Analyzing Body Asymmetry Using 3D Scans and Machine Learning: Insights from Demographic Patterns and Dominant Hand Bias

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Abstract

Accurate body measurements underpin anthropometry, ergonomics, and apparel design, yet practitioners often assume bilateral symmetry and measure only one side. The rationale for this convention is limited. Therefore, this exploratory study aimed at quantifying body asymmetries at various body locations for improving the accuracy of measurement protocols, garment patterns, and ultimately product fit. The researchers analyzed 22 paired measurements derived from three-dimensional body scans of 245 adults. Statistical tests included independent samples t-tests, Pearson correlations, and chi-square tests. The researchers further applied a Support Vector Machine model to examine relationships between asymmetry, demographics, and hand dominance. The results reveal where asymmetries are negligible versus practically meaningful, highlight relationships among body dimensions, and identify demographic and dominance factors associated with asymmetry. Based on these findings, the researchers propose actionable recommendations for refining anthropometric procedures and patternmaking standards, encouraging when bilateral measurements are warranted and when single-side measures suffice.

Keywords: 3D body scanning, body asymmetry, machine learning

1. Introduction

In fields such as anthropometry, ergonomics, product design, and apparel design, taking accurate body measurements is a critical step when designing products to fit the human body. Systematically measuring the body ensures that products fit comfortably, move with the body, and are aesthetically appealing [1]-[3]. Standard practice typically assumes bilateral symmetry, with measurements taken from one side of the body, which is most often the right side, taken at specific body landmarks based on established protocols (e.g.,[3]-[6]). For example, the handbook for U.S. Army and Marine Corps anthropometric surveys state that measurements are “routinely taken” on the right side “unless such [asymmetrical] differences are obvious and would affect a measurement” (p. 5) [4]. They go on to clarify that “athletic, surgical trauma, or birth defects...make it appropriate to measure the left instead of the right body member...and the recorder will enter into the computer a comment indicating that the dimension was measured on the left side” (p. 5) [4]. This convention, while efficient, overlooks the possibility that natural asymmetries could affect measurement accuracy, pattern development, and ultimately product fit.

With the advent of three-dimensional (3D) body scanning, researchers can efficiently extract paired bilateral measurements, enabling precise investigation of asymmetry at both individual and population levels. 3D scanning also opens the door to integrating advanced computational methods such as machine learning (ML), which can detect subtle patterns and relationships beyond the reach of traditional statistical approaches [7]-[8]. Together, these tools allow for a reexamination of measurement protocols and offer new insights into digital product development workflows.

Given this, the purpose of this study was to examine body asymmetry systematically across multiple body sites using 3D body scan data and to explore its relationships with demographic variables. By combining traditional statistical analysis with ML techniques, we aimed to evaluate whether asymmetries are significant enough to warrant revisions in current measurement practices and to identify demographic factors, particularly hand dominance, sex, and age, that may influence asymmetry. Overall, this study not only provides academic scholars and industry professionals with a quantifiable understanding of body asymmetries at various body locations but also provides recommendations for improving the accuracy of measurement protocols and ultimately the success of products worn on the body.

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1.1. Body Asymmetry

Although many human bodies appear to have bilateral external symmetry along the median sagittal plane, humans are asymmetrical between the left and right sides of the body, even in healthy individuals with no evidence of any physical disability [9]-[11]. The slight deviations from perfect anatomical symmetry in bilateral physical traits (which are close to being normally distributed and do not show any directional tendencies) is what is known as fluctuating asymmetry, henceforth referred to as asymmetry for conciseness in this paper [11]-[12].

Past studies have shown that body asymmetry is more prevalent when comparing specific body segments, particularly when looking at asymmetrical differences on the transverse plane [13]-[14]. Limb asymmetry is more common and noticeable in upper body limbs than in lower limbs and this asymmetry increases with repeated activities of force that makes one side of the body stronger than the other [11], [13]. For instance, habitual physical activity, particularly the use of a dominant limb in athletes, results in more significant asymmetry [15]-[16]. In athletes, asymmetry may present in terms of lean mass of the favored limb as well as side-to-side differences in physical performance, or functional asymmetry [17].

Asymmetry based on sexual dimorphism is mildly present between males and females, particularly relating to upper limbs [11]. The lower body shows less sexual dimorphism in asymmetry [13]-[14]. Age has also been explored in the literature regarding body asymmetry. Researchers have observed that asymmetry decreases as children age [18], however, as humans move into advanced age, more body asymmetry can be reintroduced due to age-related posture and height changes, particularly when accompanying muscle decline, injury, or illness [19]-[20]. Additionally, anthropometric factors such as BMI have been noted to impact body asymmetry. Recent studies have noted an association between increasing BMI and increasing differences between left- and right-side measurements of shoulder height, side neck to front ground, and side neck to bust [21].

