Associations of linear growth trajectories from 0-5 years with cognitive function and school achievement at 10 years of age: The Ethiopian iABC birth cohort study

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Abstract

This study aimed to identify linear growth trajectories from 0-5 years and assess their associations with cognitive function and school achievement in Ethiopian children aged 10 years. Latent class trajectory modelling was used to identify distinct height-for-age (HAZ) trajectories. Cognitive function was assessed using the Peabody Picture Vocabulary Test (PPVT), while school achievement was measured by Math, English, and Science (MES) combined scores and grade-for-age. Associations were assessed using multiple linear or logistic regressions.

We identified 4 distinct HAZ trajectories. *Decreasing* trajectory (n=145, 31.9%) started high at birth but dropped sharply. The *increasing-decreasing* trajectory (n=196, 43.2%) increased up to 3 months followed by a decrease**.** The *stable low* (n=74, 16.3%) had low HAZ at birth, followed by a slight decrease. The *rising* trajectory (n=39, 8.6%) started low but then increased to HAZ above, yet close to zero. At 10 years, children in the *rising* trajectory had 4.54 (95% CI: -0.45, 9.55, p=0.075) higher MES combined score and 2.4 times (95% CI: 1.12, 5.15, p=0.025) higher odds of being in the appropriate grade-for-age compared to those in the *increasing-decreasing* trajectory. The association between *stable low* and *decreasing* trajectory with appropriate grade-for-age had odds ratio close to null.

In conclusion, we found that three of the four linear growth trajectory classes showed a declining pattern. Data suggest that greater linear growth in early childhood may be associated with higher school achievement and better cognitive function.

Keywords: Linear growth, trajectories, cognitive function, school achievement, development, Ethiopia

Abbreviation

iABC = Infant Anthropometry and Body composition

HAZ = Height-for-age z score

LCT=Latent class modelling

PPVT = Peabody Picture Vocabulary Test

Introduction

Over the past two decades, the prevalence of childhood stunting has decreased, particularly in low- and middle-income countries. However, stunting remains a significant public health problem in many low-income countries [(1)] and is associated with several negative short- and long-term consequences. These include lower cognitive function [(2,3)], increased vulnerability to chronic diseases [(4)], reduced educational attainment [(5)], and decreased economic productivity in adulthood [(6)]. These consequences can exacerbate intergenerational cycles of poor health, hindering individual well-being, and societal and economic development [(7)].

Previous studies investigating the association of linear growth with cognitive function and school achievement often rely on data from one time point [(8–10)] or from the perspective of stunting [(2,9,11,12)]. While these studies show that height-for-age z-scores (HAZ) at specific points in time and stunting are associated with cognitive function and school achievement [(9–12)], they do not capture the relationship of distinct growth patterns longitudinally. This is important because children may exhibit different growth patterns that are not fully captured when examining growth at specific time points. In addition, children may experience growth faltering if their height is below the expected average for their age, even though their linear growth has not yet reached the level to be classified as stunted, i.e. HAZ<-2 [(13,14)].

Some children who had restricted growth might experience subsequent catch-up growth**,** a period of accelerated growth after the cause of growth faltering is resolved [(15)]. Understanding the diverse childhood growth patterns is essential for understanding growth progression and identifying hidden growth patterns within the population [(16,17)], which may have distinct associations with health and development. Previously, in the cohort used in this study, we reported that early childhood is a period where distinct body composition [(18)] and body mass index growth trajectories are observed [19]. These distinct trajectories are associated with health outcomes such as cardiometabolic indicators [19,20]. A study in Guatemala demonstrated that childhood features diverse linear growth trajectories, which were associated with adult cognitive and socioemotional functioning [21]. We have also reported the association between early childhood linear growth velocity and school achievement [22]. However, evidence on early childhood linear growth trajectories using longitudinal data and their association with cognitive function and school achievement is scarce particularly in low income countries where linear growth faltering is most prevalent [23,24]. In this study, our first aim was to identify distinct linear growth trajectories during the early childhood period (0-5 years) using latent class trajectory (LCT) modelling. Secondly, we aimed to examine associations of the identified linear growth trajectories with cognitive function and school achievement at 10 years of age.

