Innovations

Modeling Children's Weight Growth Trajectories using Latent Growth Curve Models: Socio-Demographic Influences across Low- and Middle-Income Countries

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Abstract

***Background**: Children's weight growth trajectories offer valuable insights into their development and long-term health outcomes, especially in low- and middle-income countries. These trajectories help identify early health risks such as malnutrition and obesity. **Aim**: This study aimed to analyze non-linear weight growth trajectories in children aged 1–15 years using latent growth curve models, identify key latent variables, and evaluate the influence of socio-demographic factors, including country, gender, and residence, on growth patterns across India, Ethiopia, Peru, and Vietnam. **Methods**: Longitudinal data from the Young Lives Study (2002–2016) were analyzed, comprising 7,140 children. Latent growth curve modeling was applied to explore weight growth patterns and evaluate the influences of country, gender, and rural/urban residence on growth trajectories. **Results**: The model identified significant latent variable effects on children's weight growth, including baseline weight (9.726, P < 0.001), growth acceleration (0.172, P < 0.001), and deceleration (-4.507, P < 0.001). Compared to India, Peruvian children had the highest baseline weight (1.012, P < 0.001) and steepest growth rate (0.034, P < 0.001). Vietnamese children had higher baseline weights (0.590, P < 0.001) and growth rates (0.024, P < 0.001), while Ethiopian children exhibited slower growth (-0.012, P < 0.001). Females had lower baseline weights (-0.519, P < 0.001), and rural children had lower baseline weights (-0.635, P < 0.001) and slower growth rates (-0.023, P < 0.001). **Conclusion**: Latent growth curve modeling effectively captured the non-linear nature of children's weight growth trajectories and highlighted significant socio-demographic disparities. These findings underscore the need for targeted public health interventions to address nutritional challenges, gender inequities, and rural-urban gaps in low- and middle-income countries.*

***Keywords**: Weight Growth, Latent Modeling, Non-linear Growth, Socio-Demographics, Country Differences, Child Health*

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 under nutrition, 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 modeling, particularly Latent Growth Curve Modeling (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 latent growth curve modeling (LGCM) to analyze weight growth trajectories in children aged 1 to 15 years across Ethiopia, India, Peru, and Vietnam, using longitudinal data collected over 15 years. The study focused on three key objectives: (1) analyzing non-linear weight growth trajectories using the LGCM approach, (2) evaluating the influence of socio-demographic factors such as country, gender, and residence on these trajectories, and (3) identifying latent variables, including baseline weight and growth rates, to understand how growth patterns vary across different socio-economic contexts [7, 8]. By addressing these objectives, the research provides valuable insights into the timing and nature of transitions in children's weight growth, contributing to the development of public health policies aimed at reducing malnutrition and promoting equitable growth in low- and middle-income countries [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 low- and middle-income countries (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. 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 Inclusion/Exclusion Criteria

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

Statistical Analysis (Latent Growth Curve Model)

Latent Growth Curve Modeling(LGCM) was employed to analyze longitudinal weight trajectories, offering a robust framework for capturing individual growth patterns and variability over time. This approach modeled 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:

$$\boldsymbol{y_{it} = \alpha_i + \sum_{j=1}^{p} \beta_{ji} M_t^p + \varepsilon_{it},} \qquad \boldsymbol{i = 1, 2, \dots, n;\ t = 1, 2, \dots, T}$$

Where:

- y_{it}: Observed outcome (weight) for the i^{th}individual at time t.
- 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 i^{th}individual at time t.

The parameters were estimated using maximum likelihood methods, with goodness-of-fit indices such as CFI, TLI, and 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

Covariate		Number of Children	Number of Observations	Percentage
Country	India	1,862	9,310	26.1
	Ethiopia	1,665	8,325	23.3
	Peru	1,761	8,805	24.7
	Vietnam	1,852	9,260	25.9
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 Different Ages

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).