1.1.1. Hand Dominance

When studying body asymmetry, hand dominance is one of the most consistent, measurable, and biologically relevant sources of variation. It is frequently examined as a demographic variable to capture right–left body bias [22]. Research shows that approximately 90% of the population is right-handed [10], with females displaying a stronger right-side bias than males [14]. This dominance-related asymmetry is particularly relevant for apparel, as preferential use of one side of the body can influence muscle development, posture, and body measurements, all of which affect garment fit and patternmaking accuracy.

For all sexes, the human body naturally exhibits a crossed-symmetric pattern whereby the right side of the upper body is larger than the left side of the upper body and the lower left side of the body is larger than the right side of the lower body to remain balanced [14], [23], [24]. Research has also shown greater handgrip strength [25] and musculature [11], [13] on the dominant side. However, hand dominance does not always define side dominance—left-handed individuals may still have larger right upper bodies [14], [19]. Thus, hand dominance was of interest in this study as a potential demographic variable for deciding which side of the body should be measured.

1.2. 3D Body Scanning in Anthropometry

3D body scanning has transformed anthropometric data collection by enabling rapid, repeatable, and highly detailed capture of body dimensions. Compared to manual measurement methods, 3D scanning minimizes human error, improves consistency, and allows researchers to extract hundreds of measurements from a single dataset [26]-[28]. Importantly, 3D scans capture both sides of the body simultaneously, making it possible to analyze bilateral measurements and investigate body asymmetry at scales not feasible in traditional surveys.

The accuracy and reliability of commercial 3D scanning systems have been validated across multiple studies, demonstrating their applicability for both research and industry settings [29]. Beyond basic anthropometry, 3D scans have been leveraged for apparel applications such as developing body size systems, improving garment fit, and creating digital avatars for virtual garment design and simulation [30], [31]. As such, 3D body scanning not only provides methodological advantages for collecting bilateral data but also plays a central role in advancing digital product development workflows.

1.3. Understanding Body Asymmetry for Apparel Product Development

Understanding body asymmetries can be of great significance when designing products to fit the human body [32], The impact of body asymmetry on garment development is rarely discussed and most tools (e.g., dress forms, 3D avatars, instructional patternmaking texts) assume bilateral symmetry [30], [33]. Asymmetry typically enters the process only when working with live fit models, either because the model is inherently asymmetrical or due to poor posture in the measuring or 3D scanning process. To minimize this, [26] suggests that people stand in the International Organization for Standard (ISO) [27] defined “anthropometric position” with their head looking straight ahead, shoulders relaxed, arms at the sides, hands relaxed and facing forward, and feet with heels together and toes at a 60-degree angle. The person’s postures should be “as close to bilaterally symmetrical as possible (weight equally distributed on both feet, shoulders, and hips square and balanced)” (p. 154) [26]. This position provides the most accurate body measurement data and is reliable if this posture is used across multiple people. Similarly, [1], [6], [34] describe a “normal posture” that is when the head and neck are centered over the shoulders, the shoulders sit back and down, the chest is slightly lifted, the stomach is taut, and the arms hang naturally with elbows bent forward over a straight back.

Some textbook authors do note that there are specific body locations where asymmetry may arise that could affect patternmaking such as the curve of the upper back, rounded shoulders, shoulder slope, sway back, leg length, arm circumference, and pelvic tilt [1], [6], [34]-[36]. However, the authors rarely elaborate on how to account for this in products worn on the body. Only [35] in their text provides guidance about deciding what side of the body to measure. They [35] state that "It would be well to check the two sides of the figure, using the larger of the two measurements...if there is more than a quarter of an inch difference, it will be necessary to make separate patterns for the right and left sides” (p .1). Other than this, the measurement protocols in textbooks almost always illustrate taking body measurements on one-side of the body [1]-[2], [34].

