

# Generating Longitudinal Growth Charts

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# Objective

To construct growth centile charts for preterm infants—weight (kg), length (cm), head circumference (cm)—using GAMLSS (BCCG, BCPE, BCT) on the provided dataset.

# Methods

## Normality Testing

Assessment of normality in the dataset was conducted using both the Lilliefors test and the Shapiro-Wilk test. Although each test independently evaluates the same null hypothesis—that data are normally distributed—using both methods provides a complementary perspective due to differences in their sensitivity and statistical power. The Shapiro-Wilk test is widely regarded as powerful for small to moderate sample sizes, whereas the Lilliefors test adjusts for parameter estimation and can offer robustness to deviations from classical assumptions. Given our moderately large sample size after data cleaning ( $n = 5207$ ), applying both tests allowed for a more comprehensive confirmation of distributional assumptions before proceeding with parametric modeling. This dual approach helps mitigate the limitations inherent to any single normality test and strengthens the validity of subsequent analyses.

With large sample sizes, normality tests such as Shapiro-Wilk and Lilliefors tend to detect even slight deviations from normality, which may not be practically significant. Therefore, alongside statistical testing, graphical methods including Q-Q plots and histograms were used to visually assess the normality of the distributions. This combined approach ensures a balanced evaluation, where statistical significance and substantive relevance inform the decision to proceed with parametric modeling. Employing both tests also accounts for their varying sensitivity to different types of departures from normality, thereby enhancing the robustness of our assessment.

## Modelling overview

We're building longitudinal growth centiles using the **LMS** idea inside **GAMLSS** using 5207 datapoints. In plain terms, growth data aren't perfectly bell-shaped and their spread changes with age. LMS handles that by letting **Location**, **Scale** and **Shape** (skewness—and sometimes tail weight) **vary smoothly with age**. Concretely, we model each distribution parameter as a smooth function of **postmenstrual age (PMA)**.

## What we fit

- We fit **(location/median)**, **(spread/CV)**, **(skewness)** and, where needed, **(tail weight/kurtosis)** as smooth curves of PMA using **penalised B-splines (pb())**:
  - $\sim \text{pb}(\text{PMA}, \text{df} = 4)$  (main trend)
  - $\sim \text{pb}(\text{PMA}, \text{df} = 2)$  (how spread changes)
  - $\sim \text{pb}(\text{PMA}, \text{df} = 2)$  (skewness)
  - $\sim \text{pb}(\text{PMA}, \text{df} = 3 \text{ or } 2)$  (tail heaviness, only for the 4-parameter families)
- We keep the smoothers deliberately **low-flexibility** (small df) to capture broad trends without over-fitting—exactly as in the code.

## The three distributions we compare

- **BCCG** (Box-Cox Cole-Green; 3-parameter): models  $\mu$ ,  $\sigma$ ,  $\alpha$ . A solid baseline when tails aren't too heavy.
- **BCPE** (Box-Cox Power Exponential; 4-parameter): adds  $\kappa$  to flex the tails (light/heavy). Useful if extremes need more give.
- **BCT** (Box-Cox t; 4-parameter): also adds  $\kappa$ , with **t-like heavy tails** for outlier-robust fits.

Implementation detail: these families require  $\kappa > 0$ . To respect that (and avoid fitting hiccups), we use a **log link for**  $\kappa$  in the 4-parameter fits: BCPE(mu.link = "log") and BCT(mu.link = "log"). That mirrors the code.

## How the centiles are produced

Once a model is fitted, we generate the **3rd, 10th, 25th, 50th, 75th, 90th, and 97th** centiles across the observed PMA using **centiles()**. Those are what you see as the centile curves on the plots.

## How we choose the “best” family

We compare BCCG vs BCPE vs BCT using **GAIC** (generalised AIC) with **k = 2** (i.e., standard **AIC**):

$$\text{GAIC} = -2 \log(\text{likelihood}) + k \times \text{effective degrees of freedom.}$$

Lower is better. We report the GAIC values and, for each measure (weight, length, head circumference), note which family wins.

## What the data pipeline does (in brief)

- Read the Excel sheet defined in the YAML (**file** and **sheet** names come from **params**).
- Standardise missing values in **text** fields; coerce key columns to numeric.
- Derive **weight\_kg = weight\_g / 1000**.
- For repeated measurements at the same **infant × PMA week**:
  - **weight**: average (to stabilise noise),
  - **length/head**: take the **maximum** (to avoid underestimation).
- Save a cleaned snapshot and then fit the models as above.