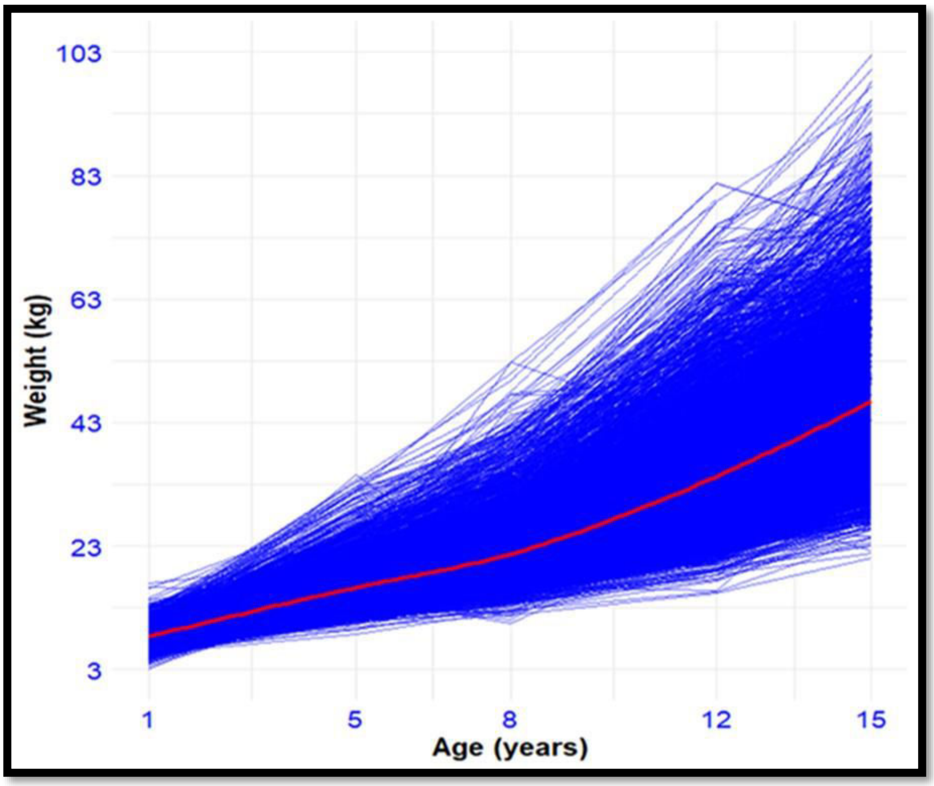

Fig1. Individual weight trajectories and mean growth trend (ages 1-15 years)

Models Comparison

The fractional polynomial latent growth curve (FPLGC) model with the loading matrix M_1provided 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 (β_1), and inverse quadratic slope (β_2), 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 (β_1=0.172, p<0.001) reflected an overall upward trend in weight, while the inverse quadratic slope (β_2=–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.

Covariates and Their Effects

Country, gender, and residence had notable effects on growth trajectories. Peru showed the strongest positive effect on baseline weight (α=1.012, P<0.001) and growth rate (β_1=0.034, P<0.001), indicating higher starting weights and more sustained growth compared to India. Ethiopia and Vietnam also had positive effects on the intercept but varied in growth rates, with Ethiopia showing deceleration (β_1=–0.012, P<0.001). Female children exhibited lower baseline weights (α=–0.519, P<0.001) compared to males, though growth rates did not differ significantly (β_1=0.002, P>0.05). Rural residence was associated with lower baseline weights (α=–0.635, P<0.001) and slower growth (β_1 =–0.023, P<0.001), reflecting socio-economic disparities.

Table 3. Parameter Estimates for the FPLGC Model with Covariates

Parameter	**Estimate**	**Std Error**	**Z-value**	**P-value**
Growth factor				
Intercept (α)	9.726	0.078	124.995*	0.000
Quadratic (β_1)	0.172	0.002	71.001*	0.000
Quad-inverse (β_2)	-4.507	0.023	-	0.000

			194.215*	
Child's gender (Reference: Male)				
α ~ Female	-0.519	0.029	-17.706*	0.000
β_1 ~ Female	0.002	0.001	1.911	0.056
Country (Reference: India)				
α ~ Ethiopia	0.110	0.042	2.622*	0.009
α ~ Peru	1.012	0.044	23.110*	0.000
α ~ Vietnam	0.590	0.041	14.512*	0.000
β_1 ~ Ethiopia	-0.012	0.001	-9.033*	0.000
β_1 ~ Peru	0.034	0.001	24.994*	0.000
β_1 ~ Vietnam	0.024	0.001	19.295*	0.000
Residence area (Reference: Urban)				
α ~ Rural	-0.635	0.033	-19.013*	0.000
β_1 ~ Rural	-0.023	0.001	-21.953*	0.000

Structural Path Diagram Analysis

Figure 2presents 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 the variances for latent and observed variables, illustrating individual differences in weight growth. The covariates significantly influence baseline weight and growth rates, with socio-economic and demographic factors playing key roles in shaping children's weight trajectories.

