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Comprehensive Analysis of Body Shapes in the Indian Female Population: A National and Regional Study

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ABSTRACT

India relies on anthropometric data sourced from foreign nations to develop products, resulting in a formidable challenge for Indian consumers in their quest for products tailored to their specific bodily attributes. The garment industry, in particular, grapples with this issue, where Indian consumers must often compromise on the fit of clothing due to the absence of comprehensive databases pertaining to Indian body shapes and sizes. Recent reports underscore the gravity of this situation, revealing that garment returns account for a substantial 20% to 40% of sales, a trend exacerbated by the burgeoning e-commerce sector. In response to this pressing need, a nationwide anthropometric survey was meticulously conducted, leveraging state-of-the-art 3D whole-body scanning technology. This extensive study encompassed a cohort of more than 13,000 female volunteers (total subjects scanned 13045 and valid subjects 12492), aged 15 to 70, meticulously selected to represent all states across India's six distinct geographic regions. Systematically, the data collected was subjected to clustering, resulting in the categorization of body shapes, both at the regional and national levels. This classification process was anchored in robust measurements of height and key girth dimensions, with a specific focus on Bust, waist, hip, and upper hip girths. This indigenous research unveiled the four most prevalent body shapes among Indian females: Hourglass, Rectangle, Trapezoid, and Bottom hourglass. Furthermore, a comprehensive regional analysis of body shapes was conducted, and it was found that while regional variations existed, the fundamental body shape clusters among Indian females remained consistent with the national clusters. The regions displayed the same four primary body shapes for females, with variations in the prevalence of these identified shapes. This groundbreaking study underscores the necessity of considering regional variations in product design and sizing to cater to the diverse Indian population accurately.

Keywords: Anthropometry, 3D body scanning, Sizing survey, Body shape and size, National and regional shape clustering

INTRODUCTION

With approximately 1.4 billion people, India is the most populated nation in the world (Worldometer, 2023). It is also the fifth largest economy (Forbes,

2023) with consumer market expected to become the third largest (after the US and China) in the world by 2027 (Jacob, 2023).

Better fits are essential for women's wear, given the predominant focus on the female body type in apparel selection. Female bodies, in contrast to male bodies, exhibit greater diversity in shapes. Research on Indian female body forms and their correlation with clothing fit remains largely unexplored. The entire Indian population faces apparel fit issues due to the absence of size charts tailored to Indian body dimensions. While some research has been conducted in this area, it remains limited in scope and scientific rigor.

This research paper examines the analysis of body shapes among Indian women, both on a national and regional scale, through a comprehensive investigation of the Indian female population. The study offers a robust mechanism for identifying body shapes. Based on indigenous research, the four most prevalent body shapes among Indian women are Bottom hourglass, Hourglass, Rectangle, and Trapezoid. This study not only illuminates the distinct body types of Indian women but also provides valuable insights for companies striving to create better-fitting products, thereby enhancing customer satisfaction and reducing financial losses linked to returns. Moreover, it underscores the importance of considering regional variations in product design and sizing to cater effectively to the diverse Indian populace.

Apparel Fit Issues

A significant portion of shoppers report having trouble finding clothes that are the appropriate fit for their body dimensions, according to global research studies on fit and human body measures. The main cause is disparities in the anthropometric make-up of people in various nations and even geographical locations of the world.

DesMarteau (2000) talked on the significance of fit, the causes of garment misfit, and its effects on service providers and consumers. According to a KSA survey, 50% of women and 62% of men struggle to find clothing that fits well, and other studies have found that 50% of catalogue returns are due to fit issues (DesMarteau, 2000). The lack of standardized Indian Size charts continues to be a key problem for clothing fit. There is a lack of comprehensive anthropometric data for Indian men that can be used to represent the entire nation and whose dimensions can be used for a variety of purposes, including clothing (Chakrabarty, 1997), (Anand, 2011).

In terms of anthropometric applications in clothing sizing, research has been conducted in India, however it hasn't received much attention. The results of the research were also not commercialized or employed in mass production (Tiwari, 2017). Currently, body-fitting, sewn clothing is preferred over conventional draping clothing. Due to this change in desire, clothing must now be mass-produced to fit Indian bodies, necessitating the development of an Indian body size chart. Due to the lack of such standards, the Indian clothing industry has been adopting American, European, and British body size measurements, which frequently results in poorly fitting clothing

(Ministry of Textiles, 2018). Currently, manufacturers "adapt" or "tweak" size charts from various nations based on their "instinct" and "experience" to create a size chart for their brand (Anand, 2011). Poor garment fit is cited as the astounding and predominant cause of the projected 25 to 40% returns for garments (Forum, 2020) which are rising with the expansion of e-commerce (Vidya, 2022).

