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Assessing the Accuracy of Body Measurements through Regression Analysis

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***Abstract*—The digitalization of individual garment pattern construction presents challenges in accurately obtaining body measurements and constructing patterns tailored to specific individuals. This paper addresses the technological and conceptual aspects of transitioning from traditional, in-person tailoring to remote, digital pattern creation. It explores the need for algorithms that describe pattern construction operations in a computationally executable manner and the reliance on self-measurements by clients or their trusted individuals. The study focuses on evaluating the reliability of self-measurements and the potential errors introduced in the pattern construction process. The paper proposes the use of regression analysis to identify suspicious or erroneous measurement sets and assess their impact on the resulting garment shape. The study investigates the hypotheses regarding the identification of incorrect measurements through regression analysis and the application of publicly available artificial intelligence solutions. The findings contribute to enhancing the precision and reliability of digital individual garment pattern construction, facilitating remote creation and production processes.**

***Index Terms*—Quality control of graphical images, regression testing, regression analysis**

I. Introduction

THE digitalization of the individual garment pattern construction process presents technological and conceptual challenges. It requires the identification of algorithms that can describe the basic construction and modelling operations of patterns in a computationally executable manner. Additionally, significant changes need to be made to the garment pattern creation process and the techniques employed. Unlike in the widely used practice of pattern construction based on standard body measurements in the garment industry, individual garment construction is tailored to each person's specific body measurements. Traditionally, this process involves:

(1) taking body measurements performed by a professional tailor,
(2) constructing individual patterns for specific garment models,
(3) cutting the garment from fabric,
(4) fitting the garment through one or multiple iterations (including adjustments),
(5) finalizing the garment.

This process has been employed in tailoring for centuries but relies on close collaboration between the client and tailor, requiring them to be present in the same space and time.

With the advancement of digital technologies and the globalization of manufacturing, remote creation of individual products becomes increasingly relevant. In the field of garment sewing, this involves two aspects: (a) individual (perfect fit) garment construction in a digital environment and (b) individual garment production in specialized factories based on digital patterns. By transitioning the described process to a digital environment, pattern creation steps (Steps 1, 2, and 4) should be facilitated digitally, while the physical garment manufacturing steps (Steps 3 and 5) can be outsourced to service providers. The in-person meetings between the client and seamstress no longer take place, and the iterative refinement of the product is no longer possible. As a result, there are heightened requirements for both input data and precision in pattern construction.

The number of prepared patterns is enormous (over 175 different clothing models for more than 1000 clients), and their inspection requires significant resources. Automated pattern inspection is proposed, where the area and perimeter of each pattern element are calculated, which are closely related. In the research, the hypothesis is being confirmed that the ratio of perimeter to area is "invariant". This allows, firstly, to control the quality of newly entered data by utilizing previously accumulated models and customer indicators. Secondly, the ratio's numerical value can be used in

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regression testing to ensure that changes in programs do not cause significant alterations in already accepted patterns.

This paper is structured as follows: problem statement (Section 2), related research (Section 3), experimental design and data set (Section 4), analysis of experiment (Section 5) and conclusion (Section 6).

II. PROBLEM STATEMENT

One of the significant challenges is evaluating the reliability of body measurements obtained in the digital environment according to the specific needs of the pattern construction method they use. In the digital environment, measurements must either be determined automatically (e.g., from photographs or using 3D scanners) or rely on self-measurements by the client (usually non-professionals). Automated body measurement determination has been extensively studied, but unfortunately, the results are unreliable in practice. Various factors contribute to this, such as the quality of the photographs, imprecise posing, the clothing worn during photography, limitations of image recognition algorithms, restrictions on the transmission of personal data, and others. This topic merits separate publications and will not be further discussed here.

The focus of this study is on measurements taken by the clients themselves or their trusted individuals. Several problems can be observed:

(1) different pattern construction methods require measurements to be taken in various ways,

(2) individuals without sewing experience may struggle to measure the body accurately, resulting in measurements that are too tight or loose, taken in incorrect locations, and so on,

(3) individuals cannot measure certain body dimensions themselves, thus relying on assistance from others, leading to stress and additional errors.