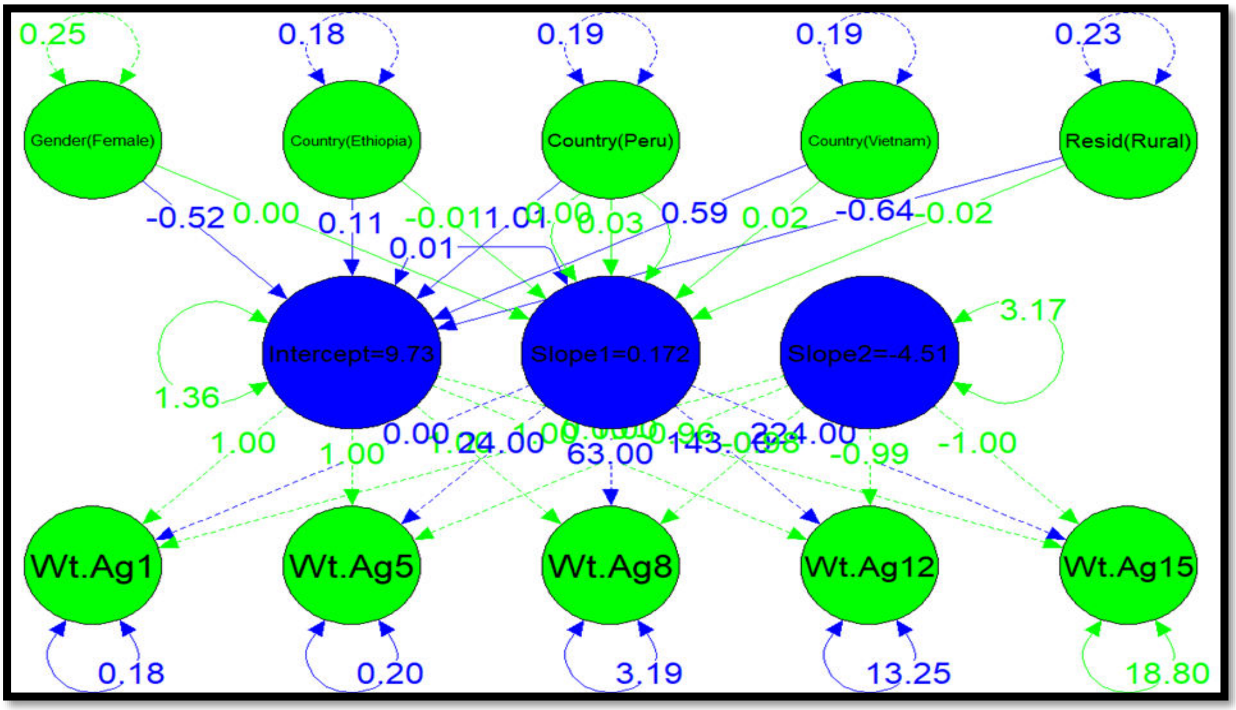

Fig 2. Structural Path Diagram for Relationships Between Covariates, Growth Factors, and Weights in the model

Comparison of Predicted Weight Growth Trajectories by Countries

Figure 3 highlights country-specific trends, with steeper weight growth trajectories observed in Peru and Vietnam, compared to the more gradual increases in Ethiopia and India. These regional disparities reflect variations in healthcare, nutrition, and socioeconomic conditions, emphasizing the need to incorporate socio-demographic factors to better understand growth patterns and guide targeted public health interventions.

