

Experimental Researches on the Durability Indicators and the Physiological Comfort of Fabrics using the Principal Component Analysis (PCA) Method

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Abstract. The work pursued the distribution of combed wool fabrics destined to manufacturing of external articles of clothing in terms of the values of durability and physiological comfort indices, using the mathematical model of Principal Component Analysis (PCA). Principal Components Analysis (PCA) applied in this study is a descriptive method of the multivariate analysis/multi-dimensional data, and aims to reduce, under control, the number of variables (columns) of the matrix data as much as possible to two or three. Therefore, based on the information about each group/assortment of fabrics, it is desired that, instead of nine inter-correlated variables, to have only two or three new variables called components. The PCA target is to extract the smallest number of components which recover the most of the total information contained in the initial data.

1. Introduction

Analysis of the Principal Components (PCA) is a descriptive method of data multi-dimensional analysis. The PCA objectives are: synthesis of the initial information contained in a big size table; visualization of the similarities and differences between individuals from the standpoint of the considered variables [1-3]. Principal Components Analysis (PCA) is a useful statistical technique that has found application in fields such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension [4-6]. This technique introduces a mathematical concept that covers standard deviation, covariance, eigenvectors and eigenvalues [7-9]. Principal component analysis is a dimension-reduction technique. It can be used as an exploratory data analysis tool, but is also useful for constructing predictive models, as in principal components analysis regression (also known as PCA regression or PCR) [10-12]. For data with a very large number of variables, the Principal Components platform provides an estimation method called the Wide method that enables you to calculate principal components in short computing times. These principal components can then be used in PCA regression [13-15]. At the beginning, the methods of multivariate analysis of data were applied in fields of humanities: biology, psychology, sociology [16-19]. Later, there were applied in many other areas, such as: psihometria, genetics, medicine, economics and industry [18-21]. Outstanding contributions to theoretical and practical development of these methods had, in particular, Galton and K. F. Pearson, by the studies in the field of regression and correlation analysis, Spearman and H. C. Hotteling by factor analysis and research of the principal components analysis. At present, the more specialized softwares enable a multitude of multivariate



analysis methods of the data for the statistics processing of the research results: SPSS, Statistics, SAS, ADDAD [20-22]. The main asset of PCA is its ability to identify genetic structures in very large datasets within negligible computational time, and the absence of any assumption about the underlying population genetic model [21-26].

2. Experimental part

2.1. Materials and methods

In this study, there were analyzed four articles from five groups of worsted type fabric, made of different compositions, representing the number of individuals like:

Group A (100% Wool) - encoded items: A1; A2; A3; A4;

Group B (45% Wool + 55% Pes) - encoded items : B1; B2; B3; B4;

Group C (45% Pes + 55%Wool) - encoded items: C1; C2; C3; C4;

Group D (44%Pes + 54% Wool +2%Dorlastan) - encoded items: D1; D2; D3; D4;

Group E (60% Pes + 40% Celo) - encoded items: E1; E2; E3; E4

In making the fabrics from groups A, B, C and E, they were used Sirospun yarns which are twisted appearance yarns, called Jasper or yarn from double roving fibers. At group D fabrics, the weft threads are elastomeric yarns with core made of filament and their sheaths are made of fibers obtained also by the Sirospun process, through simultaneous supplying of the drawing frame with the roving and the filament core. The joining of the two components takes place in front of the delivery rollers so that by simultaneous twisting of them it is made the yarn structure with the filament core covered by the fibers. Using two rovings which will be rolled separately and a filament core at one of the sides, it is obtained a twisted yarn from a spun yarn and a core yarn. Most polymers and elastomers used for industrial or commercial applications are composites, which contain solid fillers.

The values of indicators of physiological comfort and durability were obtained by standard methods and processed in SPSS. The variables included in the analysis are: tear strength, Pr (daN); volumetric filling coefficient, Cvu; tenacity, t (cN/tex); the thickness; g (mm); mass, M (g/m²); air permeability, Pa (m³/min.mm); the degree of compactness, Kt (%); rigidity, R (mg.cm); porosity, Pz (%). This technique aims to reduce the number of controlled variables (columns) of the matrix data, as far as possible at two or three. Thus, based on information about each group/types of fabrics, it is desirable that instead of nine interrelated variables to have only two or three new variables, called components. The PCA goal is to extract the smallest number of components to recover as much of the total information contained in the initial data indenter.