Methods

Study setting and participants

The Infant Anthropometry and Body Composition (iABC) birth cohort examined 644 newborns and their mothers in Jimma Town, Ethiopia between December 2008 and October 2012. This birth cohort followed the children for a decade, from birth through childhood prospectively, with a total of 14 visits: birth, 1.5, 2.5, 3.5, 4.5, 6 months, and 1, 1.5, 2, 3, 4, 5, 6, and 10 years of child's age. Newborns born pre-term, with congenital anomalies, weighing below 1500 grams, and from families residing outside Jimma town were excluded. Out of 644 children initially examined at birth, 73 were excluded based on the criteria mentioned earlier. Consequently, 571 children were enrolled and invited for follow-up visits. At enrollment, assessment was performed within 48 hours of delivery. Further details about setting and participants can be found in previous publications [25,26]. At the most recent follow-up the children's age ranged from 7-12 years, henceforward referred to as the 10-year follow-up. Mothers/caregivers and their children were traced using their last registered phone number or by a home-to-home visit by the research team using their address or landmark.

Main exposure

Anthropometry from 0-5 years

For children younger than two years of age, length was measured using SECA 416 Infantometer (Seca, Hamburg, Germany) in recumbent position. For children ≥2 years, a SECA 213 (Seca, Hamburg, Germany) was used to measure height in standing position. Each measurement was taken twice by the research nurses to the nearest 0.1 centimeter. The average of the two measurements at each time point was used in analyses.

Covariables

Background data on newborn's sex, birth order, and gestational age (determined using the Ballard score [27]) were collected by trained research nurses using a structured and pre-tested questionnaire. Maternal data including age and educational level (categorized according to the Ethiopian education system as none, primary (1-8 years), secondary (9-12 years) and higher (college and universities)) were also collected. Family socioeconomic data such as source of drinking water, type of latrine, and asset ownership were collected at enrollment.

Infant head circumference was measured using a non-stretchable tape. This measurement was taken twice to the nearest 0.1 cm. Fat mass (FM) and fat-free mass (FFM) at birth were measured using an infant-sized air-displacement plethysmograph: PEA POD (COSMED, Rome, Italy) as described elsewhere [28].

Outcomes

Cognitive function

Cognitive function was measured using Peabody Picture Vocabulary Test Fourth Edition (PPVT IV), translated for use in Amharic and Affan Oromo, languages spoken in the study area. This tool has been used in previous studies to assess cognitive function among Ethiopian children [9,29]. PPVT is a tool designed to measure receptive vocabulary acquisition from age 2.5 to 90+ years of age [30]. Receptive vocabulary measures an important facet of general intelligence and is one of the best predictors of school achievement [30,31]. The test is individually administered and norm-referenced, i.e., is a standardized test designed to compare scores among the individuals.

Each PPVT IV test contains training items to familiarize examinees with the test and 228 test items, 19 sets of 12 items arranged in order of increasing difficulty. The test starts at a set of items appropriate for the child's age. The test uses a basal and ceiling set rule to determine the start and end of the examination for each child. The basal set refers to a test set where the examinee scored one or zero errors. Once the basal set is identified, the test continues until it reaches the ceiling point. This ceiling is reached when an examinee makes eight or more errors out of 12 total items.

Ninety-seven children required retesting at home due to examination errors. However, we adjusted for place of test (home vs. facility) in all multiple linear regression models assesses the association between the trajectories and cognitive function, to account for potential systematic differences**.**

Research nurses were trained on the PPVT administration and the test was conducted in private room to ensure suitable environment for testing.

School achievement

School achievement in this study was assessed using academic subject scores and being in the appropriate, or expected grade in school for one's age (which we refer to as grade-for-age). Subject scores, school name and grade level were obtained directly from official school records. Although Ethiopian schools do not adhere to a common curriculum [32], all schools offer math, English, and science. Therefore, we selected these three subjects for further analysis and we also took into account the child's school in the analyses. A principal component analysis was performed to explore potential groupings among these subjects. However, the loading values for all three subjects (English: 0.566, science: 0.582, and math: 0.584) were close, suggesting that the three subjects are influenced by the same factors (**Supplementary figure 1**). Thus, an average value of the math, English, and science (MES) combined score was used in subsequent analyses.

Grade-for-age was computed by subtracting the current grade from the expected grade based on Ethiopia's official age of entry into primary grade 1, which is 7 years [33]. Subsequently, these grade-for-age values were divided into two categories according to the UNESCO classification [34]: children who were two or more years behind the expected grade for their age were classified as having a low grade-for-age, while those who were one year behind or at grade level were considered to have an appropriate grade-for-age.

