Journal of Developmental Origins of Health and Disease

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Original Article

Cite this article: Wake SK, Zewotir T, and Muluneh EK. (2023) Latent growth analysis of children's height growth trajectories. *Journal of Developmental Origins of Health and Disease* **14**: 294–301. doi: 10.1017/S2040174422000617

Received: 2 May 2022
Revised: 15 October 2022
Accepted: 18 October 2022
First published online: 30 November 2022

Keywords:
Child growth; fractional polynomial; latent trajectory; structural equation modeling

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Latent growth analysis of children's height growth trajectories

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Abstract

Characterizing and quantifying the trajectories of variables of interest through time in their field of study is of interest to a range of disciplines. The aim of this study was to investigate the growth speed in height of children and its determinants. A total of 3401 males and 3200 females from four low- and middle-income countries with measured height on five occasions from 2002 to 2016 were included in the study. Data were analyzed using a latent growth model. The results of the study reported that children in four low- and middle-income countries exhibited substantial growth inequalities. There was a significant gender difference in change of growth with males had a higher baseline, rate of change, and acceleration in height growth than females. Comparing the component of slopes across countries, the growth change inequalities were observed among children. These inequalities were statistically significant, with the highest rate of change observed in Peru and Vietnam.

Introduction

Children growth and growth rate are the characteristics of physical, psychological, biological, and sociological natural events.[1] Growth changes are essential for keeping track of a child's health. Assessment of the anthropometric measurement of children is one of the best indications of children's overall well-being and health. Abnormal growth could suggest the presence of an underlying health problem.[2] According to several previous studies, children who have normal trajectories have better health outcomes than those who have abnormal trajectories of growth.[1,2] Height growth is a relevant biological indicator of living standard that reflects both existing and prospective health disparities in populations.[3] As a result, comparing changes in height over time between countries may reveal important information about differences in childhood living situations.[4]

Human physical height is a common anthropometric quantitative characteristic that has been the subject of comprehensive study in several fields of science.[5] Pediatricians, for instance, study the anthropometric trajectories in children to understand the growth rate, periods of deceleration and acceleration, and determinants of growth changes.[6] Hence, human physical growth can be used as an indicator of early life experiences and can provide information about the standard of living in a country.[7] While height is primarily determined by genetics, it is also influenced by the environment in which children grow up.[8] As a result, research into differences in height growth over time and across countries can aid in identifying differences in childhood standards of living. Several studies examined differences in children's height growth as a function of socioeconomic status.[9–12]

Numerous factors influence body height, including nutrition, and genetic and environmental factors during fetal life, childhood, and adolescence.[13–16] Furthermore, it is widely accepted that height growth differs between genders.[17,18] Male and female height gains differed significantly in childhood[18] and pubertal growth spurt.[19,20] Age at height take-off and at peak height velocity is later in males than in females.21 Apart from birth cohort disparities, socioeconomic inequalities in body height are significant; those in better socioeconomic positions tend to be taller than those in lower socioeconomic positions.[13,22,23] According to Marmot,[24] the average male and female body height at the lowest position was around 5 cm lower than in the highest position.

Furthermore, investigations of differences in height growth between countries and between subgroups within one country may aid in finding differences in childhood living conditions.[8] De Groot et al.[25] studied the heights of individuals born between 1913 and 1918 in 19 places across Europe and reported that the tallest people were from northern Europe. And also the previous study conducted in four low- and middle-income countries reported that there were considerable disparities in growth changes among children.[26]

The growth trajectory in height offer information on the growth change process. However, the change process of physical growth is not observed directly, rather it is observed indirectly through repeated measures.[6] In such cases, the mixed-effects model is not flexible enough to model a growth process. As a result, advanced statistical models capable of accounting for latent variables in latent growth are required. Hence, a latent growth model is a common approach for analyzing latent variables within the framework of structural equation modeling.[27] The aim of this study was to investigate the growth speed in height of children and its determinants.