## Data and Software Environment

R (gamlss, gamlss.dist, dplyr, readxl, nortest) as loaded above.

## Data Cleaning and Preprocessing

We imported the Excel worksheet and standardized missing values. Text fields were trimmed/lower-cased; "NA"/blanks were set to NA. Key variables were coerced to numeric. For repeated measurements within the same infant and PMA week, we averaged **weight** and took the **maximum** of **length** and **head circumference** to avoid underestimation. Weight in kilograms was derived from grams. The cleaned, de-duplicated dataset was saved for reproducibility.

```
## Reading: C:/Users/nerad/Documents/Growth Chart/neonatal_growth_chart/Cleaned/cleansed.xlsx
```

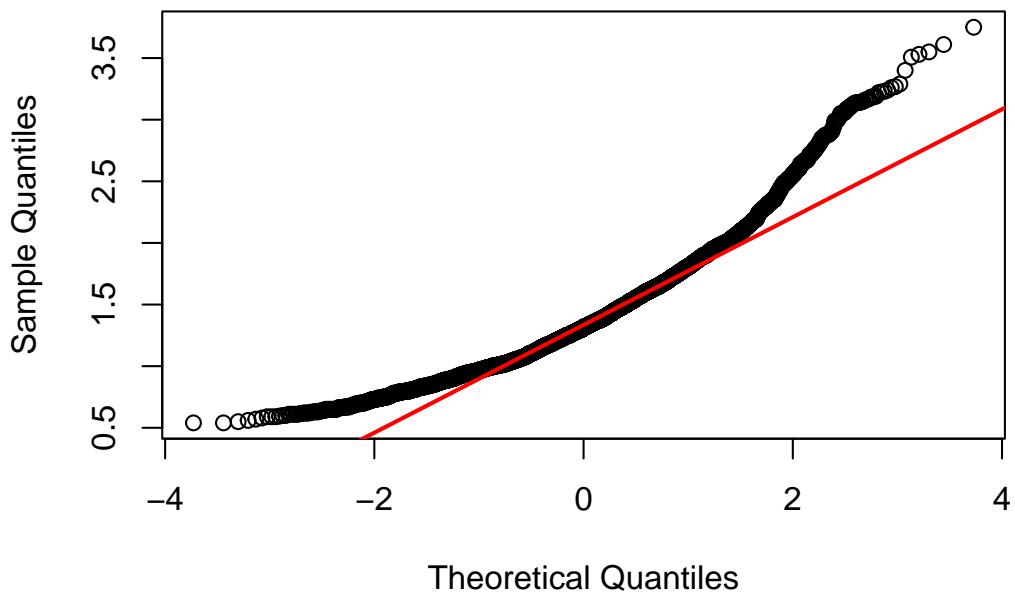
```
## Rows in raw data: 10198
## Rows after merge (infant_id x PMA): 5206
## Unique infants: 320

## Rows: 5,206
## Columns: 6
## $ infant_id <chr> "b3415", "b3415", "b3415", "b3440", "b3440", "b3440~
## $ pma_weeks <dbl> 36.14285714, 38.00000000, 40.00000000, 38.57142857, 38.71428~
## $ weight_g <dbl> 1520.000000, 1800.000000, 2260.000000, 1788.750000, 1786.666~
## $ weight_kg <dbl> 1.520000000, 1.800000000, 2.260000000, 1.788750000, 1.786666~
## $ length_cm <dbl> 41.5, 44.0, 48.0, 43.0, 43.0, 46.0, 32.0, NA, NA, NA, NA, NA~
## $ head_cm <dbl> NA, 32.0, 33.5, 33.0, 33.0, 34.0, 25.0, 25.0, NA, NA, NA, NA~
```

## Weight

```
##  
## Lilliefors (Kolmogorov-Smirnov) normality test  
##  
## data: model_data_trim$weight_kg  
## D = 0.074208001, p-value < 2.2204e-16
```