3. Results and discussions

After processing the data in SPSS programme, applying PCA, the following results were obtained on statistical variables: descriptive statistics indicators (Descriptive Statistics); the correlation matrix; calculated values for both χ^2 test statistics and KMO statistics; the variance of the variables; eigenvalues and variance explained by each factorial axis; variable coordinates on factorial axes; contributions of the variables at the inertia of factorial axes and graphics.

3.1. Descriptive Statistics Indices

The statistical parameters calculated for each variable are shown in table 1. (Descriptive Statistics Output). Statistics is concerned with the scientific method by which information is collected, organised, analysed and interpreted for the purpose of description and decision making. Methods which help us describe the key features of data from interval and ratio scale measurement, fall into two groups, these are measures of central tendency and measures of dispersion. The measures of central tendency help us to get a feel for how alike individual measurements are to one another. The measures of dispersion help us to appreciate how spreads out the individual scores are from one another.

Analyzing the data from table 1, which contains information about each independently analyzed variable, it can be observed that:

- the variable Pr (daN), the breaking strength is characterized by its 64.843 average and its 521.950 variance; the maximum force at breaking it was obtained for article E4 made of 100% Pes, Pr = 106.1 daN and the minimum value for article A1, made of 100% wool, Pr = 31.4 daN;
- the variable Cvu, volumetric filling coefficient is characterized by 39.334 average and 160,363 variance; the maximum volumetric filling coefficient was obtained to article D4, made of 44%Pes + 54%Wool +2%Dorlastan, Cvu = 65,32, and the minimum value was obtained to article A1 made of 100% wool, Cvu=21,34%;coating.

Table 1. Descriptive Statistics.

Variabile	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Pr(daN)	20	31,4	106,1	64,843	22,8462	521,950
Cvu	20	21,34	65,32	39,334	12,66344	160,363
g(mm)	20	0,2872	0,6975	0,42753	0,144938	0,021
M(g/m ²)	20	170,3	238,7	202,555	18,0991	327,578
t(cN/tex)	20	5,9	18,2	12,620	3,5847	12,850
Pa(m ³ /mm.min)	20	14,2	33,9	22,570	6,3101	39,817
Kt(%)	20	75,23	98,29	87,5275	6,47263	41,895
R(mg.cm)	20	48,22	99,10	71,7220	15,42990	238,082
Pz(%)	20	58,50	79,21	67,4185	5,17203	26,750
Valid N (listwise)	20					

Analogous to this, the other variables are analyzed too. Following this independent analysis of every variable it is observed that the homogeneous variable is that related to thickness of the fabrics. The same trend is observed for the variable fabric porosity.

3.2. Correlation Matrix (output of Correlation Matrix)

The correlation matrix shows the correlation coefficient values of the variables considered in pairs. It is a square matrix symmetrical about the main diagonal (equal to one, because a variable is perfectly correlated with itself). The shape of the correlation matrix is shown in table 2, after the data have been standardized.

The analysis of the correlation coefficients of the matrix allows the assessment of the application of the PCA. High values of coefficients (greater than + 0.5 and less than - 0.5) show that there are significant statistically links between the considered variables (direct connection if the coefficient values are positive, the reverse link if the coefficient values are negative). For example, from Table 2 it is observed that there are:

- significant statistical connections (direct link) between:
 - Pr (daN) and Pa (m³/mm.min);
 - M (g/m²) and Kt (%); Pz (%);
 - Pa (m³/mm.min) and Pr (daN);
 - Kt (%) and M (g/m²);
 - Pz (%) and M (g/m²).
- significant statistical connections (indirect link) between :
 - Pr (daN) and R (mg.cm);
 - Cvu and Pa (m³/mm.min);
 - g (mm) and Pa (m³/mm.min); Pz (%);
 - M (g/m²) and R (mg.cm);
 - Pa (m³/mm.min) and Cvu, g (mm); R (mg.cm);
 - R (mg.cm) and Pr (daN); M (g/m²); Pa (m³/mm.min); Kt (%);
 - Pz (%) and g (mm).table 2.