As a result, incorrect measurements (not corresponding to the specific body) may be obtained, resulting in garments that do not fit the individual, even if the pattern construction algorithm is flawless.

If suspicious sets of measurements or measurement's sets likely to have resulted from erroneous actions could be identified in an automated manner, it would be possible to reduce the risk of producing non-fitting (mismatched) patterns. One of the methods for identifying problematic measurement sets could involve establishing mandatory relationships between measurement definitions and the activation of control mechanisms at the time of measurement registration. Utilizing these relationships could filter out blatant errors, such as an impossible scenario where a woman's bust circumference is smaller than the under bust circumference. However, this approach does not aid in statistically identifying combinations of measurements that are highly unlikely due to the significant variability in human bodies. It is nearly impossible to find universal measurement relationships based solely on experience.

In this study, measurement relationships were analyzed using regression analysis and the capabilities of artificial intelligence on a collection of historically accumulated sets of body measurements. The following hypotheses were tested:

(Q1) Incorrectly entered individual measurements can be identified using regression analysis.

(Q2) Patterns constructed based on incorrectly entered measurements resulting in unusual garment shapes can be identified using regression analysis.

(Q3) Incorrectly entered individual measurements can be identified using publicly available artificial intelligence solutions.

III. RELATED RESEARCH

Accurate and reliable body measurement recognition is of paramount importance in diverse fields such as fashion, healthcare, ergonomics, and virtual reality. The ability to precisely capture and analyse body measurements plays a crucial role in personalized product design, fit optimization, and user experience enhancement. In recent years, significant advancements have been made in the field of body measurement recognition, leveraging cutting-edge technologies.

Traditional methods of obtaining body measurements often rely on manual measurement techniques performed by trained professionals. However, the advent of digital technologies has paved the way for alternative approaches that can enhance measurement accuracy, efficiency, and accessibility. Two prominent technological domains that have significantly impacted body measurement recognition are 3D scanning and image recognition.

A. Research on Image Recognition

There are several papers providing insights into the state-of-the-art techniques, algorithms, and challenges in the field of body measurement recognition from images [1] is a survey providing an overview of various techniques and approaches used for human body measurement estimation from images. [2] focuses on the application of image processing techniques for human body measurement and virtual try-on of clothing; it presents algorithms and methods for extracting body measurements accurately from images and simulating the try-on experience virtually.

[3] provides an overview of image processing techniques used for automatic human body measurement. It discusses various image analysis methods, feature extraction algorithms, and measurement estimation techniques employed in this field.

[4] explores the application of deep learning techniques for estimating human body measurements from images. It discusses the use of convolutional neural networks (CNNs) and other deep learning architectures to achieve accurate and robust measurement estimation.

[5] paper focuses on body measurement extraction and analysis techniques for apparel online retailing. It discusses the use of computer vision and image processing algorithms

to extract accurate body measurements from customer images and analyse them for personalized clothing recommendations.

B. Anthropometry and 3D Scanning

Anthropometry, the measurement of human body dimensions, plays a crucial role in diverse fields such as ergonomics, clothing design, healthcare, and biometrics. With advancements in technology, 3D body scanning has emerged as a powerful tool for capturing precise body measurements, offering a more comprehensive and accurate alternative to traditional measurement techniques. The "IEEE IC 3DBP" dataset [6] provides researchers with a valuable resource for comparative analysis and benchmarking of different anthropometric methods in 3D body scanning.

[7] is a study focusing on comparing different anthropometric measurement techniques based on 3D body scanning and [8], [9] explores the development of a population-specific anthropometric model based on 3D body scanning data. The findings highlight the importance of considering population-specific variations in anthropometric analysis for applications such as clothing design, ergonomics, and product development.

[10] investigates the application of machine learning algorithms in anthropometric analysis using 3D body scans. The research explores the use of machine learning models for automated feature extraction, body segmentation, and prediction of anthropometric measurements. The findings demonstrate the potential of machine learning techniques in improving the efficiency and accuracy of anthropometric analysis in large-scale datasets.

[11], [12], [13] - conduct a comparative analysis of different 3D body scanning technologies and sensor technologies". The study evaluates the performance, resolution, and accuracy of various scanning techniques, such as structured light scanning, laser scanning, and depth sensing.