Q–Q Plot of Weight (kg)



```
# Helper that respects R's Shapiro limit (n = 5000)  
sw <- function(x) {  
  x <- stats::na.omit(x)  
  if (length(x) > 5000) {  
    set.seed(1)  
    x <- sample(x, 5000)  
    message("Shapiro-Wilk run on a random sample of 5,000 (R limit).")  
  }  
  stats::shapiro.test(x)  
}  
  
sw_out_weight <- sw(model_data_trim$weight_kg)  
sw_out_weight  
  
##  
## Shapiro-Wilk normality test
```

```

##  

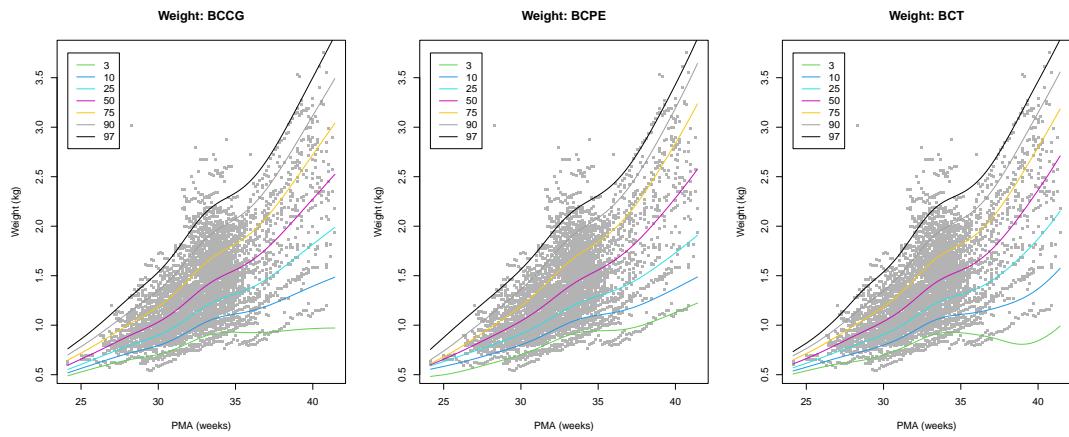
## data: x  

## W = 0.93824154, p-value < 2.2204e-16

```

Table 1: GAIC comparison for Weight (lower is better)

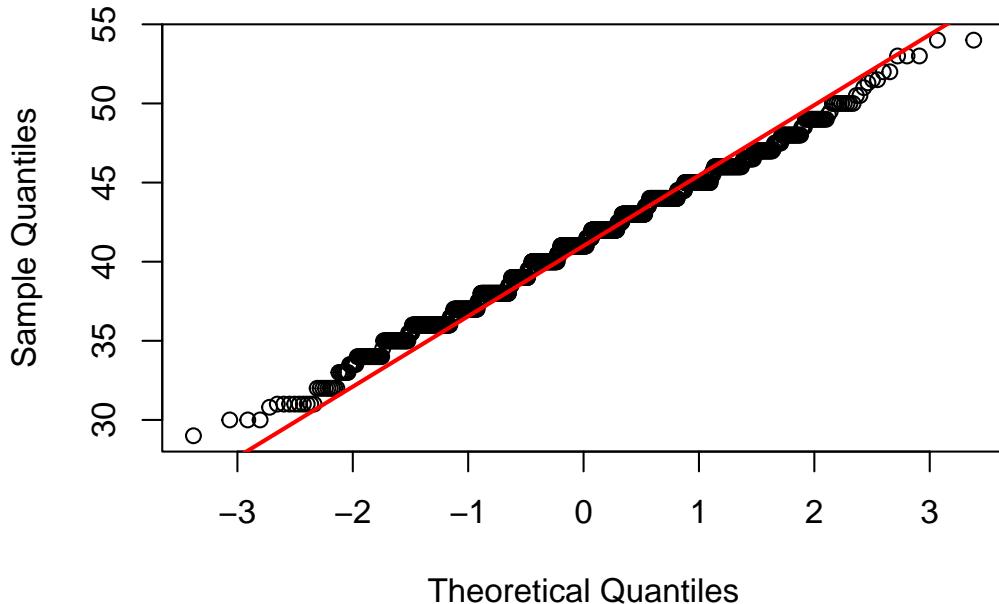
	df	AIC
model_weight_bcpe	19.00001220	2264.954943
model_weight_bct	18.00000761	2309.079815
model_weight	13.99999994	2326.401973



## Length

```
##  
## Lilliefors (Kolmogorov-Smirnov) normality test  
##  
## data: model_data_length$length_cm  
## D = 0.058197133, p-value = 7.191574e-12
```