Table 2. Correlation Matrix.

		Pr	Cvu	g	M	Pa	Kt	R	Pz
		(daN)		(mm)	(g/m ²)	(m ³ /mm. min)	(%)	(mg.cm)	(%)
Correla tion	Pr(daN)	1,000	0,105	-0,580	0,238	0,815	0,192	-0,439	0,304
	Cvu	0,105	1,000	-0,548	0,123	-0,358	0,408	0,138	0,222
	g(mm)	-0,580	-0,548	1,000	0,076	-0,041	0,052	0,097	-0,136
	M(g/m ²)	0,238	0,123	0,076	1,000	0,244	0,594	-0,162	0,684
	Pa(m ³ /mm.min)	0,815	-0,358	-0,041	0,244	1,000	0,112	-0,489	0,230
	Kt(%)	0,192	0,408	0,052	0,594	0,112	1,000	-0,069	0,252
	R(mg.cm)	-0,439	0,138	0,097	-0,162	-0,489	-0,069	1,000	-0,506
	Pz(%)	0,304	0,222	-0,136	0,684	0,230	0,252	-0,506	1,000
Sig. (1- tailed)	Pr(daN)		0,330	0,004	0,156	0,000	0,209	0,026	0,096
	Cvu		0,330	0,006	0,303	0,061	0,037	0,281	0,174
	g(mm)		0,004	0,006	0,374	0,431	0,413	0,342	0,284
	M(g/m ²)		0,156	0,303	0,374	0,150	0,003	0,247	0,000
	Pa(m ³ /mm.min)		0,000	0,061	0,431	0,150	0,319	0,014	0,164
	Kt(%)		0,209	0,037	0,413	0,003	0,319	0,386	0,142
	R(mg.cm)		0,026	0,281	0,342	0,247	0,014	0,386	0,011
	Pz(%)		0,096	0,174	0,284	0,000	0,164	0,142	0,011

^aDeterminant = 0,001

In this case, PCA can be applied. A feature of the correlation matrix is that the number of correlation coefficients increases greatly when the number of variables (k) included in the analysis increases regardless of the volume of statistics community.

The number of the correlation coefficients is: $k(k-1)/2$. For the experimental data which are showing values for nine variables, the number of the correlation coefficients is 36 (Table 3). This significant increase of the correlation coefficients shows the impossibility of explanation of the links between the variables only by analysis of the values found in the correlation matrix. In the Correlation Matrix output it is shown, also, the value of the correlation matrix determinant. It can take values in the range [0, 1] and it shows the strenght of the correlations between the variables. The determinant of the analyzed database has the value: Determinant = 0,001 which shows that there are strong statistical relations between the statistical variables (Correlation coefficient values are greater than 0.5). In this case the application of PCA can be achieved.

3.3. χ^2 and KMO statistics (output for KMO and Barlett's)

To test the hypothesis of independence between the statistical variables, SPSS provides calculated values of the corresponding test statistics. Statistics test (output KMO and Bartlett's) is used to test whether the correlation matrix is an identity (unit) matrix, so if there is a statistics connection between the statistical variables.

For this, it makes the following statistical hypotheses:

Ho: the hypothesis of independence (correlation matrix is an identity matrix);

H1: the hypothesis of dependence

To test these hypothesis, the SPSS program provides both the calculated value of the statistic $\chi^2 = 142,577$ and the probability value associated with the calculated test statistic (Sig = 0,000 lower than 0,05) thus it is rejected the H_0 hypothesis that allowed the existence of the independence of the variables (table 3). Therefore, it can be assumed with a 95% probability that between the variables there are statistical links (connections).

Table 3 KMO and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy. 0,467		
	Approx. Chi-Square	142,577
Bartlett's Test of Sphericity df		
		36
	Sig.	0,000

3.4. The Variance variables (output of Communalities)

Standardizing of the variables yields new variables of zero average and one variance. The variances of statistics variables are presented in the Communalities output. The variance of values after removing of the factors are calculated on the basis of the results from the output matrix component (table 4).