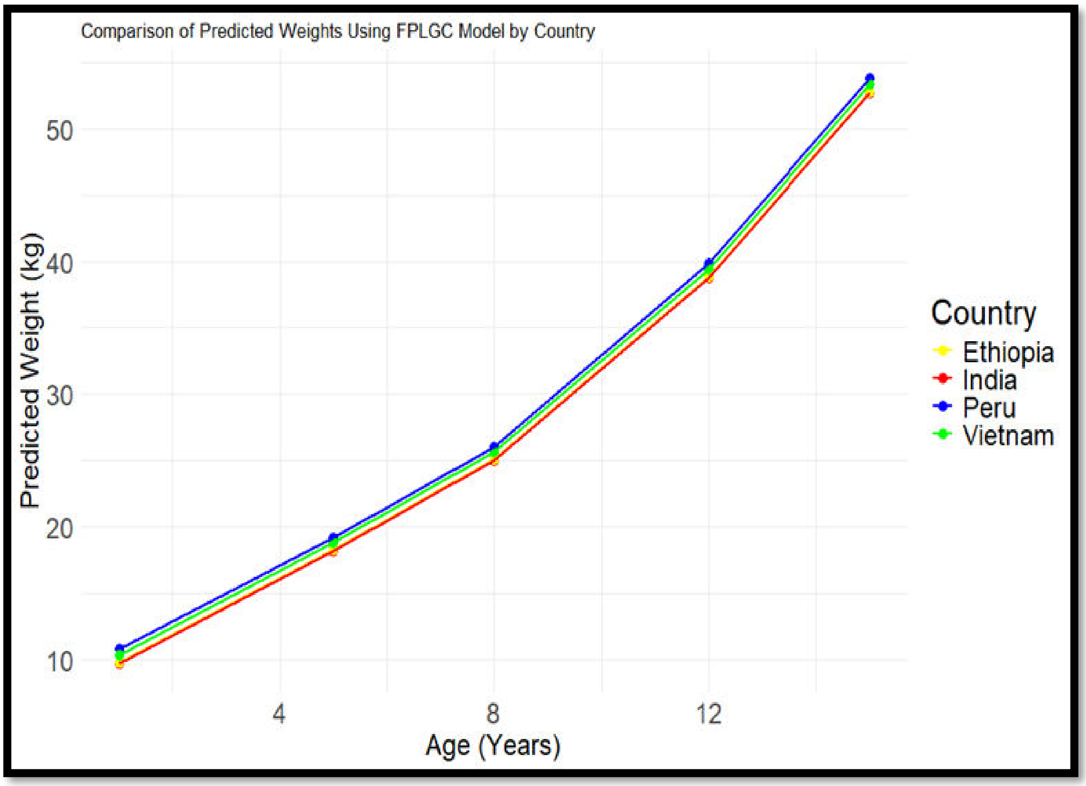

Fig3. Comparison of Predicted Weight Growth Trajectories by Country

Discussion

This study provided critical insights into children's weight growth trajectories, emphasizing the importance of modeling 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. For example, improving rural healthcare in Ethiopia or sustaining growth trajectories in urban Peru could significantly enhance outcomes. These findings emphasize the need for personalized, context-specific strategies to address disparities and promote equitable child development globally [21, 22].

Conclusion

This study demonstrated the effectiveness of fractional polynomial latent growth curve models in analyzing non-linear weight growth trajectories shaped by socio-demographic factors. Country-specific disparities, such as malnutrition in Ethiopia and rural-urban divides in India and Vietnam, highlight the need for targeted interventions to address systemic inequities. By identifying key latent variables like baseline weight and growth rates, this study provides valuable insights into childhood growth dynamics and emphasizes the importance of addressing gender disparities and improving rural healthcare accessibility. These findings offer actionable guidance for policymakers and global health initiatives to reduce malnutrition and foster equitable growth in low- and middle-income countries (LMICs).

Conflict of Interest

The authors declare no conflicts of interest regarding this work.

Acknowledgment

The authors would like to thank the Young Lives Study and the UK Data Service for providing the data used in this study.

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):427–451.*

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):1388–1399.*
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):121–136.*
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):1286-1296.*
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):701–708.*
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):1924-1933.*
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):429–453.*
17. *Sterba SK. Fitting nonlinear latent growth curve models with individually varying time points. Struct Equ Modeling. 2014;21(4):630–647.*
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. 178–192.*

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):284–294.*
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):1075–1082.*
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.*