Comparing Univariate and Multivariate Analysis of Anthropometric Measurements from 3D Body Scans for Ergonomic Work System Designs

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Abstract

To design ergonomic workplaces, planners need, among other things, anthropometric data to fit the work system to the physical body dimensions of the user group. In this design process, a general distinction between univariate and multivariate approaches can be made, if several anthropometric measurements need to be considered. The aim of this publication is to present the univariate percentile approach as well as the multivariate principal component analysis (PCA) approach and to discuss differences in the resulting total accommodation (TA). A seated office workstation with visual display terminal served as a generic use case, resulting in ten relevant ISO 7250-1 measurements. The utilized anthropometric dataset, consisting of 2313 subjects (1161 men and 1152 women), was gathered between 2014-2019 within an epidemiological health study in northeast Germany, using a Vitus Smart XXL Body Scanner. With the defined use case and user group, the univariate percentile approach and the multivariate PCA approach were performed separately for the male and female subset to achieve a desired TA of 90%. In the male subset, the total accommodation was 52.7% for the univariate percentile approach and 78.3% for the multivariate PCA approach. In the female subset, the total accommodation was 51.8% for the univariate percentile approach and 78.5% for the multivariate PCA approach. Therefore, given a multidimensional use case and an anthropometric dataset in an ergonomic design process, the results of this publication indicate that it should be examined whether a multivariate approach is superior to a univariate approach to achieve an adequate TA.

Keywords: Digital anthropometry, ergonomics, multivariate analysis, occupational safety and health

1. Introduction

The ergonomic design of workplaces is important to ensure a safe and healthy work system [1]. According to general ergonomic principles, defined in ISO 26800 and ISO 6385 [2, 3], relevant characteristics from the used group need to be considered in the design process and accommodation for (at least) 90% of the population must be ensured. Relevant characteristics are, among other parameters, anthropometric data of the user group [4], as an optimal ergonomic interaction of a human with its working environment is only possible, if the environment is adapted to the physical dimensions of the human [5]. Hence, applying the ergonomic principles from the aforementioned international standard to anthropometrics, data from all relevant anthropometric measurements need to be considered during the design process to accommodate for (at least) 90% of the user group.

In reality, for most workplaces, several anthropocentric measurements need to be incorporated. One common example would be an office workstation with a visual display terminal (VDT). As mentioned in Pheasant and Haslegrave [5], the International standard ISO 9241 *"Ergonomic requirements for office work with visual display terminals (VDTs)"* gives recommendations for the design of screen-based and office workstations. In ISO 9241-5 *"Workstation layout and postural requirements"* [6], relevant anthropometric measurements for seated and standing office workstations with VDTs are presented. For the ergonomic design of a seated office workstation with VDT, planners need to consider different types of anthropometric measurements (height, length, depth and breadth measurements) from several body segments to accommodate for 90% of the user group.

Including anthropometric data from more than one measurements in this process to achieve the desired level of accommodation, a general distinction between univariate and multivariate approaches can be made. Two very popular approaches for designing and dimension specification are the univariate percentile approach and the multivariate principal component analysis (PCA) approach [7, 8]. In the univariate percentile approach, the 5th and 95th percentile of each measurement is calculated independently. Therefore, an interval with the central 90% of the data can be defined individually for

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each body dimension and the computed percentiles are utilized as boundary values within the design process. In the multivariate approach of Zehner, et al. [9] all measurements are analyzed simultaneously. For this purpose, a PCA is performed in a first step, using the relevant anthropometric data as input variables. Afterwards, data points are transformed into the new 2D/3D PC space and a 90% enclosure ellipse/ellipsoid is constructed. Subsequently, so-called boundary cases are identified on the surface of the ellipse/ellipsoid. Using these boundary cases, boundary values are computed and can be used within the design process. Thus, in the multivariate approach, all variables are considered simultaneously, whereas the univariate approach analyzes variables individually. Nevertheless, both types of analyses make the assumption that designing for people with extreme anthropometric values (i.e. computed boundary values) ensures accommodation for people with less extreme values [4].
The aim of this paper is to explain the univariate percentile approach and multivariate PCA approach extensively and show potential differences in the resulting total accommodation (TA). Total accommodation refers to the percentage of people from a defined user group that lies within the calculated boundary values for all measurements relevant to the ergonomic design.

2. Method

Before describing the two analysis methods comprehensively, a use case for the ergonomic design process had to be determined and the corresponding relevant anthropometric measurements identified. Thereafter, the intended user group was defined.

