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Original Article

Analyzing children's weight growth trajectories and associated factors using latent growth curve model across Ethiopia, India, Peru, and Vietnam: A longitudinal study

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Abstract

Background: *Analyzing children's weight growth trajectories is essential for identifying health risks in low- and middle-income countries This study aimed to analyze non-linear weight growth trajectories in children aged 1–15 years across Ethiopia, India, Peru, and Vietnam, using longitudinal data from the Young Lives Study (2002–2016). The study also evaluated the impact of socio-demographic factors on children's growth patterns.*

Methods: *Longitudinal data were used from the Young Lives Study, which tracked 7,140 children across five time points. Data on weight, socio-economic status, gender, and residence were collected. The analysis employed Latent Growth Curve Modelling using R software to capture non-linear weight trajectories and evaluate the impact of socio-demographic factors such as gender, residence, and country on growth patterns.*

Results: *The Latent Growth Curve model revealed significant effects of latent variables on children's weight growth trajectories, including baseline weight (9.726, $P < 0.001$), growth acceleration (0.172, $P < 0.001$), and deceleration (-4.507, $P < 0.001$). Peruvian children exhibited the highest baseline weight (1.012, $P < 0.001$) and steepest growth acceleration (0.034, $P < 0.001$), followed by Vietnamese children with higher baseline weights (0.590, $P < 0.001$) and faster growth (0.024, $P < 0.001$). Ethiopian children showed slower growth (-0.012, $P < 0.001$). Female children had lower baseline weights (-0.519, $P < 0.001$), and rural children exhibited lower baseline weights (-0.635, $P < 0.001$) along with slower growth rates (-0.023, $P < 0.001$).*

Conclusion*: Latent Growth Curve Modelling effectively captured non-linear weight trajectories and revealed significant socio-demographic disparities. These findings highlight the importance of*

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addressing nutritional challenges, gender inequities, and rural-urban gaps in low- and middle-income countries to improve child health outcomes.

Keywords: *Children's Weight Trajectories, Latent Growth Curve Modelling, Cross-Country Study*

Introduction

Analyzing children's weight growth trajectories is crucial for assessing health and development, particularly in low- and middle-income countries (LMICs). These trajectories reflect the impact of nutritional and environmental factors and are essential for identifying risks such as undernutrition, stunting, or obesity, which have significant long-term health implications (1, 2). In LMICs, disparities in income, rural-urban divides, and limited access to healthcare contribute to variations in growth patterns, making it important to examine these trajectories across diverse socio-economic contexts (3, 4). Understanding these differences helps in identifying vulnerable populations and informing public health interventions aimed at improving child growth outcomes.

Many studies have traditionally used simple models, such as growth percentiles or cross-sectional data, which fail to capture the dynamic, longitudinal nature of children's growth patterns. Recent advances in statistical modelling, particularly Latent Growth Curve Modelling (LGCM), offer a more sophisticated approach to studying the trajectories of weight growth over time. LGCM allows researchers to analyze changes over time and account for latent variables, providing a deeper understanding of the underlying dynamics of growth (5-7). By incorporating these advanced methods, it becomes possible to better understand how children's weight growth evolves in response to socio-demographic and environmental factors.

This study utilized LGCM to analyze the weight growth trajectories of children aged 1 to 15 years across Ethiopia, India, Peru, and Vietnam, using longitudinal data collected over 15 years. Specifically, the study focused on three objectives: (1) analyzing non-linear weight growth trajectories using the LGCM approach, (2) examining the role of socio-demographic factors such as country, gender, and residence in influencing these trajectories, and (3) identifying latent variables, such as baseline weight and growth rates, to understand how patterns differ across socio-economic contexts (7, 8). By addressing these objectives, this research offers critical insights into the timing and nature of transitions in children's weight growth, providing valuable evidence to guide public health policies aimed at reducing malnutrition and promoting equitable growth in LMICs (9, 10).