Statistical analysis

Data was entered in Epi Data version 4.4.2.0 and exported to Stata version 17 (StataCorp LLC College Station, Texas, USA) for further analysis. All continuous variables were normally distributed; therefore, we present the mean (standard deviation (SD)). For categorical data, we computed percentages. A wealth index was computed using principal component analysis [(35)] from self-reported ownership material assets: car, motorcycle, bicycle, electric stove, refrigerator, mobile phone, land, telephone, television, radio, access to electricity, source of drinking water and type of latrine (data not shown).

HAZ was computed using Zscore06 Stata package for children younger than 60 months [(36)]. For children 60 months of age and older, we used the WHO Reference 2007 Stata macro package [(37)].

Identifying HAZ trajectories

LCT modelling was used to identify HAZ trajectories among children having at least three length/height measurements, at birth, between 0 and 6 months, and between 1 and 5 years of age using R statistical software (version 4.3.3, R Foundation for Statistical Computing, Vienna, Austria). LCT model estimates include fixed effects: average HAZ at birth and HAZ trajectory from 0-5 years for each identified class. Models were run with 30 repetitions and iterations of 100. Both class-specific and model-specific parameters were taken into account to determine the optimal number of trajectories. We ensured that each class included a minimum of 5% of the children for clinical significance and for sufficient sample size per class for subsequent analysis [(16)]. Detailed information on how we identify HAZ trajectories is provided in **Supplementary Text 1**.

Following the identification of the distinct HAZ trajectories, we compared maternal and child characteristics across the trajectories. For continuous variables, we used an ANOVA test to assess overall differences between groups. For categorical variables, we assessed differences between trajectories using Chi-square tests and Fisher's exact test for variables with cell counts < 5.

Association of HAZ trajectory and outcomes

Three separate linear regression models were fitted to examine associations between distinct HAZ trajectories with cognitive function as well as MES combined score. Similarly, 3 separate logistic regression models were used to assess the associations between distinct HAZ trajectories and grade-for-age. As a supplementary analysis we also assessed the association between HAZ trajectories with each subject separately (math, English and science). Model 1 was adjusted for age at the 10-year follow-up, and sex. Model 2 was additionally adjusted for head circumference, gestational age and birth order. Model 3 was further adjusted for maternal and household characteristics: maternal age, education and household wealth index. All PPVT models adjusted for the location where the cognitive test was administered. Current age was not included in grade-for-age models, as grade-for-age was calculated using the current age of the child. Covariates were selected following a review of the literature [9–12].

Students within schools are more homogeneous due to shared learning environments, potentially violating the independence assumption in regression [38], leading to biased coefficient estimates, inaccurate standard errors, and ultimately, misleading statistical inferences. Therefore, for models assessing associations with school achievement, each school was assigned a unique identifier (school id) for clustering. As a result, all regression models assessing the association of HAZ trajectories and MES score used cluster-robust standard errors, [39–41] taking account of clustering within school id.

Ethics

Ethical clearance was obtained from Jimma University Ethical Review Board of the College of Public Health and Medical Sciences (reference IHRPHD/333/18) and the London School of Hygiene and Tropical Medicine (reference 15076). Written informed consent was obtained from parents/care givers of all participating children after a thorough explanation of the study protocol.

Results

The iABC birth cohort initially examined 644 newborns. After excluding 63 who lived outside Jimma and 10 preterm, 571 children were enrolled and invited for subsequent visits. A total of

454 children were included in the LCT modelling, meeting the criteria of having at least three length/height measurements: at birth, between 0-6 months, and between 1-5 years. Of these, 320 children were included in the 10-year follow-up. At the 10-year follow-up, 355 children (62%) were recruited. Among them, 318 completed the PPVT test, 276 had MES combined scores, and 343 had current grade data (**Figure 1**).

A comparison revealed no differences between children included in the 10-year analysis and those who were not regarding sex, birth characteristics (length, gestational age, weight, fat mass and fat free mass), wealth index, or maternal characteristics at birth (height and education). However, children included in the 10-year analysis were more likely to be firstborn and have younger mothers compared to those who were not **(Supplementary Table 1)**.