Method

Data source

The longitudinal height data were obtained from the Young Lives prospective cohort study carried out in Ethiopia, India, Peru, and Vietnam from 2002 to 2016. The Young Lives study is a 15 years longitudinal cohort study that looked at how childhood poverty changed over time in Ethiopia, India, Peru, and Vietnam. It employed multistage sampling techniques with the first stage involving a selection of sentinel locations from each country. Sentinel site monitoring is a public health concept that entails a purposive sampling of a small number of settings that are thought to reflect a specific population or area, and then being studied uniformly at relatively wide ranges. Following that, 20 sentinel sites were selected at nonrandom in each country. Following the selection of 20 sentinel sites, households with children in the appropriate age groups were chosen at random. Then, 2000 infants (ages 6 to 18 months) were selected at random and they considered as a younger cohort.[28] Details regarding sampling and participant recruitment in the Young Lives study have been discussed in previously published works.[18,26,28–35]

The Young Lives prospective cohort study gathered data in five rounds. The first survey round was carried out in 2002 when the children were on average one year of age, the second survey was carried out in 2006, the third was in 2009, the fourth was in 2013, and the fifth was carried out in 2016.[36] Data were collected from children (8 years and older) and their primary caregivers in each round using interviewer-administered questionnaires. A child's height, on the other hand, was measured in centimeters from the age of 1 to 15 years.[35] A total of 3401 males and 3200 females with measured height five times from ages 1 to 15 years were included in this study. Data were analyzed using SAS version 9.4.

Statistical analysis

Latent growth curve model

A latent growth curve is a special case of longitudinal structural equation model that examines growth change in longitudinal data. It includes two types of variables: latent and observed variables. Observed variables are measured variables, but latent variables are not measured directly and are used to predict observed variables.[6] The random intercept and slope(s) in a latent model permit, respectively, individuals to have unique initial growth and unique growth of change over time. The growth process is latent in which it is not observed directly, but its existence will infer from the observed repeated measures.[37]

A latent growth curve model under different functional forms is modeled in different expressions. For instance, equations (1) and (2) represents the standard polynomial and fractional polynomial models, respectively.

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ij} \Lambda^{p}{}_{t} + \varepsilon_{it} \tag{1}$$

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ij} \Lambda^{m}{}_{t} + \varepsilon_{it} \tag{2}$$

The growth intercept α_i represents the individual expected value of height (y_{it}) at baseline (when t equals 0), the path coefficients β_{ij} represent the rate of change and the speed of change in growth for i-th individual, Λ_t represents the factor loading that determines the functional form of the growth trajectories, and ϵ_{it} is the disturbance for i-th individual at time t. The individual trajectories are expressed in terms of mean trajectory and variance around the mean trajectory that provide insight into between-individual variations. By allowing between-individual variation at intercept and slopes, the latent factors can be expressed in terms of average and variance as:

$$\begin{pmatrix} \alpha_i \\ \beta_{1i} \\ \beta_{2i} \\ \vdots \\ \beta_{pi} \end{pmatrix} = \begin{pmatrix} \mu_\alpha \\ \mu_{\beta 1} \\ \mu_{\beta 2} \\ \vdots \\ \mu_{\beta p} \end{pmatrix} + \begin{pmatrix} e_\alpha \\ e_{\beta 1} \\ e_{\beta 2} \\ \vdots \\ e_{\beta p} \end{pmatrix} \tag{3}$$

where μ_α and $\mu_{\beta p}$ are the population mean intercept and slope, respectively, and e_α and $e_{\beta p}$ are, respectively, the intercept and slope disturbances represent the extent to which the individual intercept and slope values deviate from the mean intercept and slope. The disturbances of e_α and $e_{\beta p}$ are distributed with means of zero and variances of $\psi_{\alpha\alpha}$ and $\psi_{\beta p \beta p}$ and covariance of $\psi_{\alpha\beta p}$.

Conventional polynomial functions are restricted in modeling nonlinear changes.[38] Alternatively, a fractional polynomial which is an extension of conventional polynomials provides a variety of curve shapes for exploring characteristics of nonlinear trajectories. In this model, the m power terms in equation(2) can be chosen from $m = (-2, -1, -0.5, 0, 0.5, 1, 2, 3)$, a combination function with the lowest deviance will be the best fit function.[38]

A path diagram presented in Fig. 1 permits a latent growth model to be expressed graphically. In this diagram, the rectangle symbols denote the observed variables and the circle symbols denote latent variables. The observed variables are the individual measures of child height and α, β_1, and β_2 are the latent variables. Each line in the path diagram stands for the trajectory of the individual from which the latent variables are estimated. Paths with single-headed arrows at the end connect unobserved and observed variables. The causal relationship and the covariance between variables are explained by single- and double-headed arrows, respectively. The variable at the arrow tail is an exogenous variable and the variable at the arrowhead is an endogenous variable. As shown in Fig. 1, there is one latent intercept, α, with one-factor loadings and two latent slopes, β_1 and β_2, with first-order polynomial (FP1) and second-order polynomial (FP2) factor loadings, respectively. The factor loadings on the latent slopes are used to determine whether the trajectory is linear or nonlinear. The coding and location of the baseline of time scores have a significant impact on the estimation and interpretation of the growth parameter.[39,40]