Methods

Study design and data source

This study utilized longitudinal data from the Young Lives Study, conducted between 2002 and 2016 across four LMICs: Ethiopia, India, Peru, and Vietnam. The dataset includes comprehensive socio-economic, demographic, and anthropometric measures collected at five time points, corresponding to children's average ages of 1, 5, 8, 12, and 15 years. A total of 7,140 children met the inclusion criteria of being aged 6–18 months at baseline and having complete weight measurements across all five survey rounds. And, children with incomplete weight measurements across all five rounds were excluded. Key measurements included children's weight at each time point, with socio-demographic factors such as country (Ethiopia, India, Peru, Vietnam), gender (male or female), and residence (urban or rural) integrated as covariates. These data provided a unique opportunity to analyze non-linear weight growth trajectories and evaluate factors influencing growth patterns across diverse LMIC settings (11-13).

Study outcomes and criteria

The primary outcome of this study was to analyze children's non-linear weight growth trajectories using LGCM, focusing on baseline weight, growth rate, and deceleration. The secondary outcome aimed to assess the influence of socio-demographic factors, including country, gender, and residence, on these growth trajectories. Inclusion criteria required children aged 6–18 months at baseline with complete weight measurements across all five rounds of data collection (2002–2016). Children outside this age range or with missing weight measurements in any round were excluded from the analysis.

Statistical analysis

LGCM was employed to analyze longitudinal weight trajectories, offering a robust framework for capturing individual growth patterns and variability over time. This approach modelled initial weight (intercept) and rate of change (slope) while incorporating socio-demographic covariates such as country, gender, and residence to assess their influence on growth trajectories (14, 15). A fractional polynomial method was applied within LGCM to account for non-linear growth patterns, addressing the complexity of weight changes across diverse socio-economic contexts (16, 17).

The general form of the latent growth curve model is expressed as:

$$y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ji} M_t^p + \varepsilon_{it},$$

$$i = 1, 2, \ldots, n; \; t = 1, 2, \ldots, T$$

Where:

- y_{it}: Observed outcome (weight) for the individual at time .
- α_i : Growth intercept (baseline weight) at age 1 year.
- β_{ji} : Growth rate coefficients for different trajectory components (linear or non-linear).
- M_t^p : Factor loadings defining the functional form of growth trajectory (linear, quadratic, or fractional polynomial).
- ε_{it} : Residual error for the individual at time t.

The parameters were estimated using maximum likelihood methods, with goodness-of-fit indices such as Comparative Fit Index RMSEA (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) guiding model evaluation. The lavaan package in R software ensured accurate handling of longitudinal data, enabling nuanced insights into the dynamic interaction of socio-demographic factors shaping children's weight growth trajectories (18, 19).

Results

Descriptive statistics

The data provided an overview of the distribution of children and observations across socio-demographic groups in the five-round longitudinal study. A total of 7,140 children contributed 35,000 observations. The highest proportions of children and observations were from India (26.1%) and Vietnam (25.9%), followed by Peru (24.7%) and Ethiopia (23.3%). The gender distribution showed a slight male dominance, with males representing 52.2% of the sample. In terms of residence, urban children were more represented (62%) compared to rural children (38%). This well-balanced design ensured broad representation across countries, genders, and residential areas, facilitating a comprehensive analysis of socio-demographic factors influencing children's weight growth trajectories (Table 1).

Table 1: Distribution of children and observations by country, gender, and residence in the Young Lives Study from 2002-2016 GC.

Covariate	Category	Number of Children	Number of Observations	Percentage
Country	India	1,862	9,310	26.1
	Ethiopia	1,665	8,325	23.3
	Peru	1761	8,805	24.7
	Vietnam	1852	9,260	25.9
Child's gender	Male	3,728	18,640	52.2
	Female	3,412	17,060	47.8
Residence	Urban	4,426	22,129	62
	Rural	2,714	13,571	38
Total		7,140	35,700	100

Correlation and covariance of children's weight growth across ages

Table 2 shows the covariance and correlation of children's weight across five ages (1, 5, 8, 12, and 15 years). Weight variability increases with age, peaking at Age 15, while correlations strengthen over time, especially between Ages 12 and 15. Mean weight rises steadily from 8.35 kg at Age 1 to 46.61 kg at Age 15, with the most significant growth occurring between Ages 1 and 5. The data highlights a consistent upward trend in weight and emphasizes the growing associations between weight at different ages, suggesting that early growth has a substantial impact on later weight development.

Table 2: Correlation and covariance matrices for children's weight at ages 1, 5, 8, 12, and 15 years in the Young Lives Study from 2002-2016 GC.