HAZ trajectories from 0-5 years

We identified 4 distinct trajectories of HAZ (**Figure 2**) 1) *decreasing* (n=145, 31.9%) had HAZ above zero at birth which declined rapidly between 3 and 24 months to below the WHO cut-off point for stunting (HAZ -2 SD) and then remained consistently low; 2) *increasing-decreasing* (n=196, 43.2%) started low at birth, followed by an increase in HAZ up to 3 months then a decrease to 18 months and stable afterwards; 3) *stable low* (n=74, 16.3%) had low HAZ at birth followed by a further decrease and then consistently low after 3 months; 4) *rising* (n=39, 8.6%) had low HAZ at birth which increased rapidly within the first 6 months, a decrease from 6-36 months, and then remained above but near the median of the WHO child growth standard [42]. The average posterior probability of assignment of each trajectory was above 80% **(Supplementary Table 2).**

Background characteristics across HAZ trajectories

Background characteristics of mothers and children across the 4 trajectory classes were presented in **Table 1**. Birth order showed statistically significant difference across the 4 trajectories (p = 0.04): children in the *rising* trajectory were more likely to be firstborns. The trajectories also showed differences among anthropometric measurements, and fat-free mass at birth. There were no statistically significant differences (p > 0.05) observed with regard to maternal characteristics at birth (maternal age, educational level, wealth index) or child sex, gestational age at birth, and fat mass at birth across the 4 trajectories.

Association between HAZ trajectory with cognitive function and school achievement

Due to minimal variation in estimations across the models (**Supplementary Table 2**), we present the final models in **Figure 3**. Though HAZ trajectories were not associated with PPVT scores overall, children in the *decreasing* trajectory had lower scores than those in the reference group, selected since the largest group, the *increasing-decreasing* trajectory (β = -0.12, 95% CI: -0.35, 0.11, p=0.29). Those in the *stable low* group had very similar scores to the reference group (β = 0.03, 95% CI: -0.25, 0.32, p=0.83). Children in the *rising* trajectory had 0.12 SD (4.8-point scores) (95% CI: -0.24, 0.47, p=0.53) higher PPVT than the reference group. Children in the *rising* trajectory class had 4.54 (95% CI: -0.45, 9.55, p=0.075) points higher MES combined scores compared to children in the reference group, the *increasing-decreasing* trajectory. Similarly, children in the *rising* trajectory had 2.4 times higher odds of being in the appropriate grade-for-age (OR = 2.40, 95% CI: 1.12, 5.15, p=0.025) compared to reference group. The association between *stable low* and *decreasing* trajectory with grade-for-age had close to 1 odds ratio compared to children in the reference group.

In the separate subject analysis**,** children in the rising trajectory had 6.38 (95%CI 1.85, 10.91, p= 0.007) higher math score and 5.14 (95% CI: 0.14, 10.13, p= 0.04) higher score in science. Children in the decreasing trajectory had 3.12 (95% CI: -0.37, 6.62, p= 0.08) higher math score compared to the children in the reference group (**Supplementary Table 4)**.

Discussion

In this birth cohort, we identified four trajectories of HAZ from 0-5 years and assessed associations of these trajectories with cognitive function and school achievement (assessed using MES combined scores and grade-for-age) at 10 years. The HAZ trajectories were: *decreasing*, *increasing-and-decreasing*, *stable low* and *rising*. Children in the *decreasing* trajectory showed a negative association with cognitive function, those in the *stable low* trajectory showed close to zero association, and children in the *rising* trajectory exhibited a positive association with cognitive function compared to those in the *increasing-decreasing* trajectory. Similarly, children in the *rising* trajectory class showed a higher MES combined scores and higher odds of being in the appropriate grade-for-age. In the analysis of the individual subjects, the association observed between the rising trajectory and the combined MES score stemmed from math and science scores.

Across all four trajectories most changes in HAZ occurred during the first six months after birth and continued until the age of two. After reaching two years of age, the HAZ trajectories were relatively stable up to the age of 5 years, indicating that most dynamic changes in linear growth occur during the first 2 years of life. This emphasizes the importance of the first two years for achieving optimal growth, development, and overall health [43,44]

Children in the three of the four trajectories, accounting for 92% of the children, exhibited different patterns of declining HAZ, resulting an average HAZ below the WHO child growth standards [42]. The observed rapid decline in HAZ trajectories, particularly after 6 months of age, might be explained by the critical role of complementary feeding in sustaining optimal growth thereafter [45,46] In addition, during this period, as children begin to explore their environment [47], their exposure to infectious agents increases which might also affect their growth. A study conducted in Guatemala demonstrated that all identified linear growth trajectories exhibited a declining pattern, particularly with a sharper decrease observed up to 24 months of age [21]. While distinct trajectories were not specified, other studies in low-and middle-income countries also reported a decline in mean HAZ during early childhood, with a notable drop observed from birth up to 24 months [48–50]. Additionally, one of these studies [49] reported that this decline in mean HAZ was accompanied by a narrowing of the HAZ distributions, implying that children initially with higher HAZ were also likely experiencing decrease in linear growth during this developmental stage.