2.1. Use case

A seated office workstation with a VDT was used as use case. According to ISO 9241-5, twelve anthropometric measurements from different body segments need to be considered in the ergonomic design process of this workplace. However, two measurements, which are important for the backrest of the chair, could not be accounted for, as they are not defined in ISO 7250-1 and therefore no data were available. ISO 7250-1 [10] determines basic human body measurements for technological designs and served as a basis for the used dataset (see next section). Overall, an exclusion of the two measurements seemed acceptable. In a comparable analysis by Gordon [7] these two measurements were also not included. Thus, only the ten ISO 7250-1 measurements, defined in ISO 9241-5, were utilized for this use case (see table 1 and figure 1).

Table 1. Anthropometric measurements from ISO 7250-1, which are relevant for the ergonomic design of a seated office workstation with visual display terminal, according to ISO 9241-5.

Reference number	Relevant anthropometric measurements	Abbreviation
6.2.2	Eye height, sitting	EyH
6.2.4	Shoulder height, sitting	SH
6.2.5	Elbow height, sitting	EH
6.2.9	Elbow-to-elbow breadth	EEB
6.2.10	Hip breadth, sitting	HB
6.2.11	Popliteal height, sitting	PH
6.2.12	Thigh clearance	TC
6.2.16	Buttock-abdomen depth, sitting	BAD
6.4.7	Buttock-popliteal length (seat depth)	BPL
6.4.8	Buttock-knee length	BKL

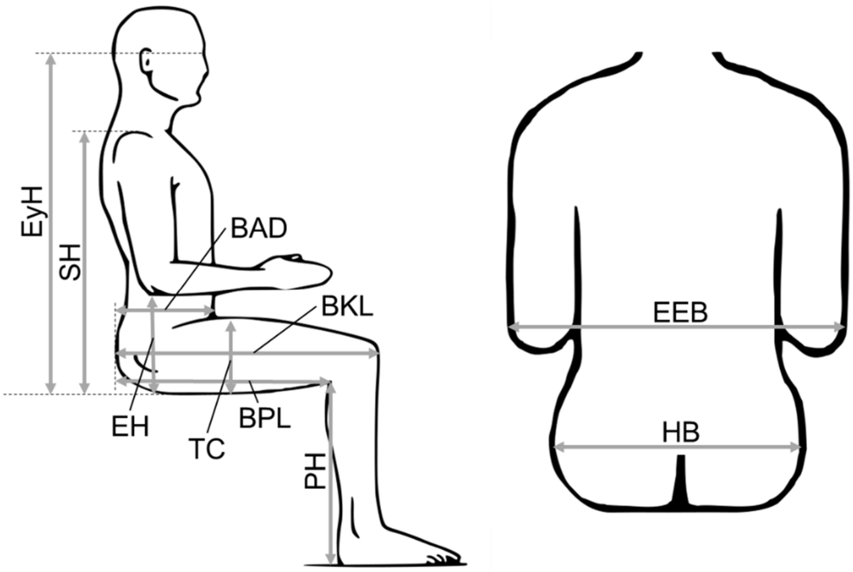

Fig. 1. Visualization of anthropometric measurements from ISO 7250-1, which are relevant for the ergonomic design of a seated office workstation with visual display terminal, according to ISO 9241-5. See table 1 for abbreviations of the anthropometric measurements (own illustration).

2.2. User group

To conduct the analyses, the anthropometric dataset calculated within the Study of Health in Pomerania (SHIP) was used. SHIP is a population-based epidemiological health study in northeast Germany, conducted by the University Medicine Greifswald [11-13]. In 2013 the Federal Institute for Occupational Safety and Health (BAuA) started a cooperation with the University Medicine Greifswald to gather 3D body scan data within SHIP. Like other studies [14, 15], the University Medicine Greifswald used the 3D body scans to identify health-related risk factors. BAuA used the scan images to generate an anthropometric dataset for the utilization in an ergonomic setting. All in all, 39 ISO 7250-1 measurements from $N = 2313$ working-age subjects (1152 women and 1161 men) were collected between 2014 und 2019, using a Vitus Smart XXL Body Scanner (Avalution GmbH, Kaiserslautern, Germany). Accordingly, this sample defined the user group for our use case.
The creation of the regional anthropometric dataset using 3D whole-body scanner is described extensively in other publications of the BAuA [16, 17] and will not be explained any further at this point. This publication focuses on the utilization of the dataset to conduct univariate und multivariate analyses.