Research on asymmetric pattern development shows that adaptive garment design for individuals with significant asymmetry, such as scoliosis or post-mastectomy patients, often relies on fully customized solutions using 3D body scanning and digital tools [37]-[40]. For example, [40] proposed a “mass-customization” system using common scoliotic curves for population-based blocks, contrasting with designs for populations with minor asymmetry. Many researchers have used 3D body scanning and digital patternmaking tools to create custom garments that fit to a specific participant’s asymmetry [37]-[39]. These studies take a markedly different approach in order to serve populations with notable asymmetries compared to designs for a population with less noticeable asymmetry. While asymmetrical patterns are “technically feasible... garments made from such patterns can exaggerate body asymmetries and may not be the best choice in some cases” (p. 115) [41]. Similarly [36] cautioned, that “overfitting” accentuates unevenness (p. 41), suggesting garments should appear “as symmetrical as possible” (p. 115). Overall, the prevailing goal for patternmaking is to develop symmetric design for “normal” asymmetry, though it remains unclear if body data supports this practice.

1.4. Machine Learning

Machine learning (ML) has become a valuable tool in anthropometric research for handling missing data, predicting body dimensions, and improving measurement accuracy. As shown in [42], machine learning (ML) can effectively predict difficult-to-extract 3D body scan measurements, enhancing dataset reliability. Similarly, [7] demonstrated ML’s ability to predict garment-related dimensions, while [43] highlighted its advantages for imputing missing stature data. Other studies have applied ML to link body shape with physiological traits [8] and to predict demographics from body measurements [44]-[45]. Collectively, these works illustrate that ML can improve dataset completeness and reliability, ensuring that body measurement prediction is both accurate and practical for apparel product development [7], [43].

1.5. Research Questions

Given the study’s aim and existing literature, no research has explicitly examined body asymmetry in relation to demographics for wearable product development. Considering the potential usefulness of ML in validating and analyzing bilateral measurements extracted from 3D body scans, this study addressed the following Research Questions (RQs):

RQ1: Within participants, do left- and right-side body measurements differ at any measured body sites? The null hypothesis of RQ1 is that there is no statistically significant difference between the left- and right-side body measurements at any body site.

RQ2: Within participants, are there any significant correlations among pairs of right–left body measurement asymmetries across the body? The null hypothesis of RQ2 is that there is no correlation among the body asymmetries at different body sites.

RQ3: Is the magnitude and/or direction of body asymmetry associated with participant demographics (age, sex,) and hand dominance? The null hypotheses of RQ3 are that there is no association between body asymmetries and the participants' demographics or hand dominance.

2. Methods

2.1. Data Collection

Prior to participant recruitment, approval was obtained from the Institutional Review Board (IRB) of the host institution. Participants were recruited from a midwestern U.S. city and ranged in age from six to 75 years. This broad age range was intentionally selected for this exploratory study to capture patterns of body asymmetry across the lifespan.

At the research site, each participant was assigned a unique participation ID once informed consent was secured. This identifier linked their demographic survey responses, manually recorded body heights and weights, and 3D body scans. Data collection began with a digital survey that gathered demographic details including age, sex, and dominant hand. For minor participants unable to complete the survey independently, parents or guardians assisted by answering on their behalf.

Following the survey, participants changed into standardized scanning attire: a sports bra (without padding) and underwear for females, and boxer shorts for males. Researchers then measured each participant's standing height and weight manually before conducting a 3D body scan using the A-frame posture [26]. Each scan was reviewed immediately to confirm correct posture; if posture was unsatisfactory, the scan was repeated until an acceptable image was captured.

2.2. Data Processing

Body measurements were obtained from the 3D body scans, either through the software's automated extraction functions or through manual procedures when needed [46]. These values were exported into an Excel spreadsheet and combined with each participant's standing height, weight, and calculated body mass index (BMI), creating a dataset, *Original Body Measurements matrix.* Later, the researchers exported demographic and dominant hand information from the surveys, creating a dataset, *Original Demographics and Dominant Hands Information matrix.* These two matrices were combined based on the assigned participants' ID. This combined matrix was then reviewed for completeness. Participants missing over half of their body measurements, as well as those with surveys lacking demographic or dominant-hand information, were excluded from the analysis. Following this screening, the refined dataset was carried forward for analysis.

Two critical processing steps are detailed in the subsequent sections: (1) the identification and extraction of 22 paired body measurements selected for this study, and (2) the generation of measurement and asymmetry matrices to support later data analyses.

2.2.1. Selection and Extraction of Key Body Measurements

For this study, a total of 22 paired body measurements identified as essential for apparel patternmaking (based on prior literature) were obtained from the 3D body scans (Table 1). A "pair" was defined as a measurement collected in the same manner on both the right and left sides of the scanned body. Of these, 14 pairs corresponded to upper-body dimensions, while the remaining eight pairs reflected lower-body dimensions (**Table 1**).