Children in the *rising* trajectory had a higher cognitive function, those in the *decreasing* trajectory had lower cognitive function and those in the *stable low* trajectory had very similar scores to the reference group, the *increasing-decreasing* trajectory. Even though distinct trajectories were not identified in previous literature, higher linear growth during early childhood was found to have a positive association with cognitive function [12,43,51]. The *rising* and the reference -*increasing-decreasing*- trajectory exhibited a similar pattern, especially up to the 3-month mark, which could have masked any potential significant difference.

Children in the *rising* trajectory had a 4.54 point higher MES combined scores and 2.4 times higher odds of being in the appropriate grade-for-age compared to those in the *increasing-decreasing* trajectory. This might be due to factors such as lower school absenteeism, which is more prevalent among children experiencing linear growth faltering [52]. These children might be more susceptible to missing school due to illness [53] or social-emotional challenges [54–56]. This explanation could extend to the social advantages that favor children with higher linear growth. Children experiencing optimal growth may come from environments offering better access to resources and educational support, thereby supporting their school achievement [57]. Additionally, children with better linear growth during early childhood may receive differential treatment from parents, teachers, and others [58], potentially leading to earlier school enrollment compared to children with linear growth faltering. The association between the *rising* trajectory and MES score was driven by Math and Science. This might be due to the fact that Math and Science share certain cognitive abilities like analytical thinking and problem-solving abilities, which differ from those needed for learning English or language studies in general. Brain regions responsible for analytical thinking and problem-solving differ from those involved in language learning, as each part of brain tends to specialize in specific cognitive ability [59].

Childhood is a critical period for brain development, laying the foundation for cognitive abilities in adulthood [60]. Furthermore cognitive function and school achievement during childhood is also vital, not just for future academic success, but also for personal development and the overall socio-economic progress of a nation [61]. During this sensitive period, early childhood feeding practices, illness, and environmental stimuli play fundamental roles in supporting optimal brain development and physical growth.

Strength and limitation

This research contributes to the limited body of literature identifying early childhood linear growth trajectories and their association with cognitive function and school achievement. A key strength of this study lies in its longitudinal design, following children from birth to 10 years of age. Secondly, we employed LCT modelling, a robust data-driven statistical method that categorizes children into distinct trajectories. The posterior probability of each class was >80, indicating good assignment.

However, the study also had the following limitations. It is important to note that these trajectories might not be generalized to other populations. Future research should investigate whether these distinct growth trajectories are commonly observed across diverse populations of the same age. The second limitation is the loss to follow-up at the 10-year follow-up. While those lost to follow-up were similar to those included in the 10 years in terms of most variables, children included in the analysis were more likely to be firstborns and have younger mothers. Third, 97 children required retesting at home due to examination errors. However, we adjusted for the testing site in all multiple linear regression models assessing the association between trajectories and cognitive function.

Conclusion: This study identified four distinct trajectories of HAZ among children from 0-5 years of age. Most of the changes in HAZ growth occur between birth and 6 months, continuing to 2 years of age. After 6 months, most children's HAZ on average fell below the median of WHO child growth standards. Children who grow fast during early infancy and stayed above the median of WHO child growth standards had better cognitive function and school outcomes. These findings underscore the necessity for targeted interventions during the crucial transition to complementary feeding and continued promotion and education of exclusive breastfeeding for the first 6 months of a child. Furthermore, monitoring childhood growth is crucial for tracking growth patterns during this period. Additionally, we suggest conducting further research to investigate the growth patterns of children within different demographic contexts. We also recommend assessing the association of different cognitive function domains and academic achievement in future studies.

Conflict of interests

The authors declare none

Authorship

The authors' responsibilities were as follows HF, JCKW, SF, TG, RW, DY, MFO, MA, and RA Conceptualize the study; RA, BZ and BSM supervised the data collection; HF, JCKW, SF, RW, MFO, MA, and RA participated in methodology; RA analyzed the data and interpreted the findings. RA wrote the first draft. BZ, BSM, DY, TG, SF, HF, DN, JCK, AAM, MFO, RW, and MA commented on the manuscript, contributed for manuscript revisions, read the final manuscript and approved it for submission.