Weight	Age 1	Age 5	Age 8	Age 12	Age 15
Age 1	1.92	2.46	3.62	6.21	7.04
Age 5	0.66	7.29	10.18	17.44	18.48
Age 8	0.60	0.86	19.14	31.96	33.73
Age 12	0.52	0.74	0.84	75.71	73.83
Age 15	0.50	0.68	0.76	0.84	102.56
Mean	8.35	16.27	21.69	34.31	46.61

Exploratory data analysis of weight growth trajectories

Exploratory data analysis reveals a non-linear progression in mean weight gain over time, with increasing variability in individual trajectories, particularly in later years. This variability likely reflects socio-demographic influences, including country, gender, and residence. These findings underscore the importance of using piecewise linear mixed-effects models to analyze stage-specific growth patterns and quantify the impact of socio-demographic factors on weight trajectories (Figure 1).

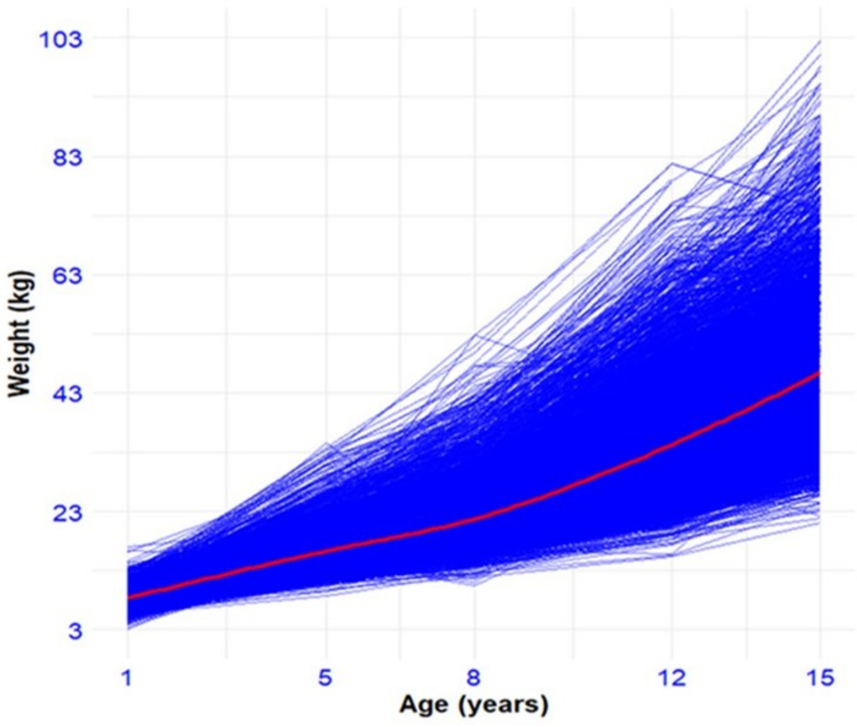

Figure 1: Individual weight trajectories and mean growth trend (ages 1-15

Models' comparison

The fractional polynomial latent growth curve (FPLGC) model with the loading matrix provided the best fit to the data compared to other models with different loading matrices, based on fit statistics. The structure of loading matrix M_1 is as follows:

$$M_1 = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 24 & -0.96 \\ 1 & 63 & -0.9844 \\ 1 & 143 & -0.9931 \\ 1 & 224 & -0.9956 \end{bmatrix}$$

Time scaling was adjusted to **(M_t^2-1)** and **(M_t^{-2}-1)** (, enabling the estimation of the latent intercept (weight at age 1), quadratic slope (rate of weight change), and inverse quadratic slope (slowing of weight growth). These matrices represented growth trajectories across socio-demographic contexts, reinforcing **M_1** as the optimal model.

Effects of latent variables on weight growth in the model

The latent variables in the FPLGC model, presented in Table 3, including the intercept (α), quadratic slope (β1), and inverse quadratic slope (β2), provided critical insights into children's weight growth trajectories. The intercept ($\alpha = 9.726$, $p < 0.001$) indicated a significant positive baseline weight at age 1. The quadratic slope ($\beta1 = 0.172$, $p < 0.001$) reflected an overall upward trend in weight, while the inverse quadratic slope ($\beta2 = -4.507$, $p < 0.001$) captured the deceleration in weight growth as children aged. These results demonstrated a non-linear growth trajectory, characterized by rapid initial increases in weight followed by slower growth over time.