[14], [15] aims to validate the accuracy and reliability of 3D body scanning measurements by comparing them with traditional anthropometric methods. The research investigates the agreement between measurements obtained from 3D body scans and manual measurements using clippers and tape measures. The findings contribute to establishing the validity and practicality of 3D body scanning as a reliable measurement technique.

IV. Experimental Design and Data Set

Within the project, more than 175 clothing pattern models have been developed. To ensure the precise fit of the intended clothing model for the customer, appropriate measurements of the customer's body are necessary. A total of 53 different body measurements (part of them see Table 1) have been identified for the developed clothing models, which enable the preparation of various clothing patterns (pants, skirts, jackets, dresses, coats, tops, etc.).

Table 1.
List of used measurements

Code	Name
Ag	Body height
Gkra	Main bust circumference
Ga1	Hip circumference
Ga2	Hip-thigh circumference
Csa	Thigh circumference
Pca	Under knee circumference
PlslL	Shoulder slope Right
Clg	Knee level
PlslKr	Shoulder slope Left
Bg	Length of trousers and maxi skirt
GdS	Hip diameter – side view
PrB	Trousers and skirt balance - Front
GdPr	Hip diameter – front view
MB	Trousers and skirt balance - Back
Ka	Neck circumference
Cstl	Groin arc
Etc.	53 in total

Each specific clothing model requires a certain set of measurements. For example, pants do not require measurements such as bust or neck circumference, but they do require hip and thigh measurements, among others. Not all 53 measurements are necessary for every clothing item. Each clothing pattern consists of multiple pieces.

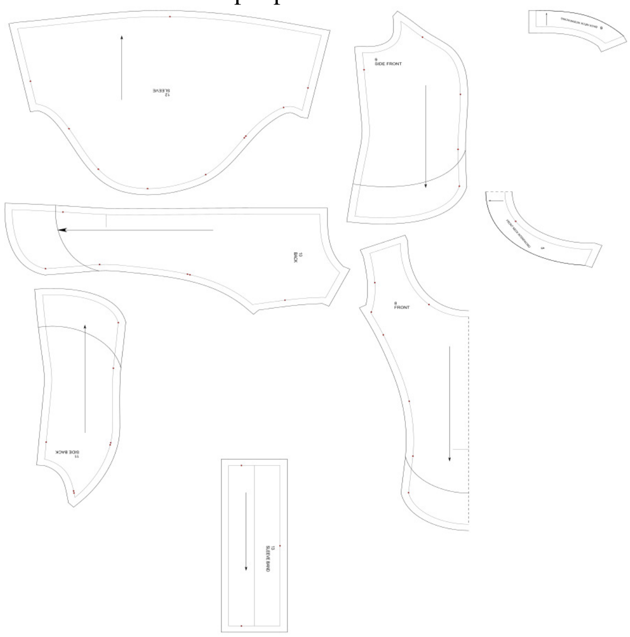

Fig. 1. Pieces of the Misses' and Women's Tops pattern

Within the scope of the study, the Misses' and Women's Tops clothing pattern was chosen, which consists of 8 pieces (see Figure 1) and utilizes 25 measurements: Ag, Gkra, PlslL, PlslKr, Ka, Plg, Trg, Pln, Ra1, Papla, Zkra, Va, Mg, Mpl, Prpl, Krg, Prgl, Krau, Zkrl, Ga1, Ga2, Sa, Elk, Pg, Ra2.

To ensure the accuracy of clothing fit or identify potential discrepancies, a comprehensive set of 274 customer measurements was used. In the following two tables (see Table 2), an example of measurements for 7 different customers is provided. The measurement GID is not included in the tables as it was not indicated for the sample customers and was not used in the data analysis of the study.

Table 1.

Example 1: Measurements of seven users (1)

	Aiga	Airita	Brandi	DANA	FT_Olivia	DINA	FT_DJ
Ag	174	173	150	170	175	164	164
ApmE	139	140		113		117	
ApmS	127	133		107		102.5	
Bg	104.5	103.5	91.44	103	99.6	102.5	104

The empty cells in Table 2 indicate that a specific measurement is not assigned to a particular customer.