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Table 1: Maternal and child characteristics across the 4 HAZ trajectories among children followed up at 10 years (n=320)[1]

Characteristics	Category	Decreasing (n=103)		Increasing-decreasing (n=141)		Stable low (n=48)		Rising (n=28)		P value
		n (%) or mean	SD	n (%) or mean	SD	n (%) or mean	SD	n (%) or mean	SD	
Maternal characteristics at birth of cohort child										
Age at delivery (years)		24.3	(4.4)	25.3	(5.0)	24.0	(4.6)	24.5	(4.4)	0.24
Maternal education (%)	No school	7 (6.8)		8 (5.6)		2 (4.2)		0 (0)		0.46
	Primary school	61 (59.2)		89 (63.1)		31 (64.6)		14 (50.0)		
	Secondary school	20 (19.4)		23 (16.3)		11 (22.9)		10 (35.7)		
	Higher education	15 (14.6)		21 (14.9)		4 (8.3)		4 (14.3)		
Wealth index (%)	Lowest	21 (20.6)		19 (13.7)		5 (10.4)		1 (3.6)		0.67
	Low	16 (15.7)		29 (20.9)		9 (18.8)		5 (17.9)		
	Middle	24 (23.5)		33 (23.7)		14 (31.3)		5 (21.4)		
	Higher	24 (23.5)		31 (22.3)		10 (20.8)		9 (32.1)		
	Highest	17 (16.7)		27 (19.4)		9 (18.8)		7 (25.0)		
Child characteristics at birth										
Male (%)		61 (59.2)		66 (46.8)		25 (51.1)		14 (50.0)		0.27
Birth order (%)	First	41 (40.6)		64 (45.4)		28 (58.3)		19 (67.9)		0.04
	Second	33 (32.7)		43 (30.5)		7 (14.6)		3 (10.7)		
	Third and above	27 (26.7)		34 (24.1)		13 (27.1)		6 (21.4)		

Gestational age (weeks)		39.1	1.0	39.0	0.9	38.8	0.8	39.0	0.8	0.45
Length (cm)		50.1	1.8	48.8	1.9	49.0	2.1	48.7	2.0	<0.001
Birth weight (kg)		3.2	0.4	3.0	0.4	3.0	0.4	3.0	0.5	<0.001
Fat mass (kg)		0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.34
Fat-free mass (kg)		3.0	0.3	2.8	0.3	2.8	0.4	2.8	0.4	<0.001
Head circumference (cm)		35.5	1.4	34.5	1.7	34.8	1.4	34.6	1.5	<0.001
Child characteristics at 10 years										
Age at 10-year visit (years)		9.7	1.0	9.9	1.0	9.6	0.7	9.7	0.9	0.34
Private School (%)		53 (64.6)		70 (59.8)		27 (67.5)		18 (78.3)		0.37

[1] Values are expressed as mean (SD) for continuous variables and as n (%) for categorical variables.

HAZ categories were derived from latent class modelling

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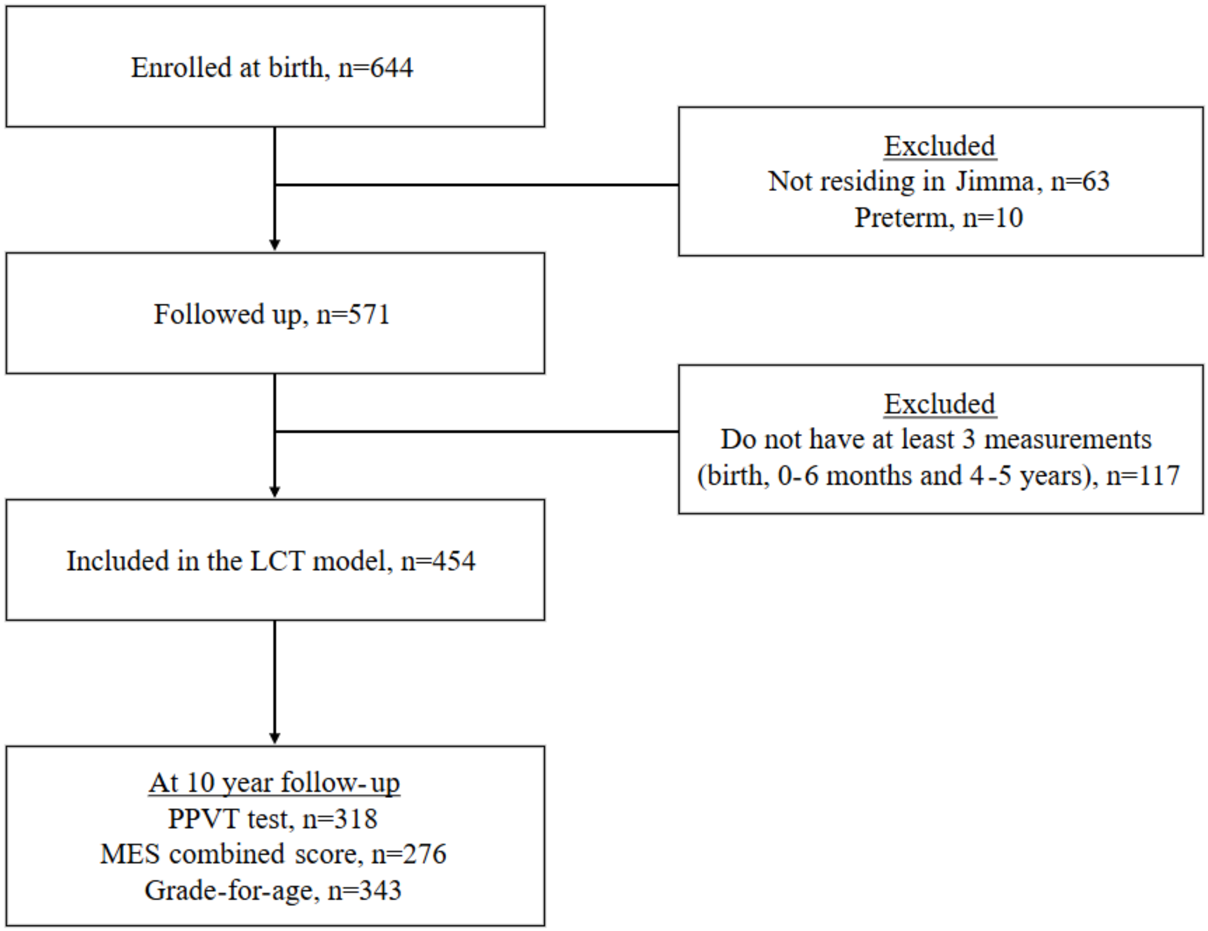