Different fit indexes were assessed to evaluate the models' goodness of fit. These include the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean square (SRMS). The higher values closed to 1 for CFI and TLI reflecting a better fit, while the lower values closed to zero for RMSEA and SRMS reflecting a better fit.[37,41]

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Table 1. Distribution characteristics and mean height of children in four study countries from 2002 to 2016

	Ethiopia		India		Peru		Vietnam	
	Male	Female	Male	Female	Male	Female	Male	Female
	n (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)	*n* (%)
	818 (51.7)	764 (48.3)	877 (53.2)	771 (46.8)	819 (50.3)	808 (49.7)	887 (50.9)	857 (49.1)
Year	Mean height (SD)	Mean height (SD)	Mean height (SD)	Mean height (SD)	Mean height (SD)	Mean height (SD)	Mean height (SD)	Mean height (SD)
2002	72.03 (5.19)	70.67 (5.40)	72.86 (4.75)	71.36 (4.74)	72.57 (4.34)	71.36 (4.74)	73.31 (4.17)	71.49 (4.02)
2006	104.96 (4.86)	103.94 (5.27)	104.86 (4.46)	104.41 (4.64)	105.53 (5.76)	104.26 (5.82)	105.91 (5.12)	104.71 (4.55)
2009	121.75 (5.55)	120.92 (5.92)	119.77 (5.29)	119.17 (5.69)	121.19 (5.49)	120.37 (5.59)	121.87 (5.88)	121.20 (5.56)
2013	141.02 (5.91)	142.61 (7.13)	140.17 (6.55)	142.36 (6.8)	142.71 (7.29)	144.61 (6.65)	144.04 (8.16)	145.69 (7.24)
2016	157.44 (7.99)	156.22 (5.98)	158.94 (7.56)	152.52 (5.35)	161.65 (6.48)	153.47 (4.96)	162.98 (6.47)	155.16 (5.31)