Covariate Effects on Growth Trajectories

Peruvian children exhibited the highest baseline weight ($\alpha=1.012$, $p<0.001$) and steepest growth acceleration ($\beta=0.034$, $p<0.001$), likely reflecting sustained nutrition investments, while Ethiopian children showed significant deceleration ($\beta=-0.012$, $p<0.001$), aligning with rural healthcare gaps. Vietnamese children demonstrated moderate baseline advantages ($\alpha=0.590$, $p<0.001$) without significant growth-rate differences from India. Gender disparities emerged in baseline weights (females: $\alpha=-0.519$, $p<0.001$), though growth rates did not differ significantly ($\beta=0.002$, $p=0.056$). Rural residence universally predicted lower baseline weights ($\alpha=-0.635$, $p<0.001$) and slower growth

Table 3: Estimated parameters in the FPLGC model in the Young Lives Study from 2002-2016 GC.

Parameter	Category	Estimate	S.Error	95% CI	Z-value	P-value
Growth factor	Intercept (α)	9.726	0.078	[9.573, 9.879]	124.995*	0.000
	Quadratic (β_1)	0.172	0.002	[0.168, 0.176]	71.001*	0.000
	Quad-inverse (β_2)	-4.507	0.023	[-4.55, -4.46]	-194.215*	0.000
Country	India (Ref.)					
	Ethiopia (α)	0.110	0.042	[0.028, 0.192]	2.622*	0.009
	Peru (α)	1.012	0.044	[0.926, 1.098]	23.110*	0.000
	Veitnam (α)	0.590	0.041	[0.510, 0.670]	14.512*	0.000
	Ethiopia (β_1)	-0.012	0.001	[-0.014, -0.01]	-9.033*	0.000
	Peru (β_1)	0.034	0.001	[0.032, 0.036]	24.994*	0.000
	Vietnam (β_1)	0.024	0.001	[0.022, 0.026]	19.295*	0.000
Child's gender	Male (Ref.)					
	Female (α)	-0.519	0.029	[-576, -0.462]	-17.706*	0.000
	Female (β_1)	0.002	0.001	[0.000, 0.004]	1.911	0.056
Residence	Urban (Ref.)					
	Rural (α)	-0.635	0.033	[-0.70, -0.57]	-19.013*	0.000
	Rural (β_1)	-0.023	0.001	[-0.03, -0.02]	-21.953*	0.000

P-value >0.05: nonsignificant; P-value <0.05: significant; P-value <0.01: highly significant

Structural path diagram analysis

Figure 2 illustrates the structural relationships between time-invariant covariates (country, gender, residence) and latent growth factors—intercept (baseline weight = 9.73), quadratic slope (growth rate = 0.172), and inverse quadratic slope (deceleration = -4.51). The diagram highlights variances for latent and observed variables, capturing individual differences in weight growth. Covariates significantly influence baseline weight and growth rates, with socio-economic and demographic factors playing key roles in shaping children's weight trajectories.

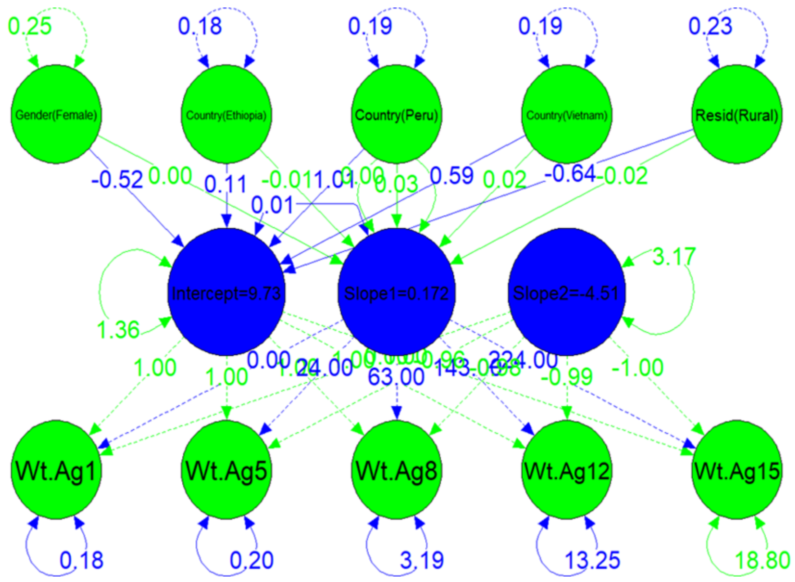

Figure 2: Structural path diagram of latent growth factors and covariates.