To evaluate the accuracy or discrepancies in the patterns, the article suggests comparing customer measurements with two pattern parameters: the length of the pattern contour line (perimeter) and the area in pixels. An example of calculating the line length and area is shown in the following figure (Fig. 2)

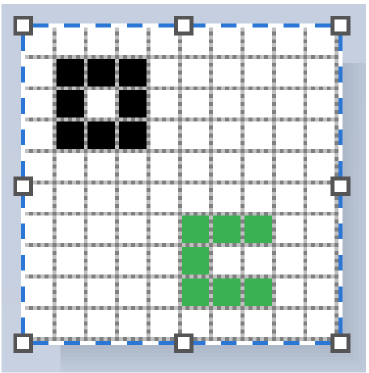

Fig. 2. Example of perimeter and area calculation

In the image (Fig. 2), two examples of pattern components are visible. The black component has an area of 9 pixels and a perimeter of 12 pixels, while the green component has an area of 7 pixels and a perimeter of 16 pixels. Using the aforementioned algorithm for calculating the area and perimeter of pattern components, the area and perimeter were calculated for the eight components of the mentioned pattern for a total of 274 customers in the study. Table 4 provides the calculated areas and perimeters in pixels for the eight pattern components for three selected customers.

Table 2.

Area and perimeter in pixels of the pattern pieces

Customer		Piece 1	Piece 2	Piece 3	Piece 4	Piece 5	Piece 6	Piece 7	Piece 8
Aiga	Area (px)	1129874	1392457	1781631	1065098	2934855	805799	218969	151424
	Perimeter (px)	17630	5906	7468	5516	8430	4180	3172	2268
Airita	Area (px)	1156991	1497732	1700162	1054941	2838373	821524	208735	155045
	Perimeter (px)	17628	6036	7132	5422	8402	4246	3058	2324
Brandi	Area (px)	738110	929129	1344574	784675	2038087	714123	194394	158019
	Perimeter (px)	15418	4962	6596	4648	7446	3824	2882	2312

V. ANALYSIS

A. *Regression Analysis of Pattern Data*

The examined dataset includes multiple measurements, some of which are correlated with each other. It is evident that the lengths of a person's right and left arms or legs are correlated. This provides an opportunity to calculate potential correlations and identify outliers from the available data. The dataset consists of measurements for 274 individuals, but all measurements are available for 100 individuals.

Correlation analysis was performed for these individuals, and Pearson correlation was calculated for each pair of measurements. The correlation was above 0.9 for 55 pairs of measurements. Scatterplots were created for these pairs, showing both the mutual dependencies of the measurements and specific outliers.

For example, in Fig. 1, there is a strong correlation between parameters Csa and Pca, but there is an outlier with coordinates (61, 49). In Fig. 2, it can be observed that there is a pronounced correlation between Ga1 and Ga2, but there is an outlier with coordinates (88.5, 70). Such outliers serve as a serious warning that there may be errors in the entered data. Though it cannot be stated with absolute certainty, it can serve as a basis for the system to verify the entered data during data entry to ensure their accuracy.

For each piece, the Pearson correlation was calculated between the piece's area and its perimeter. Although the area should ideally be quadratically dependent on the linear dimensions of the piece, all pieces of the examined model showed a high level of linear correlation between the area and perimeter of the piece. This was most pronounced for piece 5 (Fig. 5). On the other hand, scatterplot for Piece 3 Perimeter vs Area (Fig. 6) demonstrates some nonlinearity. When examining the scatterplot of each piece, where one dimension represents the piece's area and the other dimension represents the piece's perimeter, outliers were discovered in several measurements of pieces (piece 1, piece 4) (Fig. 7, Fig. 8). The outlier for piece 1 with coordinates (5002, 678011) belongs to the same individual who had a suspicious ratio of measurements Ga1 and Ga2. It is possible that the atypical measurements resulted in the creation of a piece with an atypical shape. On the other hand, the outlier of piece 4 with coordinates (10270, 2703263) belongs to piece for different individual (MF-Laura Š), that could show the problem with generated piece.