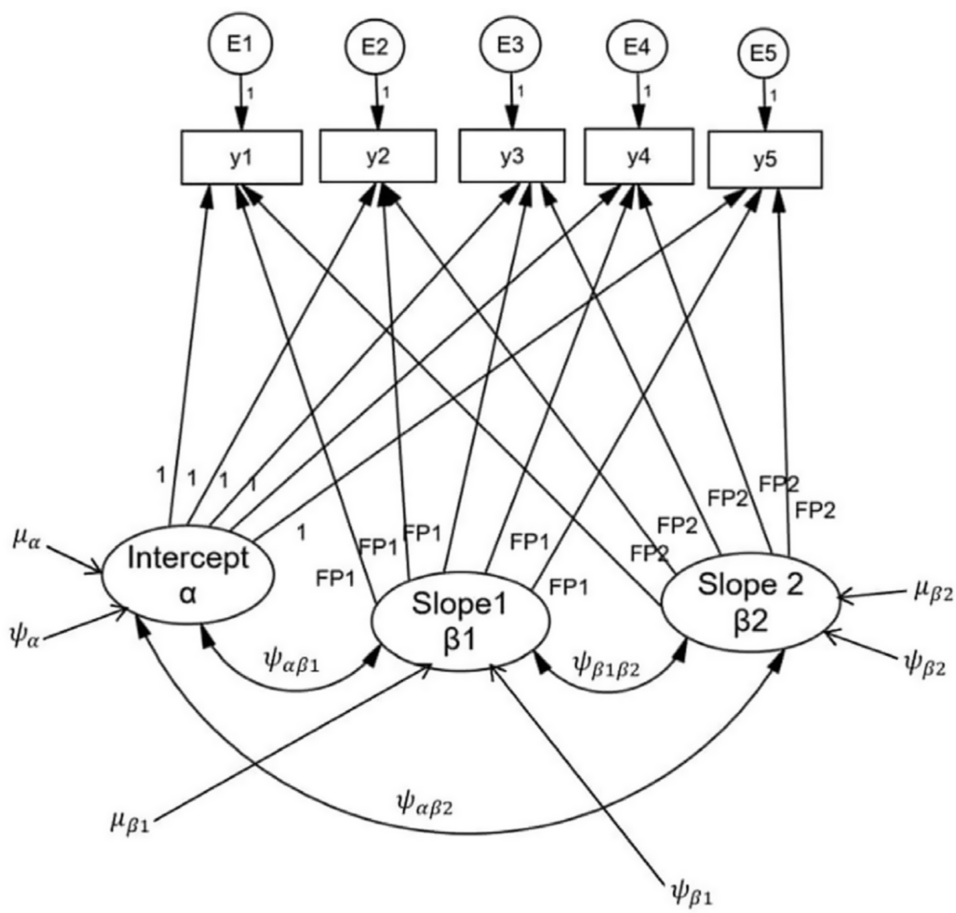

Fig. 1. Path diagram of a five-wave polynomial latent growth curve model.

Results

Sample description

The study considered a total of 6601 children: 3401 (51.5%) males and 3200 (48.5%) females. The distribution characteristics and mean height of children in four study countries are displayed in Table 1. The average height increased and varied with age in both genders. This indicates that a linear model may not be applicable to model the growth trajectories. Thus, we compared different latent growth models to identify the model that best represents the growth trajectory. The results are presented in Tables 2 and 3.

Results of linear latent growth model

To investigate variations in height growth at each measurement occasion, linear latent growth models with different origins of time were performed. For instance, to estimate mean height at age 1, we set the origin of time at age 1 by coding time = (age–1). Following that, we are also interested in examining growth variability at each

Table 2. The fit statistics of quadratic models under different time coding schemes for height growth

Index of fit	Model				
	Λ_1	Λ_5	Λ_8	Λ_{12}	Λ_{15}
TLI	0.522	0.522	0.522	0.522	0.522
CFI	0.713	0.713	0.713	0.713	0.713
RMSEA	0.36	0.36	0.36	0.36	0.36
AIC	5166.37	5166.37	5166.37	5166.37	5166.37

measurement occasion by placing the origin of time scores at ages 5, 8, 12, and 15 by coding time = (age–5), time = (age–8), time = (age–12), and time = (age–15), respectively. These would provide the following loading matrices, Λ :

$$\Lambda_1 = \begin{bmatrix} 1 & 0 \\ 1 & 4 \\ 1 & 7 \\ 1 & 11 \\ 1 & 14 \end{bmatrix}, \Lambda_5 = \begin{bmatrix} 1 & -4 \\ 1 & 0 \\ 1 & 3 \\ 1 & 7 \\ 1 & 10 \end{bmatrix} \Lambda_8 = \begin{bmatrix} 1 & -7 \\ 1 & -3 \\ 1 & 0 \\ 1 & 4 \\ 1 & 7 \end{bmatrix},$$

$$\Lambda_{12} = \begin{bmatrix} 1 & -11 \\ 1 & -7 \\ 1 & -4 \\ 1 & 0 \\ 1 & 3 \end{bmatrix}, \Lambda_{15} = \begin{bmatrix} 1 & -14 \\ 1 & -10 \\ 1 & -7 \\ 1 & -3 \\ 1 & 0 \end{bmatrix}$$

The first and the second column of the Λ matrices represent the intercept and the linear components, respectively. The fit statistics of this model showed that linear models are inconsistent with the height data, provided TLI = 0.141, CFI = 0.141, RMSEA = 0.482, and AIC = 15392.023. As shown in Fig. 2, the trajectory is not linear. Additionally, Fig. 3 exhibited that there appears to be a variation in growth trajectories of height between males and females. Under such conditions, nonlinear growth models are appropriate to analyze the trajectories.