Comparison of Predicted Weight Growth Trajectories by Countries

Figure 3 demonstrates country-specific trends, revealing steeper weight growth trajectories in Peru and Vietnam compared to the more gradual increases in Ethiopia and India. These regional disparities reflect differences in healthcare access, nutrition, and socioeconomic conditions. The findings underscore the importance of incorporating socio-demographic factors to better understand growth patterns and inform targeted public health interventions.

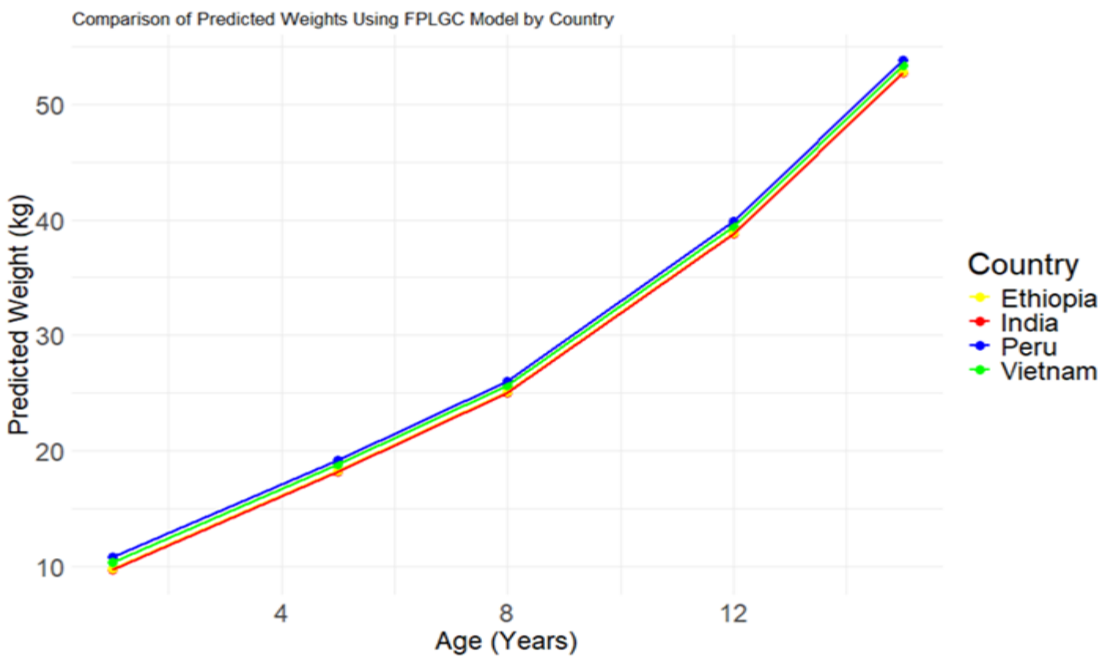

Figure 3: Comparison of predicted weight growth trajectories by country

Discussion

This study provided critical insights into children's weight growth trajectories, emphasizing the importance of analyzing non-linear patterns to understand growth dynamics. The fractional polynomial latent growth curve model emerged as the most effective approach, outperforming linear models in capturing the complexities of weight growth across socio-demographic contexts (14, 17). By incorporating key growth factors such as baseline weight, growth rate, and deceleration, the model provided a detailed understanding of how country, gender, and residence influence weight trajectories, aligning with previous research on the limitations of simpler models (20).