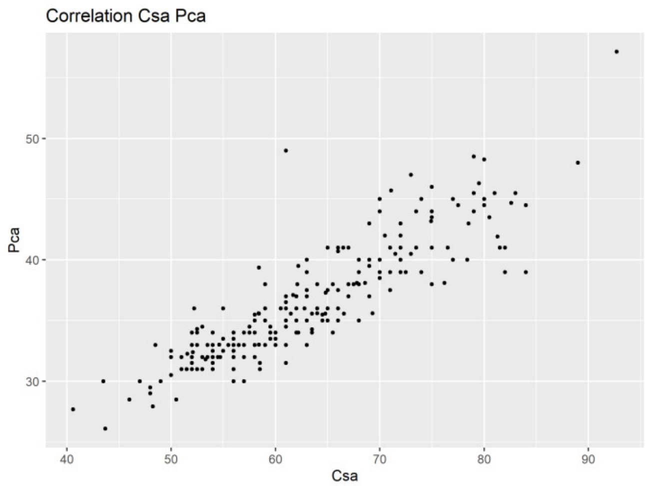

Fig. 3. Correlation Csa === Pca

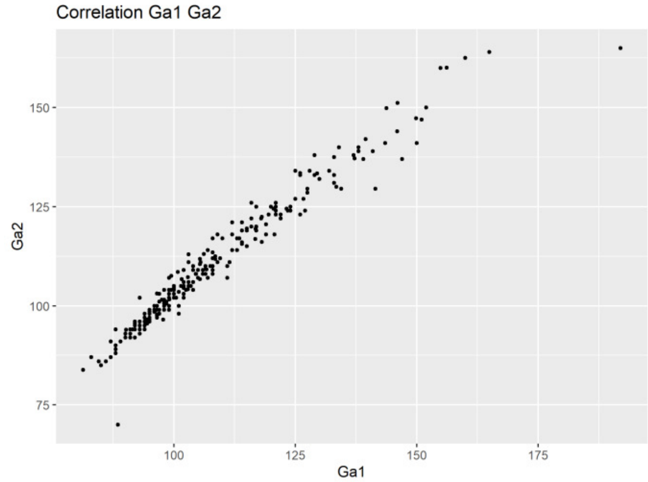

Fig. 4. Correlation Ga1 === Ga2

Fig. 5. Correlation Piece 5 Perimeter === Area

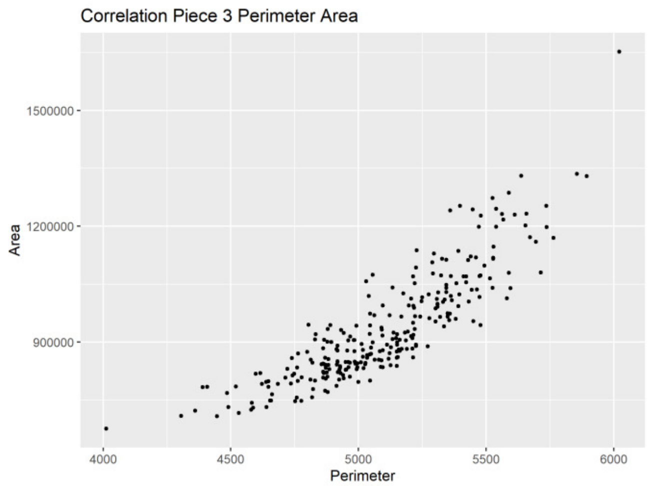

Fig. 6. Correlation Piece 3 Perimeter === Area

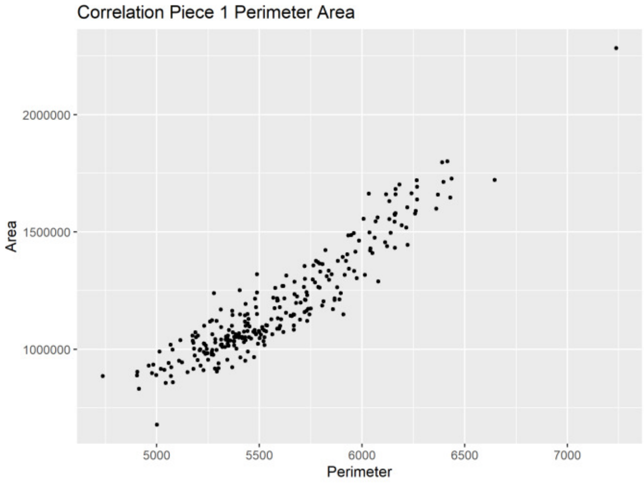

Fig. 7. Correlation Piece 1 Perimeter === Area

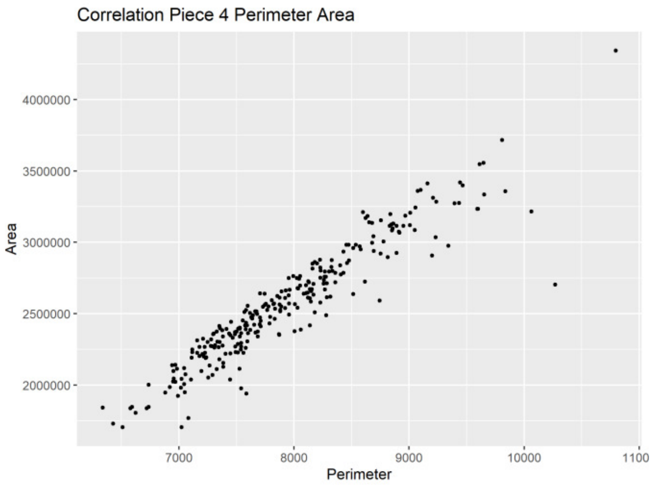

Fig. 8. Correlation Piece 4 Perimeter === Area

B. Analysis of Data Using ChatGPT

In recent times, there has been significant interest in utilizing artificial intelligence for identifying and analyzing various characteristic patterns. In our research, we also opted to employ artificial intelligence to analyze our data. This approach could allow us to gain a broader and more in-depth insight into the data structure and uncover potential correlations and characteristic trends that could be relevant to our research domain. For our study, we employed the freely available ChatGPT [16] tool provided by OpenAI [17]. Our objective was to analyze a dataset of human body measurements. However, the tool did not identify any outliers. Instead, it highlighted specific values that deviated from the overall dataset.

For example:

“Prof 1”: The body height of 164cm was relatively high compared to majority of the dataset, which primarily ranged between 156cm and 173.5cm.

“Prof 2”: The bust volume of 38 stood out as notably higher than the other values, which ranged between 31 and 36.7.

It's important to note that the tool did not provide a more comprehensive analysis of the dataset.

