, with high autism traits and elevated ADHD traits, anxiety, and behavioural difficulties. Class 5 (Typical) showed above average cognitive ability, average adaptive functioning, very low autism traits, and all other measures in the average range.

Discussion

Group-based multi-trajectory modelling across three autism trait measures from 5 months through mid-childhood identified five distinct developmental trajectories in this infant family history cohort. The trajectory classes differed not only in the timing and shape of autism trait expression, but also in their baseline predictors, patterns of earlier versus later autism diagnosis, and mid-childhood developmental and behavioural profiles (summarised in Fig. 3).

Our multi-trajectory approach, spanning infancy through mid-childhood, reveals that chronogeneity—the developmental timing and pace of change in autistic characteristics (Georgiades et al., 2017)—represents a substantial and clinically meaningful source of heterogeneity in this infant family history sample, independent of overall trait severity. This is most clearly illustrated by contrasting Classes 1, 2, and 4, all of which showed elevated autistic characteristics and high rates of autism diagnosis by mid-childhood yet follow divergent developmental pathways. Class 2 showed

Table 5 Mid-childhood outcomes by joint trajectory class

	Joint trajectory class									
	Infant low to high autism traits (with amelioration)		High early persistent autism traits		Typical (slow starters)		Later emerging autism traits		Typical class	
	Mean (SD)	*N*	Mean (SD)	*N*	Mean (SD)	*N*	Mean (SD)	*N*	Mean (SD)	*N*
FSIQ	108.40 (20.76)	10	$94.33\ (12.67)_{a}$	12	$107.78\ (14.32)_{b}$	45	$104.22\ (19.22)_{b}$	32	$113.34\ (13.61)_{c}$	126
Vineland ABC	$88.56\ (9.67)_{a}$	9	$71.69\ (9.93)_{b}$	13	$97.07\ (11.51)_{a,c}$	44	$83.74\ (12.11)_{a,d}$	31	$107.90\ (9.74)_{e}$	125
ADI social	$10.50\ (5.54)_{a}$	10	$13.64\ (6.47)_{a}$	11	$1.97\ (2.55)_{b}$	32	$7.97\ (4.01)_{a,c}$	32	$1.75\ (2.65)_{b}$	79
ADI communication	$9.90\ (3.98)_{a}$	10	$13.42\ (3.96)_{b}$	12	$2.55\ (2.37)_{c}$	33	$7.29\ (3.66)_{a,d}$	31	$1.86\ (2.37)_{c}$	76
ADI RRB	$2.40\ (1.96)_{a}$	10	$5.00\ (2.22)_{b}$	12	$0.73\ (1.13)_{c}$	33	$3.03\ (1.43)_{a,d}$	32	$0.51\ (0.95)_{c}$	81
ADOS-2 CSS	$6.00\ (3.06)_{a}$	10	$5.62\ (2.93)_{a}$	13	$2.89\ (2.33)_{b}$	45	$3.69\ (2.36)_{b,c}$	32	$2.15\ (1.76)_{b,d}$	123
SRS-2	$61.67\ (11.82)_{a}$	9	$87.23\ (8.25)_{b}$	13	$49.11\ (7.31)_{c}$	55	$77.06\ (12.55)_{d}$	35	$47.19\ (8.01)_{c}$	130
Inattention	$60.40\ (15.90)_{a}$	10	$77.15\ (14.78)_{b}$	13	$53.45\ (11.98)_{a,c}$	53	$70.94\ (12.27)_{a,b}$	35	$50.99\ (11.82)_{a,c}$	134
Hyper/impulsivity	$61.60\ (8.45)_{a}$	10	$77.62\ (13.38)_{b}$	13	$52.72\ (12.42)_{a,c}$	53	$75.51\ (12.89)_{b,d}$	35	$52.46\ (12.93)_{a,c}$	134
SCAS anxiety	$51.38\ (6.99)_{a}$	8	$63.46\ (9.08)_{b}$	13	$50.46\ (8.79)_{a,c}$	46	$61.06\ (8.41)_{b,d}$	31	$49.95\ (7.76)_{a,c}$	124
SDQ total	$10.33\ (1.37)_{a}$	6	$21.50\ (4.99)_{b}$	8	$9.36\ (5.58)_{a,c}$	36	$21.14\ (7.54)_{b}$	21	$5.96\ (4.83)_{a,d}$	102
SDQ impact	$2.33\ (1.21)_{a}$	6	$5.75\ (2.19)_{b}$	8	$1.14\ (1.68)_{a,c}$	36	$5.00\ (3.26)_{b}$	21	$0.45\ (1.35)_{a,c}$	102