Among the 22 pairs, 16 were initially extracted automatically using the measurement function within AnthroScan software [46]. These automated outputs were then examined for completeness, accuracy, and potential outliers. In instances where usable scans still showed missing values, the researchers first employed machine learning (ML) methods to predict the missing measurements and then validated these predictions by manually re-measuring the corresponding scans within AnthroScan. The ML prediction results have been reported in a publication [42], thus not detailed in this paper. This dualstep verification process also allowed the team to resolve questionable data points flagged as errors or outliers.

The remaining six paired measurements – Bust, Across Back, Front Full Length, Shoulder Slope, Waist, and Hip (indicated in bold in Table 1) – were obtained manually, as AnthroScan does not provide automated extraction for these specific dimensions on both body sides.

Table 1: Names and Definitions of Body Measurements

	NO.	*Measurement Name*
Upper Body Measurements	1	**Bust**
	2	**Across Back**
	3	**Front Full Length**
	4	Back Full Length
	5	Bust to High Point Shoulder (HPS) Distance
	6	Shoulder Width
	7	**Shoulder Slope**
	8	**Waist**
	9	Mid-Armhole to Waist Length
	10	Arm Length
	11	Elbow Length
	12	Biceps Circumference
	13	Elbow Circumference
	14	Wrist Circumference
Lower Body Measurements	15	Waist to hip
	16	**Hip**
	17	Outseam Length
	18	Inseam Length
	19	Upper Thigh Circumference
	20	Knee Circumference
	21	Calf Circumference
	22	Ankle Circumference

Note. Manually extracted measurements are shown in bold font. Please reference [42] for definitions for each of these measurement locations.

Calculating the asymmetry between the right- and left-side body measurements. The researchers adopted a three-step process to investigate the relationships between the asymmetries of any two body measurements. First, the researchers calculated the asymmetry between the right- and left-side of each body measurement in Python based on the Original Body Measurements matrix using the equation below:

$$Asymmetry = \frac{(\text{Right−side Measurement} - \text{Left−side Measurement})}{\text{Left−side Measurement}} \qquad (1)$$

Based on Equation (1), a matrix of right- and left-side Body Asymmetry, namely *BA matrix*, was obtained, where the rows and the columns represent the participants and the measurement asymmetry, respectively. Then, each element in the *BA matrix* takes a continuous fractional value centered around 0. This matrix was further converted into a new Body Asymmetry Categorical matrix called *BAC matrix*, consisting of binary values {0,1}. The positive elements in the *BA* matrix, meaning a right-side measurement was larger than the left-side counterpart, were transformed to 1 in the *BAC* matrix. Conversely, the negative elements in the *BA* matrix were converted to 0, indicating a left-side measurement was larger than the right-side counterpart. Lastly, the researchers looped over all combinations of any two measurements (i.e., any two columns in the *BAC* matrix) and came up with a total number of 242 (22×22 ÷2=242) 2x2 frequency matrices.

This conversion process is described as follows by using the Bust and Waist measurements as an example (**Table 2**). The researchers first calculated the number of participants whose Waist and Bust values in the *BAC* matrix were both equal to 1. The frequency number (n = 48), as highlighted in bold font in the table, indicated the number of participants who had both larger right Bust and Waist. The same process was repeated for the other three Bust-Waist conditions to form a 2×2 matrix representing the Bust-Waist relationship.

Table 2: Example of the Conversion of BAC matrix to represent the Bust-Waist relationship

Conditions	Right-side Bust Larger (1)	Left-side Bust Larger (0)
Right-side Waist Larger (1)	48	37
Left-side Waist Larger (0)	62	98

In the *Original Demographics and Dominant Hands Information matrix*, sex and dominant hands information were categorical variables. But ages were originally recorded as continuous numerical variables in this matrix. Therefore, the researchers recorded age into seven eight-year categories starting at 6 years; participants older than 62 were placed in Group 7. This resulted in a normal distribution of participants across age categories. Then the researchers updated the original matrix accordingly, yielding a revised *Categorical Demographics and Dominant Hands matrix*.

2.3 Data Analysis

2.3.1. Independent Sample T-test

In independent samples t-test was carried out to check if there were any significant differences between the Right- and Left-side body measurements (RQ1). The assumption of employing this statistical method was that the Right- and Left-side body measurements were independent, and this assumption was met in this study. The null hypothesis of this test in this study was that the Right- and Left-side body measurements were identical in the average (expected) values. For instance, if the p-value of a t-test result was smaller than 0.05, then the null hypothesis could be rejected, which means the right-side measurement is significantly different from the left-side measurement.