To improve results and enhance analysis, datasets for ChatGPT should be preformatted to provide additional context. Even when explicitly entering incorrect values, such as a height of 264cm, the tool only recognized the issue after performing a specific task to validate all body heights. After multiple iterations and attempts, we settled on the following prompt: "Analyze the quality of human body measurement data for sewing, identifying unusual values. The dataset contains measurements in centimeters, with column headers on the first line." However, it should be noted that the tool yielded different results with each run.

To utilize ChatGPT for data analysis, we would need to collect additional personal characteristic data such as weight, gender, geographic affiliation, and other data, which are currently unavailable to us.

VI. Conclusion

A method is proposed for automated quality control of individually tailored garment patterns. The essence of the approach is as follows: first, the designers create clothing models and present them to clients. From the various models, the client chooses the most suitable one and places an order for its production. This, in turn, requires the client to provide their body measurements, which can be significant in number, even up to 53. The designer then programs a pattern generation algorithm that considers the client's measurements and is capable to generate high-quality garment patterns. Individual garments are then sewn from these patterns, providing the client with a more suitable fit compared to mass-produced options.

Unfortunately, the number of prepared patterns is enormous (over 175 different clothing models for more than 1000 clients), and their inspection requires significant resources. Automated pattern inspection is proposed, where the area and perimeter of each pattern element are calculated, which are closely related (high correlation coefficient). If the correlation coefficient is below a critical threshold, individual pattern inspection is required. This method can also detect inaccuracies in the input of client measurements.