Results of quadratic latent growth model

Nonlinear latent growth models permit for the flexibility of time scores being related with the slope of linear latent factor. Accordingly, for a quadratic model, equation(1) can be written as:

$$y_{it} = \alpha_i + \beta_{1i}\Lambda_t + \beta_{2i}\Lambda^2{}_t + \varepsilon_{it} \tag{4}$$

The latent intercept and linear components are a child's height and the instantaneous rate of growth when time equals 0, respectively. Likewise, the quadratic component represents acceleration in height growth. To estimate the growth parameters that define means and variability in height growth at each measurement occasion, we originate the time scores at ages 1, 5, 8, 12, and 15 years as previous. Consequently, the quadratic latent models' loading matrices Λ are as follows:

$$\Lambda_1 = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 4 & 16 \\ 1 & 7 & 49 \\ 1 & 11 & 121 \\ 1 & 14 & 196 \end{bmatrix}, \Lambda_5 = \begin{bmatrix} 1 & -4 & 16 \\ 1 & 0 & 0 \\ 1 & 3 & 9 \\ 1 & 7 & 49 \\ 1 & 10 & 100 \end{bmatrix},$$

$$\Lambda_8 = \begin{bmatrix} 1 & -7 & 49 \\ 1 & -3 & 9 \\ 1 & 0 & 0 \\ 1 & 4 & 16 \\ 1 & 7 & 49 \end{bmatrix}, \Lambda_{12} = \begin{bmatrix} 1 & -11 & 121 \\ 1 & -7 & 49 \\ 1 & -4 & 16 \\ 1 & 0 & 0 \\ 1 & 3 & 9 \end{bmatrix},$$

$$\Lambda_{15} = \begin{bmatrix} 1 & -14 & 196 \\ 1 & -10 & 100 \\ 1 & -7 & 49 \\ 1 & -3 & 9 \\ 1 & 0 & 0 \end{bmatrix}$$

The fits statistics for these quadratic latent models are presented in Table 2. These models improved the fit statistics over the linear one, provided TLI = 0.522, CFI = 0.713, RMSEA = 0.360, and AIC = 5166.37. However, these models are also inconsistent with the height data. Subsequently, we should extend conventional polynomials to fractional polynomials using Equation (2).

Results of fractional polynomial latent growth model

Wake and colleagues[31] identified that the growth trajectory of children from aged 1 to 15 years was nonlinear. Thus, for the current study, we used nonlinear transformation of the loading matrix to extend conventional polynomial function to fractional polynomial functions, which are more flexible and useful in modeling nonlinear trajectories.[42] A fractional polynomial was formulated by introducing single and combinations of various forms of time scores function to models. Accordingly, a second-order fractional polynomial function with $p = -1$ and $q = 1$ power terms was found to be the best-fitting model.

The time coding was chosen as $\Lambda_t = 1, 5, 8, 12, 15$ with its linear inverse transformation, $\Lambda^{-1}{}_t = 1, 0.2, 0.125, 0.083, 0.067$. The reason why the first time coding begins with 1 is that the linear inverse of 0 is undefined. Thus, by scaling $(\Lambda_t - 1)$ and $(\Lambda^{-1}{}_t - 1)$, we placed the origin of time at age 1, estimating a child's mean height at age 1. Similarly, to demonstrate the growth variability at ages 5, 8, 12, and 15, models with varying centering points were fitted to the data. As shown in Table 3, these models substantially improved the fit statistics over the linear and quadratic models (TLI = 0.942, CFI = 0.977, RMSEA = 0.125, AIC = 451.064). Therefore, fractional polynomial models were chosen as the best-fitting models to analyze nonlinear trajectories in height growth.

Fractional polynomial latent growth models with time-invariant covariates

Gender and country effects on children's physical growth were assessed. The inclusion of these covariates improved the models' fit. For the sake of simplicity only Λ_1 model was considered in this analysis. As given in Table 4, the estimated mean intercept of 72.14 reflects the mean height of children at the initial measurement. The estimated values for the linear and its reciprocal were 5.19 and −15.07, respectively. The growth speed is the first derivative of

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Table 3. Estimates of an unconditional fractional polynomial model under different time coding schemes for height growth