2.3. Data analysis

All analyses and plots were performed using R [18]. The basis for all calculations was the anthropometric dataset gathered within SHIP. Analyzes were conducted separately for the male and female subset to avoid biases, because women and men are quite different in body shape, size and proportion. This is common practice and likewise implemented in comparable publications [7, 8, 19-21]. Since the data analysis was identical for both genders, the two approaches are explained using the male subset A as an example:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix},$$

where $n = 1161$ denotes the number of subjects within the male subset an $m = 10$ the number of relevant anthropometric measurements (see table 1). Following ISO 15535 [22], all values in the anthropometric dataset A were expressed in [mm].

2.3.1. Univariate percentile approach

The univariate percentile approach is simple and straightforward. The basic R function *quantile* was utilized to calculate the 5th and 95th percentile for each anthropometric measurement individually. These values defined the boundary values to calculate the TA.

2.3.2. Multivariate PCA approach

The multivariate PCA approach is more complex. All computations within the PCA approach are illustrated in figure 2 and described in detail hereafter.

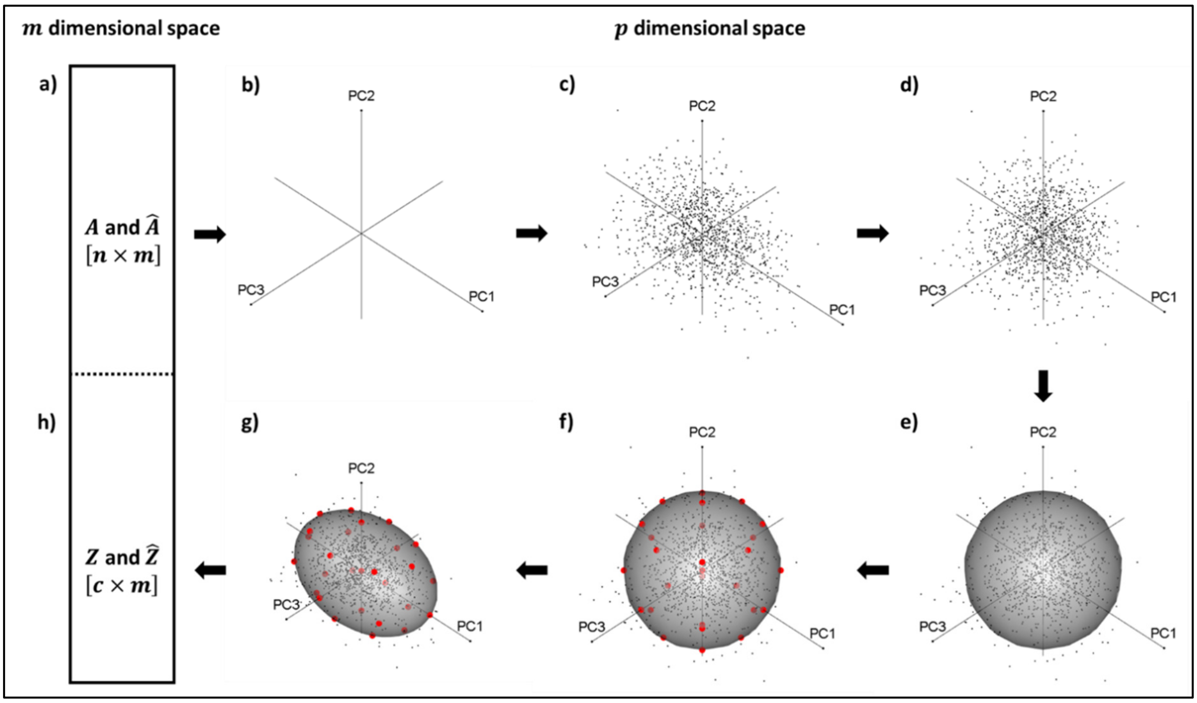

Fig. 2. Illustration of the different computations within the multivariate PCA approach. Abbreviations: PC1 = first principal component, PC2 = second principal component, PC3 = principal component. For explanations of the various mathematical variables, see main text.

Before performing the PCA, values in A were centered (subtracting column means from corresponding columns) and thereafter scaled to unit variance (dividing the centered columns by their corresponding standard deviations), using the *scale* function. Afterwards, the normalized matrix $\hat{A}$ (see figure 2a) served as input for the *prcomp* function to conduct the PCA (for clarification: in this publication the notation $\hat{X}$ denotes a matrix X with normalized values as described above, i.e. utilization of *scale* function on each column). *prcomp* uses a single value decomposition for the PCA. The Kaiser criterion [23] was used to define the number of relevant principal components (PCs). As shown in the scree plot (see figure 3) and table 2, the first three PCs had an eigenvalue ≥ 1 (i.e., $p = 3$; identical for female subset).