**Q-Q Plot of Length (cm)**



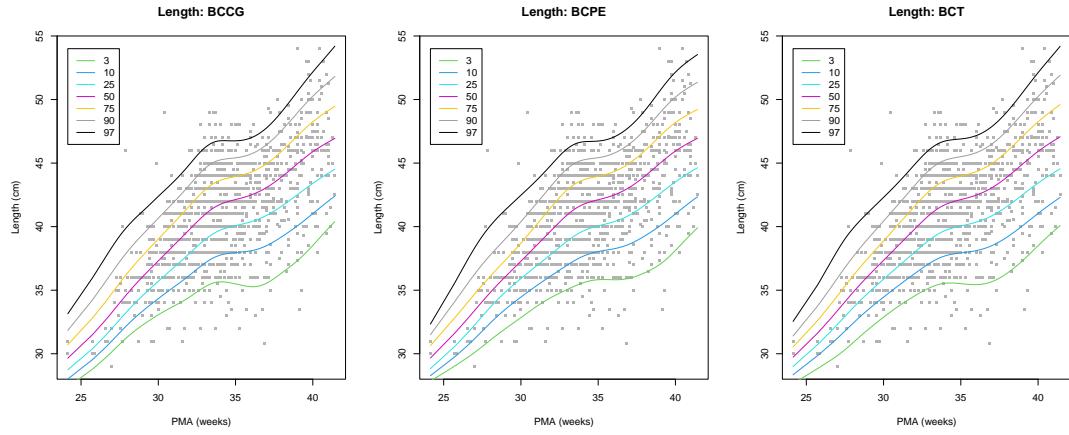
```
sw_out_length <- sw(model_data_length$length_cm)  
sw_out_length
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: x  
## W = 0.99458264, p-value = 6.528717e-05
```

Table 2: GAIC comparison for Length (lower is better)

	df	AIC
model_length_bcpe	19.05834077	6907.509874
model_length_bct	19.98205935	6913.828310

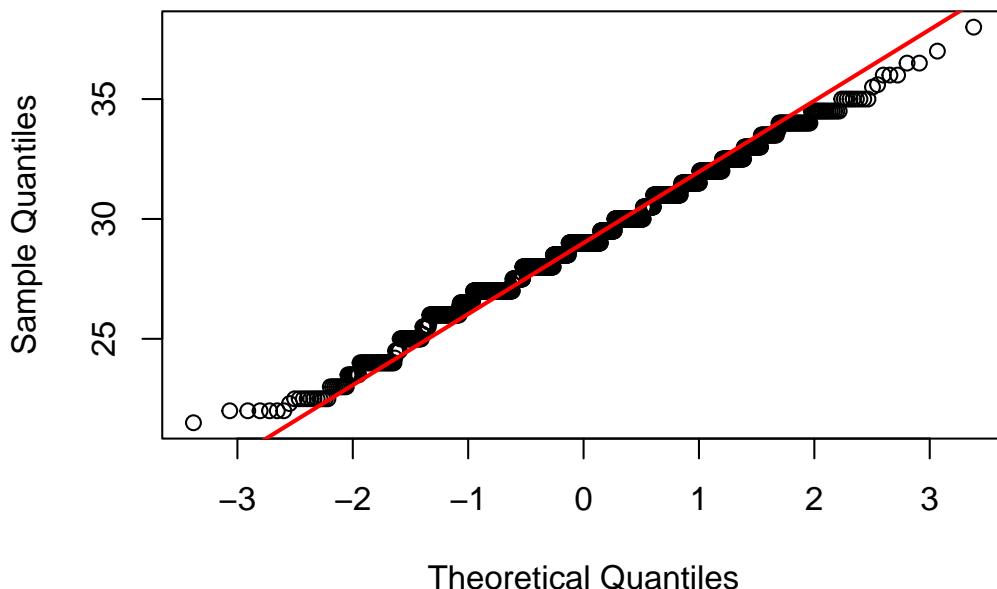
	df	AIC
model_length	19.11566423	6918.592453



## Head Circumference

```
##  
## Lilliefors (Kolmogorov-Smirnov) normality test  
##  
## data: model_data_head$head_cm  
## D = 0.062615864, p-value = 7.301096e-14
```