Shape Analysis

A sizing system indicates the total range of sizes based on the grading of dimension for a boy type (Glock & Kunz, 2005) and fitting combinations available in the garments (Cooklin, 1992). The size charts are developed as per the garment type (i.e. upper body garments or lower body garments or innerwear garment etc.) and the body type of the target market (Aldrich, 1980). Boswell (1993) discusses the requirement of a unique subset of technical descriptors indicating information about whom that garments would fit. "Drop" is also such a technical descriptor that is a relationship between two body dimensions, i.e. difference between chest girth and waist girth used for tailored suits for male bodies. The drops are dependent on the body shapes (Boswell, 1993).

The creation of sizing algorithms that classify people with similar body proportions together is a crucial first step in resolving fit and size issues in mass customization. The female body shape, or figure, is a product of a woman's skeletal structure, as well as the quantity and distribution of muscle and fat on the body. According to Fairhurst (2008), basic body forms are defined by the ratios of a few important body circumferences (Fairhurst, 2008).

Shin, Istook & Lee (2011) highlighted the lack of in-depth analysis in the area of male body shape and sizing systems. The standards are not designed according to the different drops or body types (Shin et al., 2011). Lee (2004) used statistical approached by applying factor analysis and cluster analysis for shape categorization of human heads (Lee, 2004). Body Shape Analysis Scale (BSAS©) was developed for female body shaped by Connell et al. in 2004 (Connell et al., 2002).

In the year 2004 Female Figure Identification Technique (FFIT©) was developed by Simmons et al. FFIT was developed based on the mathematical data analysis obtained from 3D scans of the female subjects. This resulted into nine different body shapes, including hourglass, top hourglass, bottom hourglass, rectangle, triangle, inverted triangle, oval, diamond, and spoon as indicated in Figure 1 (Simmons et al., 2004).

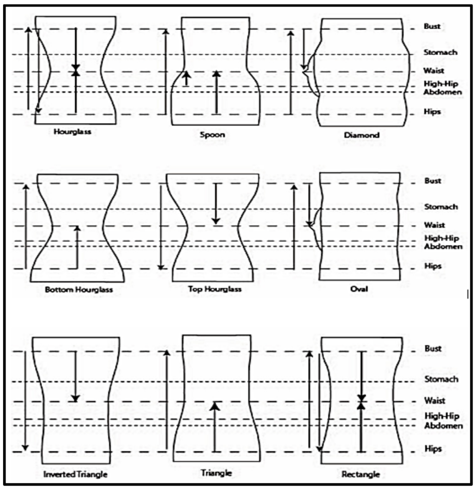

Figure 1: Female body shapes as derived from FFIT model.

The researchers also investigated the relationship of drops to male body shapes for developing sizing systems. The 3D scan data used for male body shape classification was from the SizeUSA. Three drops as Chest-Waist, Hip-Waist, and Hip-Chest were used for body shape classification, and four body shapes were identified as slim shape, heavy shape, slant inverted -triangle shape, and short round top shape (Shin et al., 2011).

Two different approaches 1. Cluster analysis, and 2. Shape cluster identification using a Microsoft Excel based MSIT (Male Shape Identification Technique). Five drop combinations as chest-waist, hip-waist, chest-high hip, waist-high hip, and hip-high hip measurements were used for body shape identification using MSIT (Male Shape Identification Technique) (Wilson & Istook, 2019), (Wilson, 2016).

Factor Analysis

Principal Component Analysis (PCA) is a variable reduction technique. Application of factor analysis using principal component analysis is used for data reduction/data compression into a few factors indicating key dimensions.

The factor analysis using Principal Component Analysis (PCA) has been widely used by various researchers in the anthropometric data analysis including Salusso (1985) in selecting dimensions for bivariate classification (Salusso et al., 1985), Salusso et al. (2006) while adopting an alternative approach named as principal component sizing system (PCSS) to sizing apparel for women of age 55 years and above (Salusso et al., 2006). By looking at factor loading values, one may verify that the PCA's method of choosing key or control measurements is based on their relationship and correlation with other measurements (Zakaria, 2014), (Veitch et al., 2007).