	Model									
	Λ_1		Λ_5		Λ_8		Λ_{12}		Λ_{15}	
Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean										
Intercept	71.956	0.058***	104.647	0.061***	121.13	0.063***	142.214	0.072***	157.803	0.085***
Linear	5.112	0.007***	5.112	0.007***	5.112	0.007***	5.112	0.007***	5.112	0.007***
Linear inverse	−15.306	0.087***	−15.306	0.087***	−15.306	0.087***	−15.306	0.087***	−15.306	0.087***
Variance										
Intercept	14.575	4.364***	20.706	0.463***	23.859	0.467***	27.922	0.62***	31.211	0.904***
Linear	0.021	0.011**	0.021	0.011**	0.021	0.011**	0.21	0.011**	0.021	0.011**
Linear inverse	9.868	7.53**	9.868	7.53**	9.868	7.53**	9.868	7.53**	9.868	7.53**
Covariance										
Intercept-Linear	0.03	0.086**	0.283	0.05***	0.363	0.042***	0.457	0.057***	0.524	0.082***
Intercept-Linear inverse	1.318	5.763**	−7.416	0.604***	−8.787	0.519***	−10.038	0.579***	−10.832	0.772***
Linear-Linear inverse	−0.21	0.14**	−0.21	0.14**	−0.21	0.14**	−0.21	0.14**	−0.21	0.14**
Index of fit										
TLI	0.942		0.942		0.942		0.942		0.942	
CFI	0.977		0.977		0.977		0.977		0.977	
RMSEA	0.125		0.125		0.125		0.125		0.125	
AIC	451.064		451.064		451.064		451.064		451.064	

***$p < 0.0001$, **$p > 0.05$.

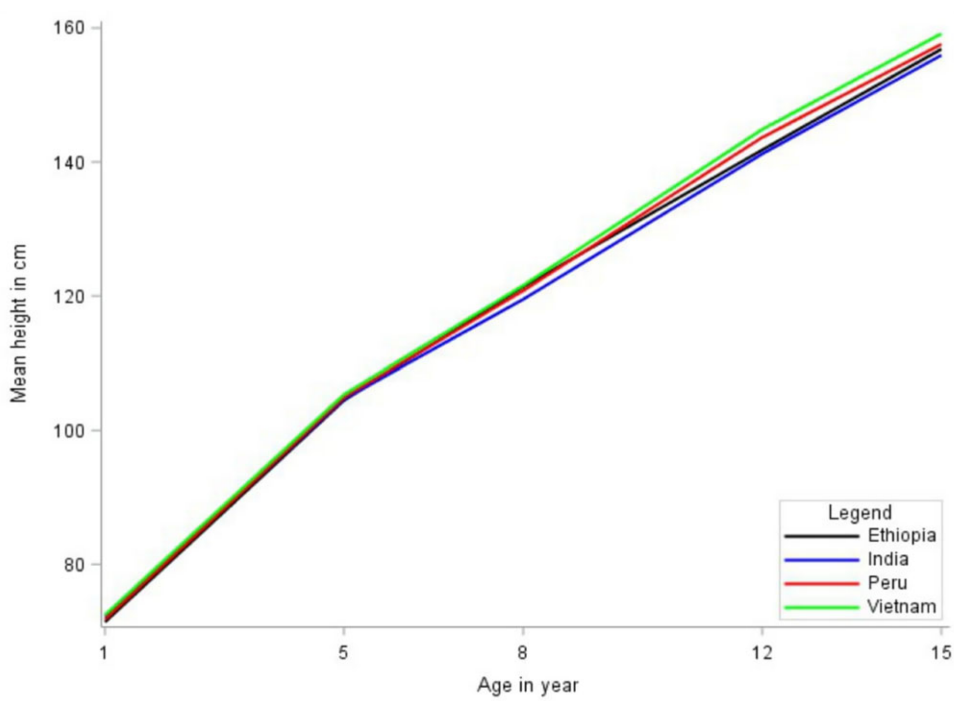

Fig. 2. Path diagram of a five-wave linear growth curve model.

the latent growth curve equation. The latent growth curve equation is therefore expressed as $72.14 + 5.19\text{time} - 15.07\text{time}^{-1}$. The linear coefficient ($5.19, p < 0.001$) represents the instantaneous rate of change when time is zero. The significant and negative value of time inverse coefficient (-15.07, $p < 0.001$) suggests that the growth speed of children decreased with age.

There was a significant negative gender difference in height growth at all components of latent factors. This implies that