Fig. 3. Scree plot for the male subset to determine the number of relevant principal components. The bold horizontal line at y-axis value 1 illustrates the Kaiser criterion.

These three PCs accounted for 79.3% of the total variance (80.2% in the female dataset). Eigenvectors and corresponding vector loadings for the male subset are shown in table 2. Pattern of vector loadings can be interpreted as follows: PC1 (accounting for 42.5% of variance in the male subset) represents overall size, PC2 (accounting for 19.2% of variance in the male subset) contrasts breadths and depths (measurements of corpulence) to lower limb lengths, and PC3 (accounting for 17.6% of variance in the male subset) contrasts trunk heights to lower limb lengths.

Table 2. Eigenvalues, the explained variances, as well as the eigenvectors and their vector loadings for the three relevant principal components of the male subset. Abbreviations: PC = principal component, PC1 = first principal component, PC2 = second principal component, PC3 = principal component.

	PC1	**PC2**	**PC3**
Eigenvalue	4.2462	1.9221	1.7603
Proportion of Variance	0.4246	0.1922	0.1760
Cumulative Proportion	0.4246	0.6168	0.7929
PC scores			
Eye height, sitting	-0.3295	0.1873	-0.4244
Elbow height, sitting	-0.2281	-0.1703	-0.5853
Elbow-to-elbow breadth	-0.2623	-0.3968	0.1412
Hip breath, sitting	-0.3496	-0.3303	0.1355
Popliteal height, sitting	-0.2847	0.4651	0.1211
Thigh clearance	-0.3282	-0.1804	0.0758
Buttock-abdomen depth, sitting	-0.2294	-0.4922	0.2228
Buttock-popliteal length, sitting	-0.3332	0.3479	0.3301
Buttock-knee length, sitting	-0.3871	0.2209	0.3145
Shoulder height, sitting	-0.3821	0.0914	-0.4013

PC1, PC2, and PC3 are orthogonal to another and were utilized to build a three dimensional PC space (see figure 2b). Using the computed eigenvector matrix V (output *rotation* from *prcomp* function)

$$V = [m \times p]\,,$$

subjects with their original variables (i.e. anthropometric measurements) were transformed in this PC space (see figure 2c)

$$T = [n \times p] = \hat{A} \cdot V\,,$$

where T defines a matrix with n male subjects and their corresponding PC values (output *x* from *prcomp* function). The distributions for each PC (i.e. each column of T) are presented in figure 4.