Clustering

Cluster analysis is one of the key data mining techniques used for data reduction through data classification. In the context of anthropometric research, the cluster analysis may be applied to classify the subject population into homogeneous groups (Zakaria & Gupta, 2014).

METHODS AND TECHNIQUES

Subject Profile

This study included total of more than 13,000 female volunteers (total subjects scanned 13045 and valid subjects 12492) aged between 15 years and 70 years spanning in eleven age groups (refer Table 1) from the six geographic regions of India, five income groups and two communities as rural and urban.

Table 1. Age-wise subjects distribution.

Age Group	Number of Subjects	Number of Valid Subjects	% Share of Valid Subjects
> 15 <= 20	1853	1791	14.34%
> 20 <= 25	1695	1660	13.29%
> 25 <= 30	1611	1546	12.38%
> 30 <= 35	1351	1281	10.25%
> 35 <= 40	1348	1278	10.23%
> 40 <= 45	1095	1023	8.19%
> 45 <= 50	1046	1000	8.01%
> 50 <= 55	825	777	6.22%
> 55 <= 60	820	787	6.30%
> 60 <= 65	668	646	5.17%
> 65 <= 70	733	703	5.63%
Grand Total	13045	12492	100.00%

The sample size for the data collection was statistically determined using stratified sampling technique applied on the census data of 2011. The six geographic regions included North, West, South, Central, East, and North-east regions. The age range of the subjects for the study was as per the definitions of National Youth Policy, 2014 (Ministry of Youth Affairs and sports, 2014) and National Council for Older People 2014 (Ministry of Social Justice & Empowerment, 2014). As recommended in the ISO 15535:2012, the subjects were divided into age groups of 5 years multiples (ISO 15535, 2012). The income categories of the subjects were based on the annual household income as per the BCG report on Indian consumers. The five income categories included as Elite : annual household income above Rs. 20 lacs; Affluent : annual household income between Rs. 10.0 to 20.0 lacs; Aspirers : annual household income between Rs. 5.0 to 10 lacs; Next Billion : annual household income between Rs. 1.5 to 5.0 lacs; and Strugglers : annual household income below Rs. 1.5 lacs (Sanghi et al., 2017).

Data Collection

The data was collected using 3D body scanning. The subjects were randomly measured manually on some key dimensions to check the 3D body scanner performance. Due ISO recommended protocols (such as ISO 8559:1989, ISO 20685:2005 and ISO 20685:2018) were followed to ensure the accuracy and validation of the 3D body scanners (Tiwari & Anand, 2020), (Tiwari & Anand, 2022). The anthropometric data was collected on various body dimensions including various heights from floor, girth measurements, depth/length measurements, segment lengths, and arc measurements as per the postures as recommended by ISO 20685: 2010-11. The definition of the body dimensions for landmark identification was ISO 8559-1:2017 and ISO 7250-1:2017 protocols. The dimensions were selected as per industry requirements to make different apparel products.

Data Preparation

The data preparation process included obtaining the composite file of anthropometric measurements as captured by 3D body scanning. In the next step, the data was cleaned by treating the extreme values and outliers which were abnormal and falling beyond ± three σ (Standard deviation) limits (Hsu, 2009), (Moon & Nam, 2003). Then the data was exported to IBM SPSS V. 28 for basic statistical analysis including descriptive statistics, factor analysis, and clustering. Post cleaning, the data of collected body dimensions was tested for normality, and it was observed that the data was almost normality distributed for the given body dimension.

Data Classification

The data classification was primarily done using IBM SPSS Modeler V. 18.2. The data was classified in total five height categories based on the standard deviation, and the body shape categories as identified using k-means clustering technique based on the six drop combinations as discussed in the next sub-sections.

Data Validation

Data validation was done by conducting 1. Test of sample adequacy, 2. Test of sphericity, and 3. Test of internal consistency of the data. These tests are prerequisite to conduct factor analysis, and ensure that the data set is suitable for further analysis (Zakaria, 2014).