2.3.2. Correlation Tests

Both Pearson’s correlation tests and Chi-square tests were used to explore whether there were any associations among the 22 paired body measurements used in this study (RQ2). Specifically, a Pearson’s correlation test was used to investigate whether there were any correlations between two continuous numerical variables, such as body measurements, in the population. The null hypothesis of this test was that there was no correlation between the two variables. The range of the Pearson’s correlation coefficient was from -1 to +1. Positive coefficient values indicated a direct relationship between the variables whereby if one variable increased or decreased, another variable has the same tendency to increase or decrease. On the other hand, a negative coefficient indicated an inverse relationship where if one variable increased the other variable will decrease and vice versa. An absolute value between 0.5 and 0.79 indicated moderate correlation while an absolute value no less than 0.8 indicates strong correlation [47].

In this study, Pearson’s correlation tests were used to test the *Original Body Measurements* matrix and *BA* matrices. Besides, the Chi-square tests were used to identify if the statistical hypothesis between two categorical variables was valid by comparing the expected frequencies with the observed frequencies in different categories. Thus, the Chi-square test was used for analyzing categorical variables in the *BAC matrix* to explore the correlations among body asymmetries. Take the same example from **Table 2**, once the 2 × 2 matrix was formed, the researchers applied Chi-square tests to calculate p-values, which indicated if Bust and Waist were independent or dependent. The p-value of this example was 0.011, which was much smaller than 0.05, therefore Bust and Waist were dependent at 95% confidence level. Following the same process, Chi-Square tests were used to test the relationships between the asymmetries of any two body measurements.

Chi-square tests were also performed to investigate the correlations among body asymmetries, demographics, and dominant hands based on the *BAC matrix and the* revised *Categorical Demographics and Dominant Hands matrix*. The null hypothesis of the Chi-Square tests was that there was no correlation among demographic variables.

2.3.3. Machine Learning Tests

In cases of categorical values such as participants' demographic information and dominant hands, a ML method, Support Vector Machine (SVM), was utilized to predict the categorical values based on their body measurements. SVM can predict discrete values (e.g., sex, dominant hand) instead of continuous ones (e.g., different body measurements). In this process, the SVM model used known body measurements as training data for predicting categorical information (demographics and dominant hands). The motivation behind this experiment was that, if categorical values could be well predicted by using ML methods, it is conceivable that there exist hidden patterns/relationships between the participants' categorical information (demographics and dominant hands) and their body measurements. Those patterns/relationships, even though implicit, could be discovered and leveraged by the state-of-the-art ML methods, leading to many applications such as customer analysis.

3. Results and Discussions

3.1. Body Asymmetry (RQ1)

Independent Sample T-test results supported the null hypothesis of RQ1, with no p-values below 0.05. This aligns with expectations, as human bodies typically show fluctuating asymmetry—normally distributed variation without directional bias [11]-[12]. If there were significant differences between the right- and left-side body measurements, the foundational practices of pattern drafting, which instructs practitioners to draft patterns for one side of a body and duplicate it for the other side of the body, may have been different.

The smallest p-values occurred for Wrist Circumference (0.09) and Across Back (0.14), with Shoulder Width (0.22), Shoulder Slope (0.27), and Ankle Circumference (0.24) also relatively small. These results suggest possible localized asymmetry. Consistently, **Figure 1** shows that these five measures had the largest absolute median asymmetries among the 22 pairs examined. This skew indicates greater directional asymmetry at these five locations. Thus, it is reasonable to recommend that practitioners use the larger measurements between the two sides for pattern drafting for Across Back, Shoulder Width, Wrist Circumference, and Ankle circumference. But use the smaller measurements between the two sides for Shoulder Slope, which is the angle between the direction of the shoulder and horizontal level. The smaller a Shoulder Slope is, the higher a shoulder is. In cases where there is a significant difference between Right- and Left-side shoulder slopes, using a shoulder pad to bring the lower shoulder up to the height of the higher shoulder to balance asymmetric shoulder slope [34].

Besides, this study found a general trend of more body asymmetry in the upper body measurements than in the lower body measurements, which supports the literature [11], [13]. Shoulder Slope and Shoulder Width show the greatest asymmetry (largest bars; medians farthest from zero), whereas Inseam Length and Outseam Length show the least.