Country-specific trends highlighted significant disparities, with Peru demonstrating the most favorable growth trajectories due to investments in healthcare and nutrition (21), while Ethiopia exhibited deceleration associated with malnutrition and limited healthcare access (22). In contrast, India, as the reference country, showed lower baseline weights and slower growth rates, reflecting persistent challenges in addressing early childhood nutrition and systemic inequalities in healthcare access. Gender and residence also played a significant role, with female children and rural populations experiencing lower baseline weights and slower growth rates. These findings underscore the importance of addressing socio-economic and cultural factors to promote equitable growth and development (8, 23, 24).The structural path diagram provided valuable insights into the relationships between covariates and latent growth factors, highlighting significant variability in weight trajectories. This variability underscores the diverse responses of children to socio-economic and environmental influences. While our primary analysis focused on broad effects of country, gender, and residence, future studies could explore subgroup interactions (e.g., country-specific rural/urban or gender effects) for more targeted interventions. For example, improving rural healthcare in Ethiopia or sustaining growth trajectories in urban Peru could significantly enhance outcomes. Future longitudinal studies should incorporate: (a) cultural determinants of nutrition practices, and (b) post-2016 data to evaluate the impact of recent sustainable development initiatives. These findings emphasize the need for personalized, context-specific strategies to address disparities and promote equitable child development globally (21, 22).

Strengths and limitations

This study's strengths include the use of fractional polynomial latent growth curve modelling to analyze non-linear weight trajectories in 7,140 children across four LMICs, providing robust evidence of socio-demographic disparities (e.g., Peru's accelerated growth, rural-urban divides, and gender-based differences). However, limitations must be acknowledged: (1) reliance on secondary data (2002–2016) may limit generalizability to current contexts, (2) unmeasured confounders (e.g., household food security, dietary diversity) could influence results, and (3) the model's complexity may pose challenges for replication in resource-limited settings.

Future Research Directions

To advance these findings, future work should investigate subgroup interactions such as country-specific rural/urban or gender effects, while incorporating cultural factors and post-2016 data to assess recent policy impacts. A critical priority will be evaluating the cost-effectiveness of targeted interventions, particularly when adapting successful programs like Peru's school nutrition model for other LMIC contexts.

Conclusion

This study demonstrated how fractional polynomial latent growth curve models effectively capture non-linear weight growth disparities across Ethiopia, India, Peru, and Vietnam. The results revealed significant country-specific variations, with Ethiopia showing slower growth trajectories compared to Peru's accelerated patterns, alongside persistent rural-urban divides and gender-based disparities. Three actionable policy recommendations emerge from this work: scaling Peru's school nutrition approach for rural Ethiopian children with focus on ages 5–8 years, developing gender-sensitive interventions to address baseline weight gaps, and implementing rigorous cost-effectiveness analyses of these programs. Looking forward, research should track the real-world implementation of these interventions while incorporating more recent data to evaluate policy effectiveness. These findings provide concrete, evidence-based guidance for improving equitable child growth outcomes in LMIC settings.

List of abbreviations

CFI: Comparative Fit Index, FPLGCM: Fractional Polynomial Latent Growth Curve Model, LMICs: Low and Middle Incomes Countries, RMSEA: Root Mean Square Error of Approximation, TLI: Tucker-Lewis Index

Declarations

Ethics approval and consent to participate

This study utilized secondary data from the Young Lives Study, which adheres to its own ethical guidelines. No additional ethical approval was required, as the study involved secondary data analysis and no clinical trials. For further details, visit Young Lives Research Ethics.

Consent for publication

Not applicable.

Availability of data and materials

The data supporting this study are available from the UK Data Service at http://ukdataservice.ac.uk. Access may require registration or approval.

Competing interests

The authors declare no competing interests.

Funding

No funding was received for this study.

Authors' contributions

ASA conceived the study, designed the methodology, analyzed the data, and drafted the manuscript. MB guided the study design and revised the manuscript. PM contributed to editing and refinement. All authors interpreted results, approved the final manuscript, and agreed to be accountable for the work.