1. **Test of sample adequacy:** The Kaiser-Meyer-Olkin (KMO) value was calculated as a measure of sampling adequacy of data. The KMO value observed was 0.951, which can be considered as excellent in comparison the acceptable value of 0.60 (Hrženjak et al., 2015).
2. **Test of sphericity:** The Bartlett's test is used to check for the sphericity of the data by checking the checks for the redundancy between the variables. The Bartlett's test result value observed was nearing 0. The test result which is less than 0.05 confirms the sphericity of data and considered as acceptable (Hsu et al., 2007).
3. **Test of consistency and unidimensionality of the data:** Cronbach's alpha was used to check the internal consistency (reliability) of the data. The Cronbach's alpha values ranges between 0 and 1 and higher score indicates more reliability. Cronbach's alpha value ≥ 0.6 is treated as satisfactory for data consistency (Cronbach, 1951). The Cronbach's alpha value observed for the dataset was above 0.95, hence the unidimensionality of the data was confirmed.

Factor Analysis

Principal component analysis was used to apply the factor analysis and reduce the amount of data in to some key factors. Following the Kaiser criterion (latent root criterion), variance criterion, scree plot, and eigenvalues, the important factors were found. The girth factor and height factor were the main factors that had eigenvalues greater than one. Principal component analysis was used to determine two main factors: length factor and girth factor.

The first two components have eigenvalues greater than 1 and the greatest possible variance coverage. The first component covered a variance of 42.44 percent, while the second component a variance of 32.152 percent. Together, these two elements accounted for 74.59 percent of the variance. The accepted recommendation is that these chosen components should account for at least 60% of the total variance in order to demonstrate the value of PCA. In this study, compared to the minimum required threshold of 60 percent, the first two components explained more variance (74.59%) (Malhotra, 2010).

The rotated component matrix indicating dimensions with factor loading >= 0.90. Stature (height) with 0.936 loading factor was observed among the top dimensions with the highest factor loadings with the length component. Since the key dimensions must be easy to measure and the body dimensions should be familiar for everybody, height was considered as one of the parameter for the data classification (Moon & Nam, 2003). Among the girths, Upper Hip Girth, Bust girth, Waist girth, and Hip girth were observed as the dimensions with highest factor loading.

Height Categories

The mean height was observed as 151.73 cm with a standard deviation of 6.28 cm. As the data witnessed a near normal distribution with the skewness observed as 0.072, while median and mode values 151.57 cm and 155.01 cm, respectively. For convenience in height categorization, the central value was considered as 152.0 cm, and the central height category was determined with +/– 4.0 cm from this value. The total dataset was divided into five height categories as indicated in Table 2. It can be noticed that the Average height category covered almost 48% of the subjects, followed by Short normal (24.71%), and Tall normal category with 22.11%. The categories Short and Tall height categories covered relatively lesser number of subjects with just 2.86% and 2.79% subjects respectively. The central three height categories covered a whopping 94.35% of the subjects.

Table 2. Height categories.

Sr. No.	Height Category Name	Height Range (cm.)	Percentage Share
1	Short	Height <140.00 cm	2.86%
2	Short Normal	>=140.00 cm to <148.00 cm	24.71%
3	Average	>=148.00 cm to <156.00 cm	47.53%
4	Tall Normal	>=156.00 cm <164.00 cm	22.11%
5	Tall	Height >=164.00 cm	2.79%
Total			100.00%

Drop Combinations for Body Shape Clustering

Data clustering was done based on the different drop combinations by selecting the girth dimensions. The selection of the girth dimensions was based on the factor loading as observed in the PCA. Six different drop combinations were identified for the clustering analysis as Bust – Waist, Hip – Waist, Bust – Hip, Bust – Upper Hip, Hip – Upper Hip, and Waist – Upper Hip. The k-means clustering was applied for the body shape analysis, and total 4 different clusters (body shapes) were identified for the female population. The identified body shapes are indicated in the Table 3.

Table 3. Body shape clusters.

Body Shapes Clusters Female				
Drop Combination	Body Shape			
	Hourglass	Rectangle	Trapezoid	Bottom Hourglass
D1(Bust girth – Waist girth)	11.38	5.971	7.132	12.976
D2(Hip girth – Waist girth)	12.342	5.026	14.041	20.422
D3(Bust girth – Hip girth)	−1.311	0.14	−9.4	−7.618
D4(Bust girth – Upper Hip girth)	6.681	1.137	−1.891	7.379
D5(Hip girth – Upper Hip girth)	7.993	0.997	7.51	14.997
D6(Waist girth – Upper Hip girth)	−4.698	−4.834	−9.022	−5.596
Percentage of subjects	26.51%	19.63%	23.90%	29.96%

As mentioned in the Table 3, total 6 drop combinations (D1 to D6) were employed for clustering of the data. clustering The values associated with the drop combinations represent the average difference between the dimensions of that drop combination for a given body shape. For instance, in case of the Hourglass body shape, the average difference between bust girth and waist girth is 11.38 cm, while the same difference is 5.97 cm, 7.13 cm, and 12.97 for the Rectangle, Trapezoid, and Bottom Hourglass shapes respectively.