Figure 1: Flow diagram of the study participants. LCT (latent class trajectory), PPVT (Peabody Picture Vocabulary Test), MES (Mathematics, English and Science) combined score.

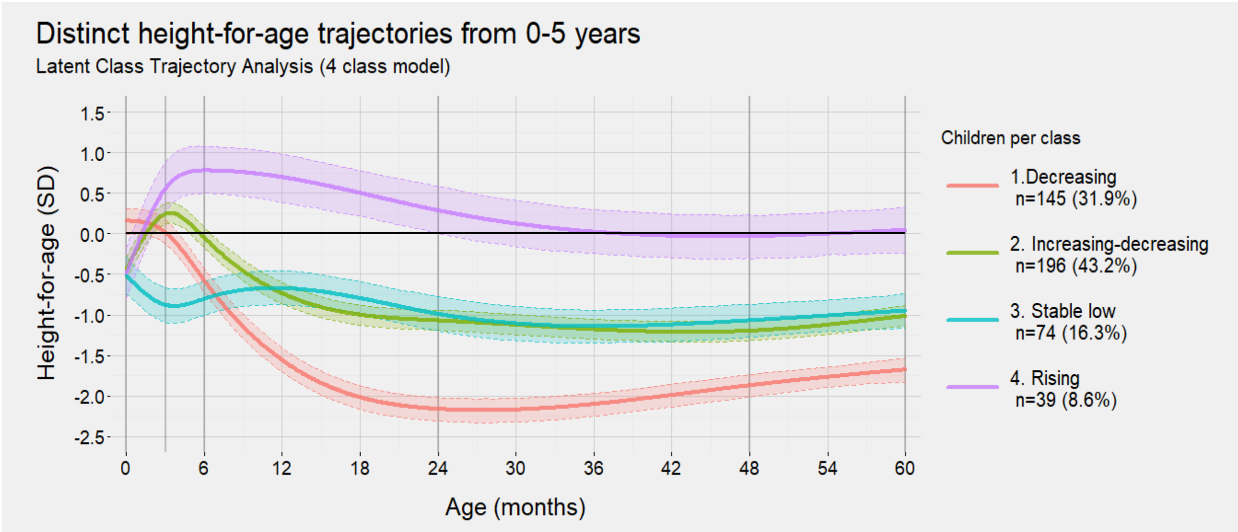

Figure 2: Height-for-age z-scores (HAZ) trajectories from 0-5 years among children in the Infant Anthropometry and Body Composition birth cohort study. These four distinct trajectories were identified using latent class trajectory modelling. Solid lines represent the average HAZ as a function of age for each trajectory, and the color shaded areas with dashed lines illustrate the estimated 95% confidence intervals. The black horizontal zero-line indicates the median value of the WHO child growth standards.