Notably, participants in this study tended to have larger left-side upper body measurements (8 of 14 pairs) and larger right-side lower body measurements (5 of 8 pairs). This contrasts with prior research documenting the opposite cross-symmetric pattern – right-side dominance in the upper body and left-side dominance in the lower body [14], [23]. Given the racial diversity of our sample compared with earlier, more homogenous studies, these differences may reflect sample variation. Larger samples are needed to investigate these potential population-level differences.

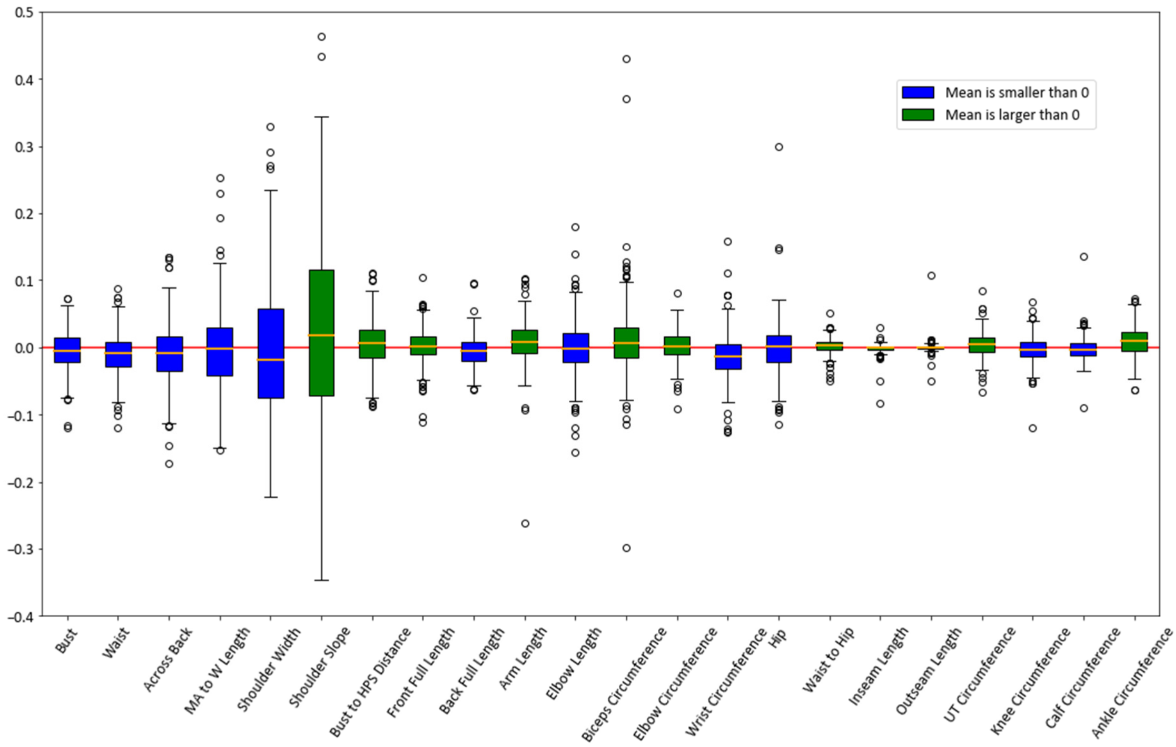

Fig. 1: Right- and Left-Side Body Asymmetries of Twenty-Two Pairs of Body Measurements

Note. MA to W Length indicates Mid-Armhole to Waist Length; UT Circumference indicates Upper Thigh Circumference. The height of the boxplot represents the Inter Quartile Range (IQR), where the bottom of the box is the lower 25% (Q1) and the top is upper 75% (Q3) of the data. The lower fence and upper fence represent the minimum and maximum range which are Q1-1.5×IQR and Q3 + 1.5 × IQR, respectively. The orange line represents the median, and the color of the bars indicates whether the mean of a pair of body measurements is larger than zero or not. A green bar indicates on average the right measurement is larger than the left measurements while a blue bar indicates the opposite. Lastly, the circles represent outliers.

3.2. Correlations among Body Asymmetries (RQ2)

The null hypothesis of RQ2 was rejected by Pearson's tests and Chi-square results.

3.2.1. Pearson's Correlations

It is worth noting first that in the Pearson's correlation tests of this study, the differences of the p-values between the two sides of a body measurement were negligibly small. Thus, for presentation simplicity, the two sides measurements are discussed together unless specifically noted, and Pearson's values are presented as an average in parentheses. For example, the Bust–Waist correlation (0.81) averaged across the four left/right pairings (0.82, 0.81, 0.80, 0.80).