FSIQ full scale IQ, *ADI* autism diagnostic interview-revised current domain score, *ADOS-2 CSS* autism diagnostic observation schedule-2 calibrated severity score, *SRS-2* social responsiveness scale-2, *SCAS* Spence children's anxiety scale—parent, conners-3 inattentive and hyperactive/impulsive scales, *SDQ* strengths and difficulties questionnaire total difficulties score and impact score

Classes with different subscript letters (a, b, c) differed significantly from each other on Tukey–Kramer post-hoc comparisons ($p<.05$)

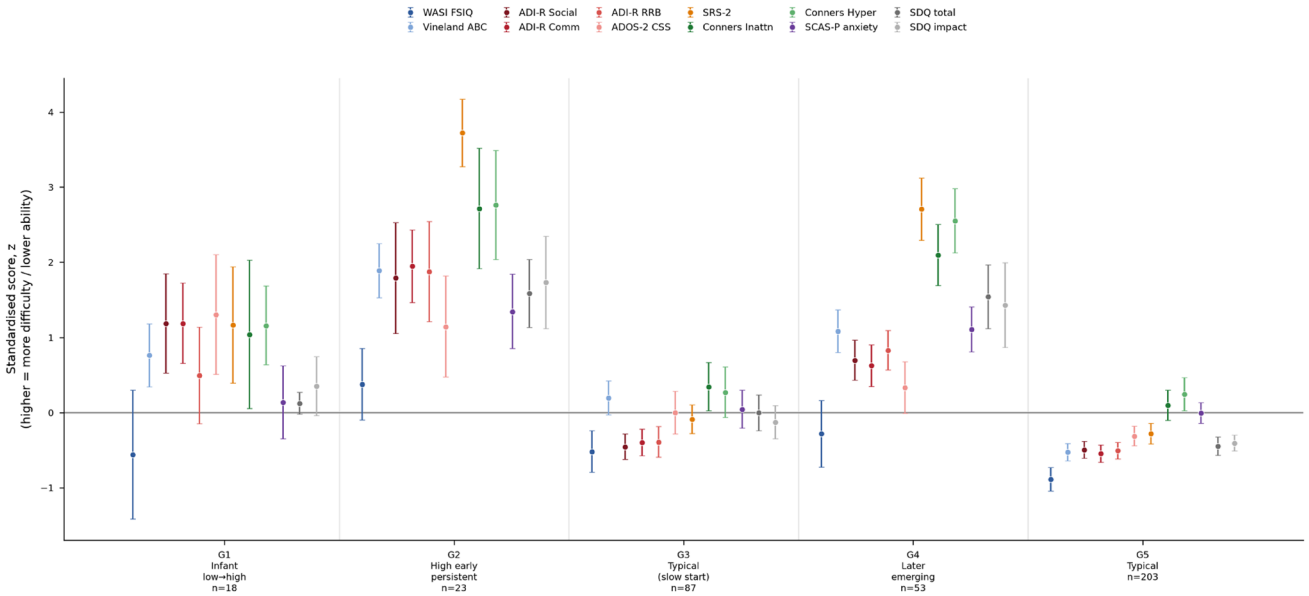

Fig. 2 Mid-childhood outcome signatures of the five trajectory classes. For each class, markers show the group mean with 95% confidence intervals across 12 standardised mid-childhood measures, coloured by measure and grouped by domain (blues = cognitive/adaptive: WASI FSIQ, Vineland ABC; reds = autism-diagnostic: ADI-R Social, Communication and RRB domains, ADOS-2 CSS; orange = autism traits: SRS-2; greens = ADHD traits: Conners-3 Inattention and Hyperactivity; purple = anxiety: SCAS-P; greys = general difficulties: SDQ total and impact). The dashed line at z = 0 is the reference. All measures are oriented so that higher z indicates greater difficulty or lower ability (WASI FSIQ and Vineland ABC are reverse-scored to this convention). z-scores use published norms where available (WASI FSIQ, Vineland ABC: M = 100, SD = 15; SRS-2, Conners-3, SCAS-P: T-scores, M = 50, SD = 10) and within-sample standardisation for measures without applicable norms (ADI-R domains, ADOS-2 CSS, SDQ total and impact). ADI-R autism diagnostic interview-revised, ADOS-2 CSS autism diagnostic observation schedule calibrated severity score, SRS-2 social responsiveness scale, SCAS-P spence children's anxiety scale, parent report, SDQ strengths and difficulties questionnaire

persistently high traits from the earliest assessments, consistent with an early-emerging neurodevelopmental phenotype. Class 1, by contrast, showed low traits in early infancy followed by a steep increase to high levels in toddlerhood before partial amelioration—a pattern that was associated with a distinct profile of a high rate of autism family history, predominantly early autism diagnosis but average cognitive ability and low average adaptive functioning in mid-childhood. Class 4 represented a further distinct developmental pattern: low early traits with a gradual increase through to mid-childhood, associated with later diagnosis, co-occurring ADHD family history, and an outcome profile characterised by elevated autism, ADHD, and anxiety traits alongside emotional and behavioural