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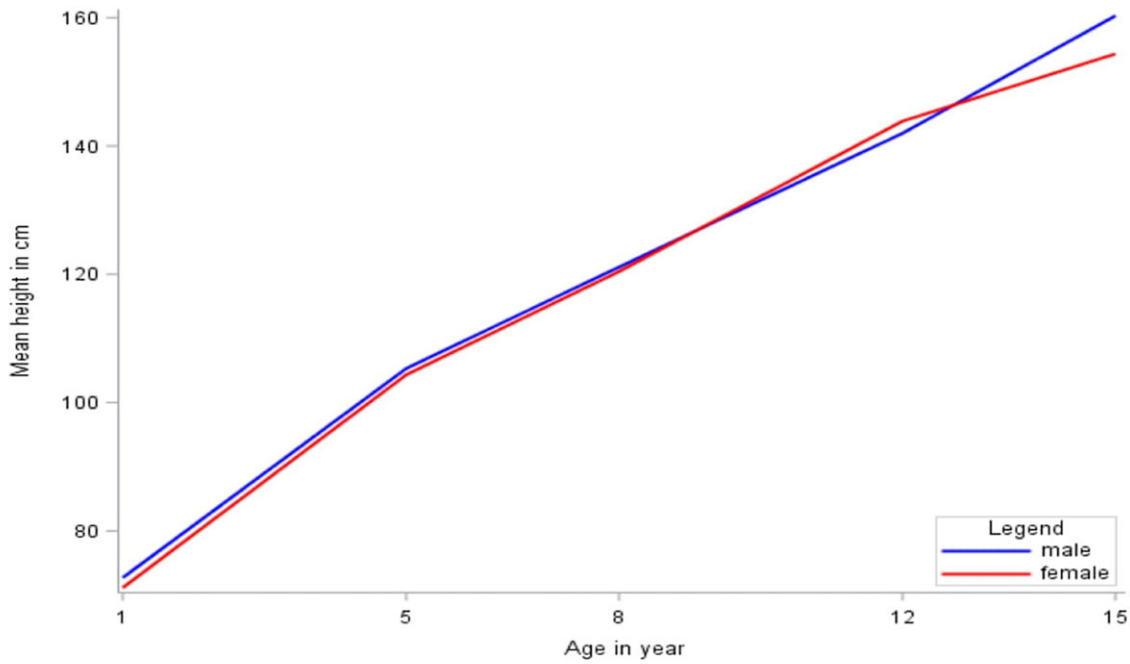

Fig. 3. Growth trajectory differences in four countries.

females had lower mean intercept, linear slope, and linear inverse slope ($\alpha = -1.65, \beta_1 = -0.37, \beta_2 = -3.06$) than males. When compared to Ethiopian children, children in India ($\alpha = 0.836$, $p < 0.001$), Peru ($\alpha = 0.478, p = 0.004$), and Vietnam ($\alpha = 1.102$, $p < 0.001$) had positive and significant baseline measurements. Likewise, the linear slope for children in Peru ($\beta_1 = 0.110$, $p < 0.001$) and Vietnam ($\beta_1 = 0.231, p < 0.001$) were significantly positive, indicate that children in these two countries had a higher instantaneous rate of change than that of children in Ethiopia. However, a negative and significant linear slope was observed for children in India ($\beta_1 = -0.067$, $p = 0.001$). This implies that Indian children had a lower instantaneous rate of change than Ethiopian children. The growth acceleration for children in India ($\beta_2 = 1.189$, $p < 0.001$), Peru ($\beta_2 = 1.088$, $p < 0.001$), and Vietnam ($\beta_2 = 1.945, p < 0.001$) was significantly positive. This suggests that children in India, Peru, and Vietnam grew at lower decrement with age when compared to children in Ethiopia.

The variance-covariance of the model components examined the variation in growth between individuals. The significant variances indicate that individuals begin their growth progression at distinct values and growing at different rates. The significant negative covariance of $\psi_{\alpha\beta 1}$ indicates that children who were taller at baseline tended to grow at a lower rate. The significant positive covariance of $\psi_{\beta 1\beta 2}$ suggests that children who had a higher rate of growth tended to be growing at a faster acceleration.

Discussion

The growth trajectories of children aged 1 to 15 years were studied using linear and nonlinear latent growth models. The study revealed that the functional relationship between physical height growth and a child's age is nonlinear. Similar data were examined using a latent basis model, and it was shown that the functional changes in children's height are not linear.[31] As a result, a nonlinear latent growth model was chosen to depict the growth trajectories. Thereafter, among the families of nonlinear polynomial functions, the quadratic and fractional polynomials were examined for the trajectories. Lastly, a second-order fractional polynomial was found to be the best-fitting model.