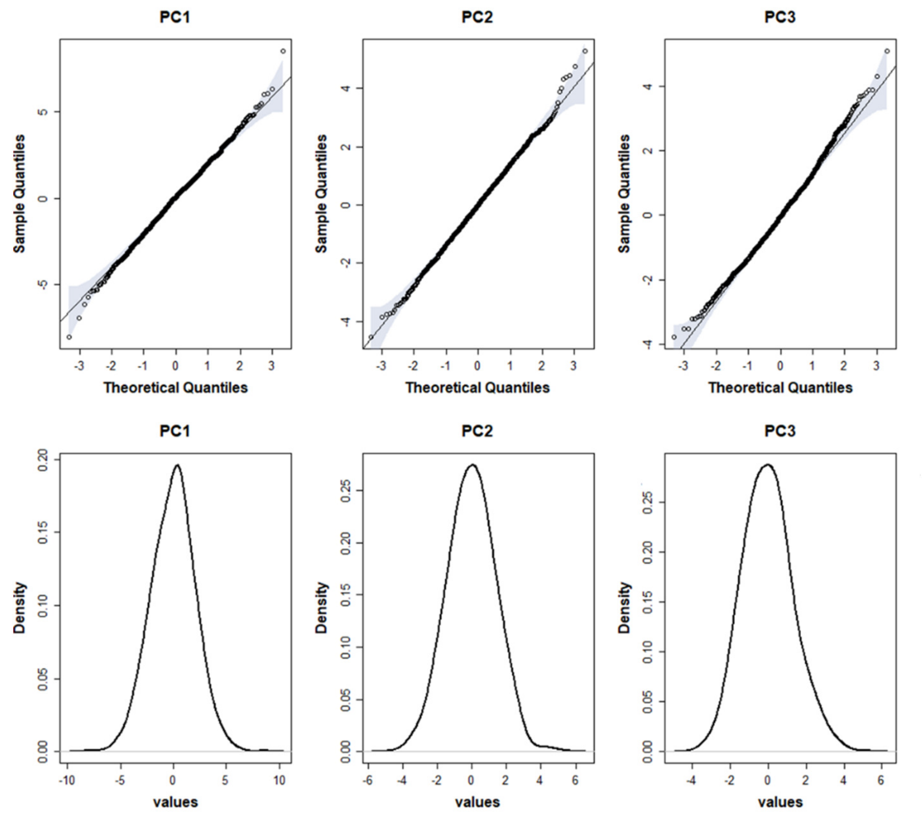

Fig. 4. Density and Q-Q plots for the three relevant principal components of the male subset. Abbreviations: PC1 = first principal component, PC2 = second principal component, PC3 = principal component.

In the next step, following the procedure of Guan, et al. [20] and Hsiao [19], values were normalized with the *scale* function to compute $\hat{T}$ (see figure 2d) and construct a 3D ellipsoid with only one single radius parameter r ($r = 2.50$ for the male and female subset), which enclosed the middle 90% of all data points. Accordingly, the 3D ellipsoid was a sphere with a 90% enclosure criterion (see figure 2e). Then, 26 points on the sphere surface, representing the diverse body shape and size combinations, were calculated with the given radius parameter r and, if necessary, a rotation matrix. The matrix consisted of two rotations $R_y(\theta)$ and $R_z(\psi)$ around the PC2 and PC3 axis with angles θ and ψ

$$R = R_y(\theta) \cdot R_z(\psi) = \begin{pmatrix} \cos(\theta) & 0 & \sin(\theta) \\ 0 & 1 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) \end{pmatrix} \cdot \begin{pmatrix} \cos(\psi) & -\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{pmatrix}$$
$$= \begin{pmatrix} cos(\theta)\cos(\psi) & -cos(\theta)\sin(\psi) & sin(\theta) \\ \sin(\psi) & \cos(\psi) & 0 \\ -sin(\theta)\cos(\psi) & sin(\theta)\sin(\psi) & cos(\theta) \end{pmatrix}.$$

Relevant intersect points could be easily defined with r. For example, the vectors $v_1, v_2, \ldots, v_6$ determined the six possible intersect points in the PC space with normalized values:

$$v_1 = \begin{pmatrix} r \\ 0 \\ 0 \end{pmatrix};\ v_2 = \begin{pmatrix} -r \\ 0 \\ 0 \end{pmatrix};\ v_3 = \begin{pmatrix} 0 \\ r \\ 0 \end{pmatrix};\ v_4 = \begin{pmatrix} 0 \\ -r \\ 0 \end{pmatrix};\ v_5 = \begin{pmatrix} 0 \\ 0 \\ r \end{pmatrix};\ v_6 = \begin{pmatrix} 0 \\ 0 \\ -r \end{pmatrix}.$$

To determine relevant surface points between two intersect points or one of the eight octant midpoints located at the surface center of each of the eight sections (octants) the rotation matrix R and v_1 was used. For example, the surface point between the intersect points v_1 and v_5 could be calculated with

$$R_y(-45) \cdot R_z(0) \cdot v_1,$$

and the octant midpoint at the surface center between v_1, v_3, and v_5 with

$$R_y(-45) \cdot R_z(45) \cdot v_1.$$

All in all, the 26 surface points along with the centroid point defined relevant boundary cases ($c = 27$; see figure 2f) and were saved in a matrix $\hat{Y}$

$$\hat{Y} = [c \times p].$$

As it can be seen from the density and Q-Q plots (see figure 4), values for PC3 were slightly right skewed in the male subset (similar pattern for PC2 in the female subset). Non-normality was confirmed by a Shapiro-Wilk test ($p = 0.001$). Since the presented approach assumed normally distributed data, accuracy of the boundary case selection might have been negatively influences. Some original variables in matrix A were right skewed, which may occur in an anthropometric dataset of ordinary working-age subjects [5]. Transforming (log or Box-Cox) the original data or excluding extreme outliers did not show the desired effect on the distributions within the PC space. In the end, authors decided to conduct the boundary case selection with unchanged original data and consider the non-normality of PC3 (and PC2 in the female subset) in the interpretation of results.

After calculating the male boundary cases and their normalized values in the PC space, several back transformations were necessary to obtain their non-normalized original variables (i.e. anthropometric measurements). In a first step, normalization in the PC space was reversed (see figure 2g). Thereafter, normalized original variables $\hat{Z}$ were computed using the transposed eigenvector matrix (see figure 2h)

$$\hat{Z} = [c \times m] = Y \cdot V^T.$$

Subsequently, normalization of the original values was reversed to get Z. Each row in Z represents a male boundary case model with its non-normalized anthropometric values.