difficulties. We previously reported mid-childhood outcomes by diagnostic timing in a subsample of this cohort, finding earlier diagnosis associated with higher autism scores on some measures but similar levels of IQ, adaptive function, ADHD, and anxiety traits (Bazelmans et al., 2024). However, the current developmental trajectory approach reveals more nuanced developmental patterns and outcome associations than our previous cross-sectional approach (see also Charman et al. (2026)).

Two classes showed broadly typical development. Class 3 showed slightly elevated traits in infancy that diminished through toddlerhood, with few autism diagnoses and typical mid-childhood functioning, demonstrating that trajectory pattern across the first two years, rather than early trait level alone, better differentiated typical from atypical development in this family history sample. Class 5, the largest class, showed stable low traits throughout, with less autism and ADHD family history, higher socioeconomic background, and above average mid-childhood functioning.

This study extends prior trajectory work by using multi-trajectory modelling across three complementary measures: parent-reported traits, clinician-observed characteristics, and adaptive social functioning. Previous studies in both diagnosed and infant family history cohorts have modelled single measures (Gentles et al., 2024; Hiralal et al., 2025; Pender et al., 2020), which cannot capture whether children showing similar trajectories on one dimension (e.g., parent-reported traits) diverge on others (e.g., adaptive functioning). Multi-trajectory modelling identifies individuals who share coherent developmental profiles across multiple facets of the autistic phenotype simultaneously (Jones & Nagin, 2013; Nagin et al., 2018), providing more robust class identification through triangulation across informants and methods, and capturing the coordinated evolution of different dimensions of autistic characteristics over time. For instance, children who show declining parent-reported traits

Fig. 3 Summary of classes

Class 1: Infant Low to High Autism Traits (with Amelioration) showed low autism traits in early infancy that steeply increased to high levels by toddlerhood before ameliorating. All children had autism family history and were more likely to be boys. One fifth had parent-reported regression. Two-thirds had autism (all diagnosed at 3 years). Mid-childhood profiles showed average cognitive ability but low average adaptive functioning, high autism traits, slightly elevated ADHD traits, and average anxiety and emotional/behavioural difficulties.