Using averaged p-values, strong positive correlations included Waist with Bust (0.81) and Hip (0.85), and Hip with Upper Thigh (0.87) and Knee (0.83). Moderate correlations included Bust–Hip (0.71), Hip–Calf (0.79), and the unexpected Bust–Elbow (0.79). On the other hand, the correlations between the other body measurements were dispersed. Shoulder Width, Shoulder Slope, and Waist to Hip measurements were not correlated with any other body measurements. Thus, the researchers recommend taking these three measurements directly from a live model or scan for patternmaking purposes, instead of calculating them based on formulas or estimating them on experience.

3.2.1. Chi-square tests results

Chi-square tests further revealed correlations between asymmetries (**Figure 2**). Outseam Length asymmetry correlated with seven other measures (Bust, Bust to HPS Distance, Front Full Length, Back Full Length, Elbow Length, Wrist Circumference, Hip, Waist to Hip, and Knee Circumference), the broadest set of associations. This likely reflects postural asymmetry, where uneven waist or shoulder levels create cascading measurement differences [6], [34]. For practice, we recommend recording both sides of Outseam Length in 3D scans, correcting posture and rescanning if discrepancies appear, or extracting bilateral values when necessary.

Bust, Waist, and Hip asymmetries were strongly intercorrelated, reinforcing their role as indicators of broader asymmetry. Shoulder Width and Shoulder Slope each correlated with Across Back but not with each other. Front Full Length correlated with Bust to HPS Distance and Mid-Armhole to Waist Length, but not with Back Full Length, suggesting that asymmetries in front versus back body lengths may occur independently.

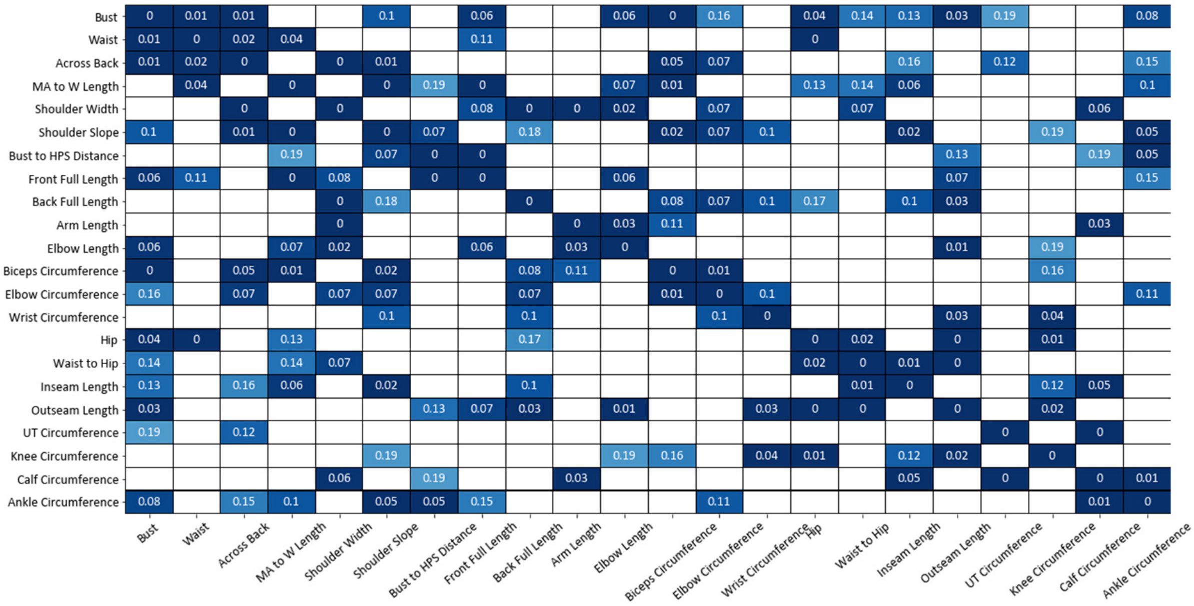

Fig. 2: Chi-square Test p-values in Heatmap

Note. MA to W Length indicates Mid-Armhole to Waist Length; UT Circumference indicates Upper Thigh Circumference. Only p values smaller than 0.2 were presented in this heatmap. The smaller a p value is, the darker the color of a blank is.