To generate a mixed gender model family for a design process without ignoring gender-specific characteristics ,Guan, et al. [20] and Hsiao [19] present a procedure to transform identified boundary cases of on gender into the PC space of the other gender. Afterwards, obsolete cases are discarded, a mixed gender model family with relevant boundary cases are identified, and back transformations are performed. Since workstations are usually not specifically designed for women or men, this can be a logical and necessary next step. However, as the scope of this publication is to show solely differences between univariate and multivariate approaches, the authors decided to keep the data analysis straightforward and conduct the comparison of the two approaches separately for men and women.

Moreover, it should be mentioned that the boundary cases in Z are statistically calculated models and no “real persons” from dataset A. At this point, some publications identify their closest-neighbor subjects within A to use the 3D scans for a virtual “try-on”, for example. Nevertheless, following the

statement of Hsiao [19], the calculated models in Z define better design targets and were therefore used in this study to compute the TA for the PCA approach.
The basic R functions *min* and *max* were utilized to calculate the minimum and maximum value for each anthropometric measurement within Z. The computed minimum and maximum values specified the boundary values to calculate the TA for the multivariate PCA approach.

2.3.3. Total accommodation

As already implied at the end of the introduction (see chapter 1), a subject from the dataset A was scored as accommodated only if his anthropometric values were within the calculated boundary values for every measurement defined in table 1. The percentage of dataset subjects scored as accommodated defined the TA.

3. Results

The calculated male boundary values for the univariate percentile approach and the PCA multivariate approach are presented in table 3. Boundary values for the female subset are shown in table 4.

Table 3. Calculated male boundary values in [mm] for the univariate percentile approach (P5 = 5th percentile, P95 = 95th percentile) and the multivariate principal component analysis (PCA) approach. See table 1 for abbreviations of the anthropometric measurements.

	EyH	SH	EH	EEB	HB	PH	TC	BAD	BPL	BKL
Univariate percentile approach										
P5	744	574	197	515	361	404	136	244	463	573
P95	860	668	289	680	456	480	182	383	553	672
Multivariate PCA approach										
Min	724	551	183	503	346	392	134	217	445	557
max	881	687	304	694	466	494	182	404	570	685

Table 4. Calculated female boundary values in [mm] for the univariate percentile approach (P5 = 5th percentile, P95 = 95th percentile) and the multivariate principal component analysis (PCA) approach. See table 1 for abbreviations of the anthropometric measurements.

	EyH	SH	EH	EEB	HB	PH	TC	BAD	BPL	BKL
Univariate percentile approach										
P5	705	541	199	453	359	373	123	241	460	553
P95	810	630	284	619	482	448	174	388	547	656
Multivariate PCA approach										
Min	684	523	181	435	337	360	119	205	440	533
max	831	650	301	628	489	456	176	402	565	671

Dataset subjects scored as accommodated for the univariate and multivariate approach are visualized in parallel coordinates plots, separately for the male and female subset (see figure 5 and 6). In the male subset, the total accommodation was 52.7% for the univariate percentile approach and 78.3% for the multivariate PCA approach. In the female subset, the total accommodation was 51.8% for the univariate percentile approach and 78.5% for the multivariate PCA approach.