Class 2: High Early Persistent Autism Traits showed high and increasing autism traits from infancy to mid-childhood. All but one child had autism family history, with lower maternal education and household income. One quarter had parent-reported regression. Three-quarters had autism, mostly diagnosed early. Mid-childhood profiles showed low average cognitive ability, well below average adaptive functioning, and very high autism and ADHD traits, emotional/behavioural difficulties, and anxiety.

Class 3: Typical (Slow Starters) showed slightly elevated autism traits in infancy that diminished by toddlerhood through to mid-childhood. Maternal education was lower on average. Few had autism. Mid-childhood profiles were in the average range across developmental and behavioural measures.

Class 4: Later Emerging Autism Traits showed low autism traits in infancy that gradually increased through to mid-childhood. Associated with both autism and ADHD family history. . One tenth had parent-reported regression. Half had autism, two-thirds diagnosed later. Mid-childhood profiles showed average cognitive ability but below average adaptive functioning, with high autism, ADHD, and anxiety traits and emotional/behavioural difficulties.

Class 5: Typical Class was the largest class (over half the sample) and showed stable low autism traits throughout. Children had less autism/ADHD family history, were more likely to be girls, and had higher maternal education and household income. Few had autism. Mid-childhood profiles showed above average cognitive ability and average-range developmental and behavioural functioning.

but stable impairment in adaptive functioning would be grouped differently in single- versus multi-trajectory models. A further difference from prior work is that trajectory studies in diagnosed cohorts examine a fundamentally different question: developmental heterogeneity among children who have already met diagnostic criteria. In contrast, prospective family history designs track developmental pathways before and across diagnostic outcomes, capturing variation that diagnostic selection obscures.

We find classes consistent with those reported previously (Franchini et al., 2023; Georgiades et al., 2022; Gotham et al., 2012; Kim et al., 2018; Zwaigenbaum et al., 2021): most clearly the stable-low autistic trait classes (our typical Classes 3 and 5) and the stable-high class (Class 2), and we also find a later-increasing class (Class 4). Class 1, however, shows an unusual profile, with steep increases in autistic traits from infancy to toddlerhood followed by partial amelioration through to mid-childhood. In view of this we conducted an exploratory of regression using 3-year ADI-R data. Regression was reported in 10–20% of children in Classes 1, 2 and 4, mostly in those who received an autism diagnosis, but was not specific to Class 1 and did not differ significantly between these classes. Low rates of parent-reported regression are consistent with other family history infant samples, but measure-defined regression has been found to be more frequent, although the agreement between these methods is low (McAllister et al., 2025; Ozonoff & Iosif, 2019).

Predictors of trajectory class membership included autism family history which was associated with Classes 1 and 4. However, ADHD family history was uniquely associated with Class 4, where emergence of autistic traits was later and mid-childhood levels of ADHD traits were high, consistent with bidirectional genetic and environmental influences between the two conditions (Taylor et al., 2013). Substantial shared liability between autism and ADHD is evidenced by cross-condition familial trait associations (Ghirardi et al., 2019; Rommelse et al., 2010), overlapping polygenic architecture (Askeland et al., 2022; Warrier et al., 2022), and a strong genetic correlation (Lichtenstein et al., 2010). ADHD family history may therefore index a broader neurodevelopmental liability shaping the timing of autistic trait emergence, and future studies with genetic data should examine whether shared polygenic liability specifically predicts later-emerging trajectory membership.

Sex only showed one association: boys were over-represented in Class 1. Sociodemographic characteristics (maternal education and household income) were also associated with class membership, predominantly being higher in the typical classes Class 3 and Class 5. Unlike Franchini et al. (2023) we did not examine whether initial assessment early infancy autism trait scores or developmental abilities were associated with trajectory class membership since these are confounded with the variance used to model trajectories.