3.3. Correlations among Body Asymmetries and Demographics/Dominant Hands (RQ3)

The null hypotheses of RQ3 were partially rejected, as Chi-square tests revealed correlations between body asymmetries and demographic variables or dominant hand. Specifically, Chi-square tests showed significant associations between: 1) between sex and the asymmetry at Shoulder Width ($p=0.04$), 2) between age and the asymmetry at Bust to HPS Distance ($p=0.05$), and 3) between dominant hands and the asymmetry at Elbow Circumference ($p=0.04$). Similarly, SVM showed potential in predicting demographics such as age and sex and dominant Hands based on body measurements (**Table 4**), which implies some unknow patterns/relationships between body measurements and demographics and hand dominances.

Table 4:SVM Prediction Results

Groups of measurements	Sex prediction rate	Age prediction rate (eight-year intervals)	Dominant hand prediction rate
Whole Body Measurements	100%	75.6%	80%
Upper Body Measurements	86.50%	28%	80%
Lower Body Measurements	81.10%	44%	64%

Specifically, as shown in the Table 2, SVM proved that sex could be predicted at 100% accuracy level based on Whole Body Measurements, which included all twenty-two pairs of measurements. If only the Upper Body Measurements or the Lower Body Measurements were used for predicting sex, the prediction accuracy was lowered to 86.5% and 81.1% respectively, but still acceptable prediction levels.

Similar results were found for predicting hand dominances. SVM could predict hand dominance by using either the complete group of Whole Body Measurements at a prediction rate of 80%, and/or by using only the Upper Body Measurements (80% prediction rate), but prediction rate lowered to 64% if only using the Lower Body Measurements. These findings suggest that upper body asymmetries contribute more strongly than lower body asymmetries to predicting both sex and hand dominance, consistent with prior literature [13], [14] and with trends observed in this sample.

Finally, age could also be predicted by using the entire group of Whole Body Measurements at the accuracy level of 75.6% if ages were categorized in eight-year increments. The prediction accuracy decreased when the age categories decreased. For example, our tests showed that prediction accuracy was 72% when ages were grouped in five-year increments and dropped to 56% with two-year increments, indicating that the SVM model performs reliably when age categories span at least five years.

4. Conclusion

Measurement protocols and product design often assume bilateral symmetry, yet even small left–right differences can affect fit, comfort, and performance. A clear, data-driven account of where asymmetry occurs and which demographic factors relate to it is therefore needed, especially now that 3D body scans allow precise bilateral assessment. Thus, this study systematically examined bilateral body asymmetries using 22 paired measurements from 3D body scans of 245 participants. For RQ1, the analyses confirmed that while most left–right differences were small and aligned with expectations of fluctuating asymmetry, localized asymmetries, particularly in the upper body at sites such as Shoulder Width, Shoulder Slope, Wrist Circumference, and Across Back, were more pronounced and may influence apparel fit and patternmaking practices. These body locations may warrant closer attention in patternmaking. For RQ2, correlation analyses further highlighted that certain asymmetries are interdependent (such as Waist, Hip, and Thigh), which indicates shared postural or structural factors that affect multiple measurements. On the other hand, other body measurements like Shoulder Width and Shoulder Slope were independent, underscoring the need to record them directly. For RQ3, asymmetry showed associations with sex, age, and hand dominance. ML analyses demonstrated the potential to predict demographic characteristics, including sex, hand dominance, and age categories, from bilateral body data with high levels of accuracy. Notably, upper-body measures were more informative than lower-body measures for predicting sex and dominance, underscoring their role in understanding functional asymmetry. These findings suggest that 3D body scanning combined with ML methods can enrich both anthropometric research and apparel product development by identifying when bilateral data are necessary and by leveraging predictive models to handle incomplete datasets.

4.1. Implications and contributions

This research contributes to the growing body of evidence that natural asymmetries should be considered in design and measurement protocol to ensure garment fit. For practitioners in apparel and product development, the results provide actionable guidance: when asymmetries are minimal, single-side measurements remain sufficient; when localized asymmetries are present, using the larger or smaller side strategically (depending on the measure) can improve fit outcomes. For researchers, the study illustrates how 3D body scanning paired with ML can refine anthropometric databases, improve accuracy, and support digital product workflows.

4.2. Limitations and future work

In this study, findings are limited by the sample size and demographic distribution. Differences from prior research may reflect population diversity, but larger and more stratified datasets are needed to confirm these trends. Future work should expand to continue this analysis with larger databases and data collected over time to observe how asymmetries evolve with age, activity, or health status, and to applied studies that directly test how accounting for asymmetry influences garment fit and wearer comfort.

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