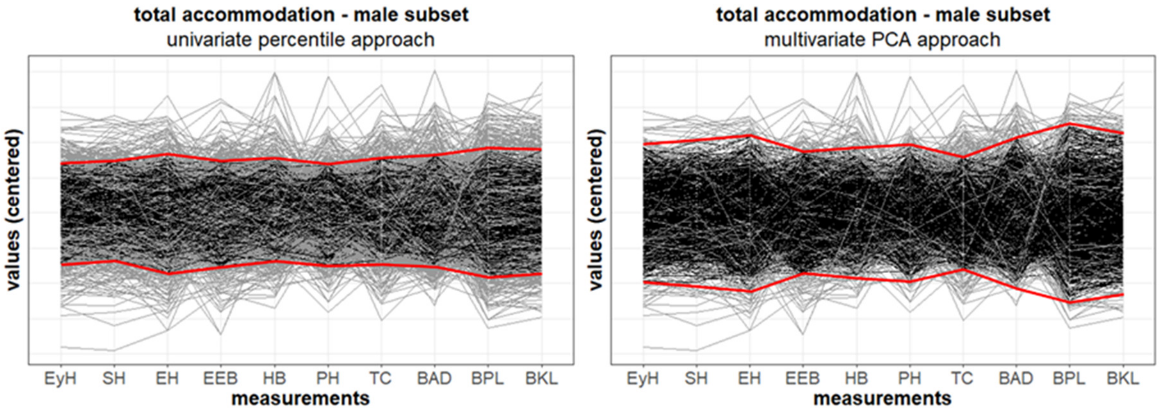

Fig. 5. Parallel coordinates plots to illustrate the calculation of the total accommodation for the male subset, separately with the univariate and multivariate approach. Bold red lines indicate computed boundary values, black lines accommodated subjects, and grey lines subjects, who were scored as not accommodated. See table 1 for abbreviations of the anthropometric measurements.

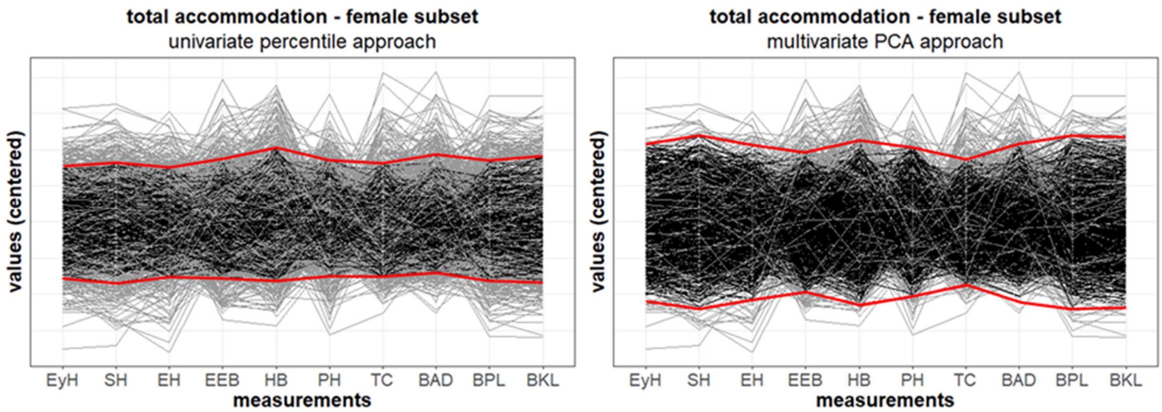

Fig. 6. Parallel coordinates plots to illustrate the calculation of the total accommodation for the female subset, separately with the univariate and multivariate approach. Bold red lines indicate computed boundary values, black lines accommodated subjects, and grey lines subjects, who were scored as not accommodated. See table 1 for abbreviations of the anthropometric measurements.

4. Discussion and Conclusion

This paper describes a comparison between the univariate percentile approach and the multivariate PCA approach in terms of their ability to achieve a desired TA for a given use case and user group. Boundary values were computed to determine the TA for both approaches separately (see table 3 and 4 and figure 5 and 6), assuming that designing for people with extreme anthropometric values (i.e. computed boundary values) ensures accommodation for people with less extreme values. With a TA of 78.3% for the male and 78.5% for the female subset, the multivariate PCA approach outperformed the univariate percentile approach with only 52.7% and 51.8%, respectively. One might annotate that in the univariate percentile approach many subjects were scored as not accommodated because of solely one anthropometric measurement outside the determined boundary values. An additional 23.1% in the male and 22.9% in the female subset would be considered accommodated, if the TA computation would have allowed one parameter to be outside the defined boundary values. However, there is a reason TA is defined in the way it is. For example, if a person has a value above the 95th percentile for the measurement "hip breadth, sitting", it does not matter that the design of the seated office workstation with a VDT fits the other nine parameters such as "thigh clearance", "Eye height, sitting" and so on. Ultimately, an ergonomic interaction between the subject's lower extremities and the seat pan is not assured and thus the overall workstation does not accommodate this person properly.

All in all, the results in this publication confirm that a multivariate approach obtains higher TA scores than a univariate approach in a in multidimensional use case, which is in line with the results of other studies [7, 8, 24, 25]. Nevertheless, to the authors' knowledge, this is the first publication to perform such a comparison using anthropometric data from Germany. Furthermore, as mentioned in Garneau and Parkinson [26], despite the well-known importance of multivariate approaches for several decades, poorly designed environments indicate that multidimensional accommodation problems find their way into the hands of designers and industrial engineers who do not have the knowledge or resources to solve them properly. The implementation of multivariate methods requires considerable expertise in statistics and human anatomy. By providing detailed explanations, the authors hope to lower the barriers for the utilization of multivariate methods within ergonomic design processes.