References

1. Kramer MS, Kakuma R. Optimal duration of exclusive breastfeeding. Cochrane Database Syst Rev. 2012;8(CD003517).
2. Black R, Victora C, Walker S, Bhutta Z, Christian P, de Onis M, et al. Maternal and child undernutrition and overweight in low-income and middle-income countries. Lancet. 2013;382(9890):427–51.
3. Kumar K, Kumar S, Singh A, Ram F, Singh A. Heterogeneity in the effect of mid-childhood height and weight gain on human capital at age 14-15 years: Evidence from Ethiopia, India, Peru, and Vietnam. PLoS One. 2019;14(2):e0212783.
4. Victora C, Christian P, Vidaletti L, Gatica-Dominguez G, Menon P, Black R. Revisiting maternal and child undernutrition in low-income and middle-income countries: variable progress towards an unfinished agenda. Lancet. 2021;397(10282):1388–99.
5. Beaujean AA. Latent variable modeling using R: A step-by-step guide. 1st ed. New York: Routledge; 2014.
6. Curran PJ, Obeidat K, Losardo D. Twelve Frequently Asked Questions About Growth Curve Modeling. J Cogn Dev. 2010;11(2):121–36.
7. Stull DE. Analyzing growth and change: latent variable growth curve modeling with an application to clinical trials. Qual Life Res. 2008;17(1):47–59.
8. Argawu AS, Muniswamy B, Punyavathi B. Analyzing Children's Weight Growth Variations and Associated Factors in Ethiopia, India, Peru, and Vietnam: Using Fractional Polynomial Mixed-Effects Model. Ethiop J Health Sci. 2024;34(1):27–38.
9. Benny L, Boyden J, Penny M. Early is best but it's not always too late: Young Lives evidence on nutrition and growth in Ethiopia, India, Peru and Vietnam. Summative Report. Oxford: Young Lives, Development ODoI; 2018.
10. Jaacks LM, Kavle J, Perry A, Nyaku A. Programming maternal and child overweight and obesity in the context of undernutrition: current evidence and key considerations for low-and middle-income countries. Public Health Nutr. 2017;20(7):1286-96.
11. Barnett I, Ariana P, Petrou S, Penny ME, Duc LT, Galab S, et al. Cohort profile: the Young Lives study. Int J Epidemiol. 2013;42(3):701–8.
12. Humphries DL, Dearden KA, Crookston BT, Fernald LC, Stein AD, Woldehanna T, et al. Cross-sectional and longitudinal associations between household food security and child anthropometry at ages 5 and 8 years in Ethiopia, India, Peru, and Vietnam. J Nutr. 2015;145(8):1924-33.

13. Lives Y. A guide to Young Lives research. Guidance Report. Development ODoI; 2017.
14. Bollen K, Curran P. Latent curve models: A structural equation perspective. 1st ed. Hoboken, NJ: John Wiley & Sons; 2006
15. Duncan TE, Duncan SC, Strycker LA. An introduction to latent variable growth curve modeling: Concepts, issues, and application. 2nd ed. New York: Routledge; 2013.
16. Royston P, Altman D. Regression using fractional polynomials of continuous covariates: parsimonious parametric modelling. J R Stat Soc Ser C Appl Stat. 1994;43 (3):429–53.
17. Sterba SK. Fitting nonlinear latent growth curve models with individually varying time points. Struct Equ Modeling. 2014;21 (4):630–47.
18. Preacher KJ. Latent growth curve models. In: Hoyle R, editor. The reviewer's guide to quantitative methods in the social sciences: Routledge; 2018. p. 178–92.
19. Kline RB. Principles and practice of structural equation modeling. 5th ed. New York: The Guilford Press; 2023.
20. Grimm KJ, Ram N, Estabrook R. Growth modeling: Structural equation and multilevel modeling approaches. 1st ed. New York: The Guilford Press; 2016.
21. Cole T, Lobstein T. Extended international (IOTF) body mass index cut-offs for thinness, overweight and obesity. Pediatr Obes. 2012;7(4):284–94.
22. Wake SK, Zewotir T, Muluneh EK. Latent growth analysis of children's height growth trajectories. J Dev Orig Health Dis. 2023;14(2):294–301.
23. Williamson DF, Thompson TJ, Anda RF, Dietz WH, Felitti V. Body weight and obesity in adults and self-reported abuse in childhood. Int J Obes. 2002;26(8):1075–82.
24. Wake S, Baye B, Gondol K. Longitudinal study of growth variation and its determinants in body weight of children aged 1-15 years in Ethiopia. Iran J Pediatr. 2022;32(4):e122662.