The clustering of the anthropometric data based on the 6 drop combinations revealed relationship among the key body dimensions i.e. bust girth, waist girth, and hip girth. These relationships, or rules, are valuable may be useful in defining the body shapes for the India female population is indicated in Table 4.

Table 4. Body shapes and relationship among body dimensions.

Body Shape	Relationship Among Body Dimensions	Remark
Hourglass	Difference between Bust girth and Waist girth is between +11 cm to +12.0 cm. Difference between Bust girth and Hip girth is between -4.0 cm. to +1 cm. Difference between Hip girth and Waist girth is between +11.0 cm. to +15.0 cm.	This shape can be classified as **Hourglass** due to the noticeable difference between Bust and Waist girth.

(Continued)

Table 4. Continued

Body Shape	Relationship Among Body Dimensions	Remark
Rectangle	Difference between Bust girth and Waist girth is +5 cm to +7.0 cm. Difference between Bust girth and Hip girth is between -3.0 cm. to +3.0 cm. Difference between Hip girth and Waist girth is between +4.0 cm. to +8.0 cm.	This shape can be classified as **Rectangle** because the measurements indicate a relatively similar distribution of girth throughout the body.
Trapezoid	Difference between Bust girth and Waist girth is between +6.0 cm to +8.0 cm. Difference between Bust girth and Hip girth is between -11.0 cm. to -9.0 cm. Difference between Hip girth and Waist girth is between +16.0 cm. to +19.0 cm.	This shape can be classified as **Trapezoid** due to the significant difference between Bust and Hip girths without a well-defined waist.
Bottom Hourglass	Difference between Bust girth and Waist girth is +12 cm to +13.0 cm. Difference between Bust girth and Hip girth is between -9.0 cm. to -7.0 cm. Difference between Hip girth and Waist girth is between +19.0 cm. to +21.0 cm.	This shape can be classified as **Bottom Hourglass** because of the substantial difference between Bust and Hip girths and the presence of a defined waist.

From the Table 4, it is clear that the shapes identified are quite distinguished from each other and can be noticed based on the conditions indicated.

National Shape Clustering

The clustering of the entire data was done by combining all the geographic regions for identified body shapes with height categories. This distribution can be seen in the Table 5.

Table 5. Body shape clustering - national.

Geographic Region	Height Category	Hourglass	Rectangle	Trapezoid	Bottom Hourglass	Total
		% Subjects				
All Regions	Short	0.97%	0.76%	0.65%	0.48%	2.86%
	Short Normal	7.59%	6.27%	5.38%	5.48%	24.71%
	Average	12.67%	9.46%	11.42%	13.98%	47.53%
	Tall Normal	4.73%	2.93%	5.75%	8.70%	22.11%
	Tall	0.55%	0.21%	0.71%	1.32%	2.79%
	Total	26.51%	19.63%	23.90%	29.96%	100.00%

The analysis reveals (refer Table 5) that the Bottom Hourglass body shape category, characterized by relatively larger hip girth, and hip girth by an average of 20.42 cm as compared to the waist girth, is the most prevalent, encompassing 29.96% of the subjects. Following closely, the Hourglass category, where both the bust girth and the hip girth are more or less same, but the waist girth is relatively smaller, constitutes 26.51% of the subjects. The Trapezoid body shape, where waist girth is smaller than hip girth by average 14.0 cm, and bust girth is smaller than hip girth by 9.4 cm constituted 23.90% subjects. The Rectangle body shape, in which the bust, waist, and hip girths are nearly identical, accounts for 19.63% of the subjects.