**Q–Q Plot of Head Circumference (cm)**



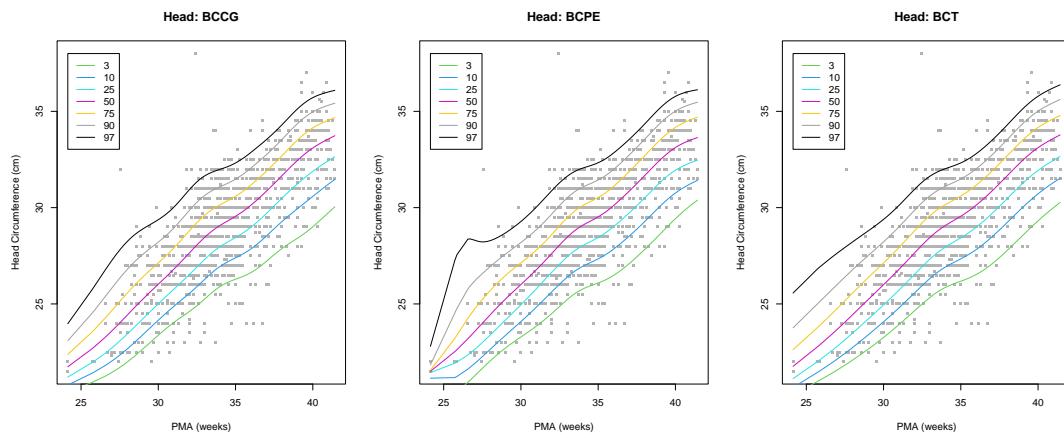
```
sw_out_head <- sw(model_data_head$head_cm)  
sw_out_head
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: x  
## W = 0.99356837, p-value = 1.032804e-05
```

Table 3: GAIC comparison for Head Circumference (lower is better)

	df	AIC
model_head_bcpe	19.53716117	5335.392002

	df	AIC
model_head	13.83365802	5350.215044
model_head_bct	18.56503712	5358.135647



## Conclusion

Across all three anthropometric measures, the BCPE family consistently yielded the lowest GAIC values, with a particularly substantial margin for weight ( $\Delta$  44 versus BCT,  $\Delta$  61 versus BCCG) and head circumference ( $\Delta$  15–23), and a smaller yet consistent advantage for length ( $\Delta$  6–11). This pattern aligns well with biological expectations for preterm cohorts, where neonatal growth typically exhibits positive skewness and heavier tails. Such distributional characteristics arise from heterogeneous growth patterns including intrauterine growth restriction (IUGR), small for gestational age (SGA) status, rapid catch-up growth, variable fluid status, and occasional measurement outliers.

The BCPE model's flexibility stems from its inclusion of a tail-weight parameter ( ) alongside a skewness parameter ( ) that varies smoothly with postmenstrual age (PMA), allowing it to adapt both the asymmetry and kurtosis of the distribution in an age-dependent manner. In contrast, the BCCG family, with only three parameters, cannot accommodate varying tail heaviness, while the BCT family assumes symmetric, t-distributed tails that may inadequately represent the empirically skewed neonatal data.

Practically, the improved fit of the BCPE family is expected to enhance calibration of the extreme centiles (3rd and 97th), thereby minimizing systematic under- or overestimation at the tails—a critical factor for accurate clinical assessment. For length, the smaller GAIC differences suggest near-equivalent model performance, though BCPE remains favorable. Accordingly, tail fit quality and residual diagnostics should be carefully evaluated to confirm these findings.

Overall, the superior performance of BCPE models highlights the necessity of accommodating skewness and heavy-tailed behavior when modeling neonatal growth, ensuring more reliable and clinically meaningful centile estimates that better reflect the complex heterogeneity inherent in this vulnerable population.

### Normality summary (all measures)

Table 4: Normality tests by measure (Shapiro–Wilk capped at n = 5,000)

Measure	n	Shapiro_W	Shapiro_p	Lillie_D	Lillie_p
Weight (kg)	5205	0.9382	0e+00	0.0742	0
Length (cm)	1384	0.9946	1e-04	0.0582	0
Head circumference (cm)	1385	0.9936	0e+00	0.0626	0

### Extract GAIC winner

Table 5: Best GAIC model by measure

Measure	Best family	GAIC
Weight (kg)	BCPE	2265.0
Length (cm)	BCPE	6907.5
Head circumference (cm)	BCPE	5335.4