Recent evidence suggests that genetic, neurobiological, and phenotypic profiles differ between earlier and later diagnosed autism (Bazelmans et al., 2026; Litman et al., 2025; Mandy et al., 2022; Zhang et al., 2025). Although symptom severity, degree of functional impairment, presence of co-occurring conditions, service availability, and clinical recognition all affect age of autism diagnosis (Fountain et al., 2011; Mandell et al., 2005) these findings suggest that earlier vs. later manifesting autism may represent distinct biological subtypes. However, these studies have categorised diagnostic timing using binary comparisons (earlier vs. later diagnosis), with varying age cut points across studies, rather than examining developmental trajectories. Our multi-timepoint prospective design extends this work by directly addressing the chronogeneity framework. We demonstrate that the timing and developmental course of autistic traits—beyond diagnostic age alone—may be associated with early predictors, diagnostic outcome, and functional prognosis; information obscured when heterogeneity is examined at a single timepoint or defined solely by diagnostic status.

We recognise that the current observational study was post-hoc and exploratory, and the trajectory classes we identified are descriptive and hypothesis-generating. The mechanisms generating these distinct developmental pathways, however, remain to be established. Biopsychosocial models such as Anterior Modifiers in the Emergence of Neurodevelopmental Disorders (AMEND; Johnson et al., 2021) and Bradshaw et al.'s (2022) 'developmental cascade framework' propose that trajectory patterns emerge from dynamic interactions among genetic liability, early neurodevelopmental processes, emerging cognitive and behavioural characteristics, and environmental factors. Testing these models requires identifying early-stage predictors of trajectory divergence (genetic liability, brain biomarkers, attention, sensory processing) alongside later intrinsic (emerging executive function, language development, co-occurring conditions) and extrinsic modifiers (intervention, caregiving quality, stress exposure) that may shape developmental course. This requires intensively and repeatedly sampled cohorts to capture both the early vulnerabilities that predict which pathway children follow and the ongoing processes—both within-child and environmental—that influence trajectory shape over time. Early intervention and support, which we did not capture systematically in this cohort, may also shape or modify the developmental trajectories observed across groups.

Strengths and Limitations

The study has several strengths, including a moderate-to-large sample assessed at multiple timepoints from early infancy to mid-childhood. We used group-based multi-trajectory modelling across different measures of autistic traits—an approach not previously reported in autism research with clinical or infant family history cohorts, which have relied on single instruments (Gentles et al., 2024; Hiralal et al., 2025; Pender et al., 2020). This involved repeated sampling across six, five, and four timepoints over more than 10 years. The measurement methods (Vineland Social domain, parent-reported autism traits, research-observed autism traits) differ and deriving joint trajectory classes across multiple measures guards against measurement biases and confounds. By design, mid-childhood outcome measures (IQ, ADI-R current domain scores, ADHD, anxiety, SDQ Total Difficulties and Impact scores) had minimal overlap with trajectory measures, though Vineland ABC includes the Vineland Social domain.

However, several limitations warrant consideration. Classes 1 (N = 18, 4.7%) and 2 (N = 23, 6.0%) contained small numbers, at the lower bound for robust class identification (Nagin, 2005; Nagin et al., 2018), though posterior probabilities were adequate. Missingness was considerable, particularly at 5-month and mid-childhood timepoints (Table 2), although maximum likelihood estimation accounted for missing data. Not all participants were invited to 5-month visits, and only a subset ($N = 360$) were invited for mid-childhood follow-up, yielding 72% retention (260/360). Retention was lower in Black/African/Mixed children but there was no evidence of more or less affected infants being retained from 10 months of age.