Within the "Average height" category, with 13.98% of the subjects are represented, the Bottom hourglass body shape remains the dominant choice. It is followed by the Hourglass shape at 12.67%, Trapezoid shape at 11.42%, and Rectangle shape at 9.46% for individuals of the same height category. It is worth noting that body shapes in the "Short" and "Tall" height categories have a substantially smaller presence, each constituting less than 2.0% of the total subjects. Consequently, it is advisable to exclude these shape categories when developing a size chart (Petrova, 2007), (Kwon et al., 2009), (Zakaria, 2011).

Regional Shape Clustering

The body shape clustering pattern with respect to height categories was also checked for the geographic regions. The objective was to investigate and understand the body shape deviations in the given geographic regions from the national shape pattern. Further, in case there are significant deviations in the shape in some specific geographic regions, it may justify the requirement for creating an exclusive size charts for such geographic region(s).

RESULTS AND DISCUSSIONS

The regional analysis of female body forms unveiled crucial insights into body shape patterns across different geographical regions of India, highlighting disparities from the national body shape clusters.

Regional body shape clustering showcased diverse patterns. Notably, none of the regions precisely mirrored the national clustering, with North India, East India, and North-east India showing a predominant Hourglass body shape, followed by Bottom Hourglass, Rectangle, and Trapezoid. It's worth mentioning that North India and North-east India had slight variations in populations with Hourglass and Bottom Hourglass shapes, reflecting a 3.44% difference.

Conversely, West India and South India exhibited a reverse body shape sequence. In West India, the predominant shape was Bottom Hourglass, followed by Trapezoid, Rectangle, and Hourglass, while South India displayed the reverse order. Central India had the highest population with Trapezoid (38.4%), followed by Bottom Hourglass, Rectangle, and Hourglass.

In the North-east India region, the majority of subjects fell within the Short Normal (Height >= 140 cm and < 148 cm) and Average (Height >= 148 cm and < 156 cm) height categories, accounting for approximately 78%. This shift towards shorter height categories led to the emergence of Hourglass body shape as a valid category for the Short height group (comprising over 2% of subjects). The variations in body shape patterns in North-east India may be attributed to the relatively shorter height of the population in this region.

In South India, the observation of Bottom Hourglass shape in the Tall height category was significant. The inclusion of these new shape categories in North-east India and South India is valuable for brands and clothing manufacturers catering to region-specific consumers.

CONCLUSION

It is evident that different geographic regions show varied body shape patterns and such regional body shape patters do not align with the national body shape patterns. Here are the key observations:

- For the Average height group, West, South and Central India exhibited similar body shape patterns, featuring the Bottom Hourglass and Trapezoid body shape as the as the predominant categories with marginal difference, followed by Hourglass and Rectangle body shapes. The North India and North-east India displayed similar body shape patterns with Bottom Hourglass and Hourglass as leading shape categories with marginal difference followed by Rectangle and Trapezoid body shapes.
- In the Short Normal height category, the body shape patterns of West, South and Central India showed consistent body shape patterns with Trapezoid shape being the most prevalent, followed by Rectangle, Hourglass, and Bottom hourglass shape categories. In the North India, Hourglass body shape took precedence, followed by Bottom hourglass and Rectangle with same percentage share of subjects followed by Trapezoid body shape. In the East India region, Hourglass body shape was followed by Rectangle, Bottom hourglass, and Trapezoid body shapes.
- In the Tall Normal height category, the body shape patterns the body shape patterns of West, South and Central India were observed similar with Bottom hourglass as the leading shape category, followed by Trapezoid, and Hourglass and Rectangle with marginal difference in the percentage share of subjects. North India and East India followed a similar body shape pattern like national body shape pattern, however in the East India region, there were marginal differences between Bottom hourglass and Hourglass, and Rectangle and Trapezoid body shape percentage coverage.
- The North-east region, the Hourglass body shape dominated, followed by Bottom hourglass, Rectangle and Trapezoid body shapes. In the height categories, Average height and Short Normal covered approximately 78% of the subjects. A substantial coverage of 36.56% in the Short Normal height maybe due to the relatively shorter stature of individuals in this region.

From a size chart development perspective, considering the wide range of height categories (with the central three height categories covering 94.35% of the subjects across all three body shape categories), it is anticipated that subjects from the North-east region can be accommodated within the same national size charts.

This ground-breaking research study focuses on the diverse spectrum of Indian female body forms, meticulously classifying them into four distinct body types based on crucial body measurements, including Bust girth, Waist girth, and Hip girth. This research serves as a robust foundation for the development of a comprehensive sizing system based on body shape, specially tailored for Indian females.

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