References

[1] Ruiz N., Bueno M.B., Bolkart T., Arora, Lin M., Romero J., Bala R. Human body measurement estimation with adversarial augmentation. International Conference on 3D Vision, 2022 https://www.amazon.science/publications/human-body-measurement-estimation-with-adversarial-augmentation (Accessed 23.05.2023).

[2] Roknabadi A.D., Latifi M., Saharkhiz S., Aboltakhty H. Human body measurement system in clothing using image processing. World Applied Sciences Journal 19(1):112-119 DOI: 10.5829/idosi.wasj.2012.19.01.1306, January 2012.

[3] Liu X., Wu Y., Wu H. Machine Learning Enabled 3D Body Measurement Estimation Using Hybrid Feature Selection and Bayesian Search. Appl. Sci. 2022, 12(14), 7253; https://doi.org/10.3390/app12147253.

[4] Ashmawi S., Alharbi M., Almaghrabi A., Alhothali A. Fitme: Body Measurement Estimations using Machine Learning Method. Procedia Computer Science. Volume 163, Pages 209-217, 2019. https://doi.org/10.1016/j.procs.2019.12.102.

[5] Bye E., Labat K.L., Delong M. R. Analysis of Body Measurement Systems for Apparel. Clothing and Textiles Research Journal 24(2):66-79, March 2006 DOI: 10.1177/0887302X0602400202

[6] https://ieee-dataport.org/open-access/dataset-ieee-ic-3dbp-comparative-analysis-anthropometric-methods.

[7] Bartol K., Bojanić D., Petković T., Pribanic T. A Review of Body Measurement Using 3D Scanning, IEEE Access, DOI: 10.1109/ACCESS.2021.3076595, 2021.

[8] Lu J., Wang M.J. Automated anthropometric data collection using 3D whole body scanners, DBPL, Expert Systems with Applications 35(1-2):407-414, July 2008. DOI: 10.1016/j.eswa.2007.07.008

[9] Kuribayashi M., Nakai K., Funabiki N. Image-Based Virtual Try-on System With Clothing-Size Adjustment. DOI: 10.48550/arXiv.2302.14197, 2023.

[10] Pleuss J.D., Talty K., Morse S., Kuiper P., Scioletti M., Heymsfield S.B., Thomas D.M. A machine learning approach relating 3D body scans to body composition in humans. Eur J Clin Nutr. 2019 Feb; 73(2): 200–208, published online 2018 Oct 12. doi: 10.1038/s41430-018-0337-1

[11] Bartol, K., Bojanić, D., Petković, T., Peharec, S., Pribanić, T. Linear Regression vs. Deep Learning:A Simple Yet Effective Baseline for Human Body Measurement. Sensors, 22, 1885, 2022. https://doi.org/10.3390/s22051885

[12] Kus A., Unver E., Taylor A. A Comparative Study of 3D Scanning in Engineering, Product and Transport Design and Fashion Design Education. Computer Applications in Engineering Education 17(3):263 – 271, September 2009DOI: 10.1002/cae.20213

[13] Seifert, E., Griffin, L. Comparison and Validation of Traditional and 3D Scanning Anthropometric Methods to Measure the Hand. Paper presented at 11th Int. Conference and Exhibition on 3D Body Scanning and Processing Technologies. https://doi.org/10.15221/20.41 , 2020.

[14] Skorvankova, D., Riečický, A., Madaras, M. Automatic Estimation of Anthropometric Human Body Measurements. 17th International Conference on Computer Vision Theory and Applications. (2021) DOI: 10.5220/0010878100003124, https://www.scitepress.org/PublishedPapers/2022/108781/108781.pdf

[15] Rumbo-Rodríguez L, Sánchez-SanSegundo M, Ferrer-Cascales R, García-D'Urso N, Hurtado-Sánchez JA, Zaragoza-Martí A. Comparison of Body Scanner and Manual Anthropometric Measurements of Body Shape: A Systematic Review. Int J Environ Res Public Health. 2021 Jun 8;18(12):6213. doi: 10.3390/ijerph18126213

[16] ChatGPT May/, 12 Version, https://help.openai.com/en/articles/6825453-chatgpt-release-notes

[17] OpenAI. https://chat.openai.com