Trajectory models used nominal rather than exact assessment ages, following standard practice; a sensitivity analysis using exact ages reproduced the classification almost exactly ($\kappa = 0.87$), indicating the solution is robust to this choice. The mean (SD) age of the mid-childhood assessment was 8.65 (1.27) years but following closely spaced assessment timepoints from early infancy to 3 years the extended interval to this timepoint means that the trajectories identified may primarily reflect early patterns rather than continuous developmental change. Therefore, caution is warranted in interpreting the shape of trajectories across the unobserved interval. Related to this, the classification of autism diagnoses as 'earlier' (age 3) or 'later' (mid-childhood) reflects the two assessment timepoints available (Bazelmans et al., 2024) and will have missed diagnoses occurring in

the intervening period. Unlike autism, ADHD was assessed only via parent-report trait measures rather than diagnostic assessment at mid-childhood, so ADHD diagnoses across the trajectory groups were not available.

Modest cross-time correlations for Vineland Socialization and clinician-observed characteristics (AOSI/ADOS-2)—reflecting developmental change and varying assessment contexts—may have introduced additional measurement variability into trajectory estimation. In addition, we z-scaled the questionnaire and observational measures within-measure and within-timepoint; by construction this removes mean-level change, so trajectories reflect relative standing within the cohort rather than absolute trait change. If possible, alternative scaling approaches should be explored in future work. The Vineland Socialization domain measures adaptive social functioning rather than autism traits directly, but correlates moderately to strongly with autism severity measures such as the SRS and ADI-R (Kanne et al., 2011; Tillmann et al., 2019), and its inclusion adds methodological breadth by complementing questionnaire and observational measures.

We did not conduct direct assessments for autism and ADHD in older probands or parents themselves and the inclusion criteria for the sample was parent-report of a community clinical diagnosis of autism and/or ADHD which was supported by clinical reports shared with the team. We did not systematically collect broader neurodevelopmental or psychiatric condition family history or genetic data. These may be important for a fuller understanding of family influences on trajectories and outcomes for the infant siblings and should be addressed in future work, alongside more detailed characterisation of child and family sociodemographic factors—including finer-grained measures of ethnicity, socioeconomic circumstances, and other contextual variables.

We selected GBTM over GMM for three reasons. First, GBTM is optimal for person-centred classification questions when the primary goal is to identify and describe (unknown) distinct developmental pathways or typologies (Nagin, 2005; Nagin & Odgers, 2010; Nagin et al., 2024; Nguena Nguefack et al., 2020). Second, simulation studies suggest GMM requires around twice the sample size for reliable convergence in models of this complexity than does GBTM (Kim, 2012; Loughran & Nagin, 2006). Third, the multi-trajectory structure—jointly modelling three outcome series—increases parameter demands further, reinforcing the case for GBTM's more parsimonious specification. Unlike GMM, GBTM assigns fixed intercept and slope values to classes rather than estimating within-class variance, which improves model stability but means that individual variation within classes is not modelled. The identified trajectory classes should therefore be understood as approximations of developmental patterns rather than discrete subtypes.

There has been increasing recent interest in the autism field in using longitudinal trajectory modelling approaches to better understand developmental variability in autism outcomes (Gentles et al., 2024; Hiralal et al., 2025). Despite challenges in identifying invariant measures across wide developmental windows and maintaining sample retention, future studies should adopt standardised measurement protocols that enable multi-trajectory modelling and cross-cohort data pooling.

Taken together, the modest sample size, small classes in two of the five trajectory groups, reliance on a single cohort, and the descriptive and exploratory nature of the analyses mean that these findings should be regarded as hypothesis-generating. Replication in larger independent family history cohorts is a priority before conclusions about the stability, generalisability, or mechanistic significance of the identified trajectory classes can be drawn.