The advantage of the multivariate PCA approach compared to the univariate percentile approach lies in the nature of anthropometric datasets and the utilized use case. Due to variability in the human body, people differ in body proportions [5], which means persons within an anthropometric dataset are typically ranked in different percentiles for different measurements. A subject with a specific percentile value for the parameter "Eye height, sitting" probably has another percentile value for the parameter "Elbow height, sitting" or "Buttock-abdomen depth, sitting". In literature, this issue is sometimes referred to as "myth of the nth percentile person" [27] and to cite Garneau and Parkinson [26] "the notion of an 'nth percentile man' with all body dimensions belonging to a certain percentile is fundamentally false and was labelled an 'unobtainable abstraction' over 50 years ago". This variability in human body proportions leads to a correlation coefficient $r < 1$ between different measurements of an anthropometric dataset. Accordingly, if the univariate percentile approach is utilized for the ergonomic design process of a multidimensional use case, like the seated offices workstation with VDT ($m = 10$), the specific correlations within the dataset are ignored. Ultimately, this lead to less accommodated dataset subjects than one might expect. As more parameters are included, the discrepancy between desired and achieved TA typically increases (see figure 7).

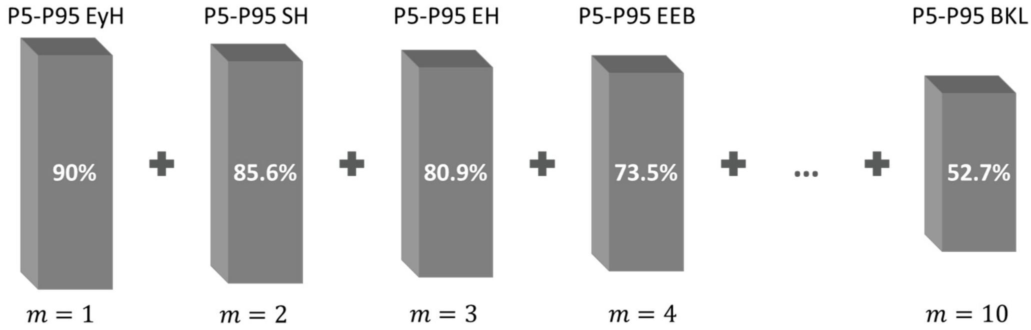

Fig. 7. Image to illustrate the diminishing total accommodation for the univariate percentile approach with each subsequent relevant anthropometric measurement (adapted from Zehner, et al. [9]). For a better understanding of this graph, it should be noted that the exact value of the TA for $m = i \; (2 \leq i \leq 9 \mid i \in \mathbb{N})$ depends on the selection of the added anthropometric measurement. The final TA for $m = 10$ is fixed. See table 1 for abbreviations of the anthropometric measurements.

The multivariate PCA approach considers the variability of human body proportions and the specific correlations between different measurements, which is evident in the calculated TA. However, the achieved TA of 78.3% for the male and 78.5% for the female subset is still lower than the desired 90%. This is concordance with other studies [8, 25] and can be explained by limitations of the PCA approach. To reduce the dimensionality of the dataset, the Kaiser criterion was used to determine the number of relevant PCs. However, the first three PCs with an eigenvalue ≥ 1 account for only 79.3% of the variability in the male subset (80.2% in the female subset), which is a limitation of the study. Furthermore, the approach to identify boundary cases on the surface of a 90% ellipsoid assumed normally distributed data. As shown in figure 4, values for PC3 were slightly right skewed (similar for PC2 in female subset) and non-normality was confirmed by a Shapiro-Wilk test ($p = 0.001$), which is why the accuracy of the boundary case selection might have been negatively influenced. Nevertheless, analyzing the Q-Q plots, deviations were rather small and the influence on model selection most likely marginal. Hence, differences between desired and achieved TA were probably due to the neglected variance.
The findings of this publication can be summarized as follows: Given a multidimensional use case and an anthropometric dataset (i.e. variables are not perfectly correlated), it should be examined whether a multivariate approach is superior to a univariate approach to achieve an adequate TA. In contrast to the univariate percentile approach, multivariate approaches incorporate all anthropometric measurements simultaneously and consider the specific correlations between different variables, given by the variability of human body proportions. The PCA approach is a popular and suitable multivariate method. However, other approaches exist (e.g. archetypal analysis). Thus, future studies should investigate whether such approaches are better suited for this particular use case and user group to achieve the desired TA.

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