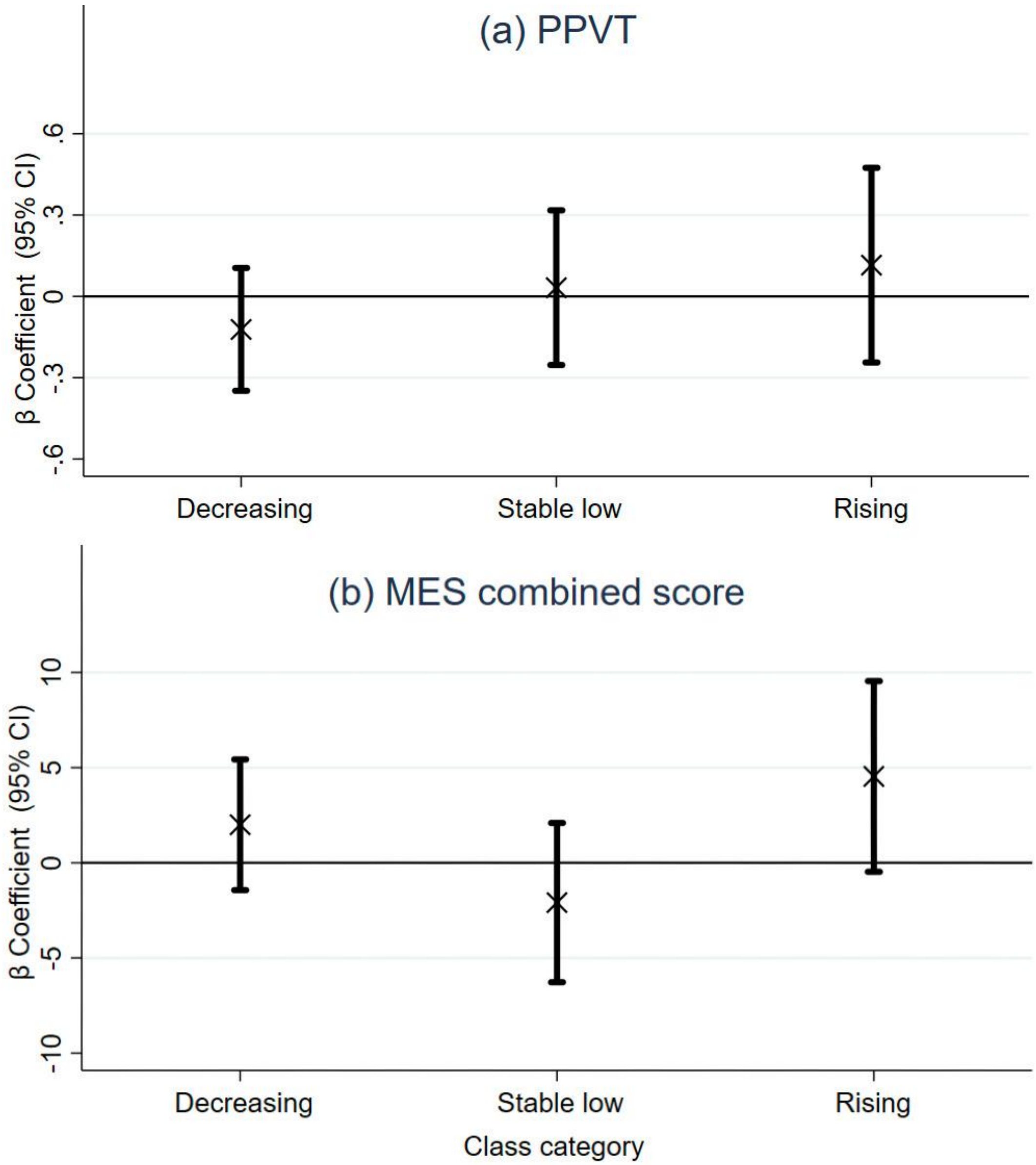

Figure 3: Association of height-for-age z-score trajectories from 0-5 years with (a) PPVT (b) MES combined score at 10 years. β coefficients (95% CIs) displayed in the figure were derived from the final adjusted model. The final model for PPVT score included HAZ trajectories, PPVT score, sex, current age, place of test, head circumference at birth, birth order, gestational age, maternal education, maternal age at child birth and wealth index. The final model for MES combined score included HAZ trajectories, MES combine score, sex, current age, head circumference at birth, birth order, gestational age, maternal education, maternal age at child birth, wealth index and child's school type. Reference group = increasing-decreasing trajectory