Conclusions

Using multi-trajectory modelling across multiple measures of autistic traits from infancy through mid-childhood, we extend previous work in ways directly relevant to understanding chronogeneity (Georgiades et al., 2017). The heterogeneity we observed was not simply a matter of varying trait levels—it concerned when traits emerged, how they changed, and what that pattern meant for later outcomes. These findings demonstrate that chronogeneity may reflect underlying mechanisms relevant to aetiology, diagnostic outcome, and functional prognosis that is not captured by cross-sectional measurement. Children with similar mid-childhood profiles may have followed heterogeneous developmental routes, while children with similar early profiles may diverge substantially in later outcomes. This has implications for how putative autism subgroups are conceptualised, when surveillance and diagnostic assessment are timed, and how early intervention might be targeted in infant family history and other early autism populations.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10803-026-07481-3.

Acknowledgments The authors are grateful to all the families who took part in this study. The BASIS/STAARS team consists of: Rowan Arthur, Jeni Baykoca, Anna Blasi, Patrick Bolton, Celeste Cheung, Kenny Chiu, Leila Dafner, Kim Davies, Mayada Elsabbagh, Janice Fernandes, Laurel Fish, Isobel Gammer, Teodora Gliga, Jeanne Guiraud, Rianne Haartsen, Sarah Kalwarowsky, Anna Kolesnik, Michelle Liew, Sarah Lloyd-Fox, Helen Maris, Luke Mason, Mia Medas, Bosiljka Milosavljevic, Louise O'Hara, Andrew Pickles, Laura Pirazzoli, Helena Ribeiro, Erica Salomone, Elizabeth Shephard, Chloë Taylor,

Leslie Tucker. For the purposes of open access, the author has applied a Creative Commons Attribution (CC BY) license to any Accepted Author Manuscript version arising from this submission.

Author Contributions Funding, Conceptualization, Statistical analysis, Writing—Original draft preparation: Tony Charman. Funding, Conceptualization, Writing—Reviewing and Editing: Emily J. H. Jones, Mark H. Johnson. Data collection, Data curation, Writing—Reviewing and Editing: Tessel Bazelmans, Greg Pasco, Jannath Begum Ali. Data collection: The BASIS/STAARS Team.

Funding Supported by awards from the Medical Research Council (MR/R011427/1, G0701484, MR/K021389/1, MR/T003057/1), Autistica, Autism Speaks. The results leading to this publication have received funding from the Innovative Medicines Initiative 2 Joint Undertaking under grant agreement No 777394 for the project AIMS-2-TRIALS. This Joint Undertaking receives support from the European Union's Horizon 2020 research and innovation programme and EFPIA and AUTISM SPEAKS, Autistica, SFARI. Any views expressed are those of the authors and not necessarily those of the funders (IHI-JU2). European Union Horizon Europe grant no. 101057385 (R2D2-MH) and UK Research and Innovation (UKRI) under the UK government's Horizon Europe funding guarantee [grant no.10039383] and by the Swiss State Secretariat for Education, Research and Innovation (SERI) under contract number 22.00277. Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union. TB is supported by a grant from the UK Medical Research Council (MR/X010716/1). Capital equipment funding from the Maudsley Charity (980) and Guy's and St Thomas' Charity (STR130505). The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Data Availability Data available following review as indicated here: https://www.basisnetwork.org/collaboration-and-project-affiliation/

Declarations

Declaration of Generative AI and AI-assisted technologies in thewriting process During the preparation of this work the authors used Claude Sonnet 4.5™ in order to refine phrasing for clarity and conciseness, suggest alternative word choices and identify redundant content. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Conflict of interest TC consultancy fees from F. Hoffmann-La Roche Ltd. and royalties from Sage Publishing and Guilford Press. MHJ royalties from Wiley-Blackwell, OUP and MIT Press. The remaining authors have declared that they have no competing or potential conflicts of interest.

Ethical Approval Ethical approval from NHS National Research Ethics Service (NHS RES London REC 14/LO/0170) and Psychiatry, Nursing and Midwifery Research Ethics Subcommittee, King's College London (RESCM-18/19-10556).

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