The analysis of the data and application of the model indicates that gender was significantly associated with the growth parameters. In contrast to our study, Faye et al.[43] found gender differences in linear growth, with females growing at a higher rate than males.[43] The study also identified that the growth acceleration of children in four low- and middle-income counties decreased with age. This is consistent with the previous study of Haymond et al.[2] noted that the maximum rate of growth occurs at birth and gradually slows until the pubertal growth spurt.[2] Regarding the country's effect on child growth, there were significant differences in growth change and individuals showed substantial variation in their particular latent components. In addition, the findings of the study show that inequalities of height growth were observed in all four countries, with high values for children in Peru and Vietnam. This could be due to socioeconomic differences among countries. Children of higher socioeconomic status were taller than those of lower socioeconomic status.[9,44] The well-living condition may lead to improvements in childhood health, social conditions, and a reduction in negative environmental effects.[10,23]

Furthermore, it was found out that all the path coefficients of latent components were positive and significant except for children in India was negative and significant at linear component. This indicates that children in India showed a lower change in growth compared to children in Ethiopia. The intercept and linear component of the model had variability between children, while the linear inverse component had no variability between children, suggesting that the curvature of the linear inverse was identical for all children. This finding is consistent with the findings of a previous study comparing height across geographic regions, which found that environmental effect was highest during the first years of life and decreased throughout childhood and adolescence.[5] Socioeconomic variations in height growth were present at birth and widened through infancy and early childhood.[12]

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Table 4. Parameter estimates of latent growth curve model with time-invariant covariates

	Estimate	SE	CR	*P*-value
Latent factor				
α	72.143	0.129	558.264	<0.001
β_1	5.193	0.017	312.282	<0.001
β_2	−15.072	0.196	−76.980	<0.001
Time-invariant covariate				
α <— Gender (Female)	−1.646	0.117	−14.027	<0.001
Country <— Ethiopia (Reference)				
α <— India	0.836	0.166	5.048	<0.001
α <— Peru	0.478	0.165	2.897	0.004
α <— Vietnam	1.102	0.162	6.794	<0.001
β_1 <— Gender	−0.367	0.017	−21.638	<0.001
β_1 <— India	−0.067	0.021	−3.252	0.001
β_1 <— Peru	0.110	0.021	5.292	<0.001
β_1 <— Vietnam	0.231	0.020	11.373	<0.001
β_2 <— Gender	−3.061	0.183	−16.770	<0.001
β_2 <— India	1.189	0.250	4.760	<0.001
β_2 <— Peru	1.088	0.249	4.370	<0.001
β_2 <— Vietnam	1.945	0.245	7.945	<0.001
Variance-covariance				
$\psi_{\alpha\alpha}$	9.194	4.396	2.092	0.036
$\psi_{\beta1\beta1}$	0.108	0.010	11.106	<0.001
$\psi_{\beta2\beta2}$	7.986	7.394	1.080	0.280
$\psi_{\alpha\beta1}$	−0.232	0.086	−2.703	0.007
$\psi_{\alpha\beta2}$	−6.240	5.792	−1.077	0.281
$\psi_{\beta1\beta2}$	0.471	0.116	4.058	<0.001

Note: β_1 is the coefficient of linear time and β_2 is the coefficient of time inverse.

The key strength of this study is the long-term follow-up of children's height measures that give insight into the longitudinal variations in height trends in four low and middle-income countries. The study has also its own limitations. It was restricted to four low- and middle-income countries, which may not be representative of all low- and middle-income countries. Furthermore, potential factors which can influence the height growth are not considered in this study. As a result, further study is needed to address these limitations.

Conclusion

Understanding and enhancing the health of children require not only their perspective but also understanding the ecological nature of their health and the interdependence of the biological, physical, and socioeconomic background is also important. Therefore, studying the growth of children plays a significant role in determining and eventually improving their health status. The results of this study may help to inform better policy for children to ensure that every child has the best possible start in life and that those who are at risk of being left behind have access to interventions and support to maximize their opportunities and well-being.

A clear understanding of these country growth variations is important for finding key possibilities to promote healthy growth in early life of children. We believe that our findings point to an underlying relationship between children's physical growth and their biological and socioeconomic backgrounds. In addition, further study is needed to identify age-specific growth variations and the direct and indirect effects of potential covariates on children's growth trajectories.

Acknowledgments. We thank the Young Lives study for giving us access to the data files.

Financial support. This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

Conflicts of interest. None.

Ethical standards. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national guidelines on human experimentation (national and institutional guidelines: Ethical Conduct for Research Involving Humans) and with the Helsinki Declaration of 1975, as revised in 2008. This study was based on publicly available, anonymized data and therefore did not require approval by an institutional committee.

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