For example, for the volumetric filling coefficient **Cvu** it is obtained $\sigma_1^2 = 0,882$. Low values of the variance of the variables after extraction of the factors (Extraction column) shows that those variables can be eliminated from the proper analysis because they are not correlated to the factorial axes.

Table 4. Communalities.

Variable	Initial	Extraction
Pr(daN)	1,000	0,711
Cvu	1,000	0,882
t(cN/tex)	1,000	0,852
g(mm)	1,000	0,550
M(g/m ²)	1,000	0,346
Pa(m ³ /mm.min)	1,000	0,812
Kt(%)	1,000	0,258
R(mg.cm)	1,000	0,562
Pz(%)	1,000	0,499

Extraction Method: Principal Component Analysis

3.5. The Eigenvalues λ_k associated with each factorial axis and the total variance explained by each factorial axle (output of Total Variance Explained)

The eigenvalues of the correlation matrix are shown in the Total Variance Explained output, initial Eigenvalues column (Table 5). In Table 5 it is shown that the eigenvalues of the correlation matrix are:

$$\lambda_1 = 3,532; \quad \lambda_2 = 1,941; \quad \lambda_3 = 1,651; \quad \lambda_4 = 0,895; \quad \lambda_5 = 0,545; \quad \lambda_6 = 0,243; \quad \lambda_7 = 0,107; \\ \lambda_8 = 0,079; \quad \lambda_9 = 0,007;$$

The eigenvalues correspond to inertia explained by the factorial axes. Their sum is the total inertia of the cloud of points equal to the number of statistical variables of the original data table or the amount of elements from the main diagonal of the correlation matrix.

Table 5. Total Variance Explained.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,532	39,245	39,245	3,532	39,245	39,245
2	1,941	21,564	60,808	1,941	21,564	60,808
3	1,651	18,348	79,156	1,651	18,348	79,156
4	0,895	9,945	89,102			
5	0,545	6,059	95,161			
6	0,243	2,696	97,857			
7	0,107	1,185	99,041			
8	0,079	0,877	99,919			
9	0,007	0,081	100,000			

Based on the values from Table 6 it may result:

$$\sum_{k=1}^k \lambda_k = In \quad (1)$$

where: In is the total inertia of the cloud of points.

Based on the values from Table 6 it may result:

$$\sum_{k=1}^k \lambda_k = 3,532 + 1,941 + 1,651 + 0,895 + 0,545 + 0,243 + 0,107 + 0,079 + 0,007 = 9$$

Factorial variance explained by each axis is calculated from the relationship:

$$\%Varian'a = \frac{\lambda_k}{In} \quad (2)$$

The first factorial axis explains $3,532/9=39,244\%$ of the total variance of the cloud points.

The first two factorial axes together explain $60,808\%$ of total variance.

The first three factorial axes together explain $79,156\%$.

The number of factorial axes which are to be interpreted in the PCA was chosen according to two criteria:

- the Kaiser criterion which implies the choice of that number of factorial axes for which the corresponding of own values are higher than one. According to this criterion, three factorial axes are chosen, corresponding to their own values:

$$(\lambda_1 = 3,532, \lambda_2 = 1,941, \lambda_3 = 1,651) > 1.$$

These axes explain the biggest differences between statistical units in terms of the considered variables.

- Cattell's criterion involves the graphical representation of its own values (the Scree Plot chart) and the pursuit of a sudden fall of inertia explained by them. There are chosen the axes that precede this sudden change in the slope of the chart of the eigenvalues (Figure 1).

From the diagram shown in Figure 1, three factorial axes are selected for interpretation. These axes explains the biggest differences between statistical units in terms of the considered variables.

3.6. The eigenvectors

The eigenvectors associated with eigenvalues of the correlation matrix allow obtaining the coefficients of the variables in the linear equation of the main axes. Eigenvectors coordinates do not appear in the results of PCA but serve to calculate the coordinates of the variables in the principal axes.



Figure 1. Graphical representation of the eigenvalues of the correlation matrix.

3.7. The coordinate of X_j variable on k factorial axis (output of the Component Matrix)

The values of the coordinates of the variables on the factorial axes show the correlation of the value of coefficients, between the variables X_j and that factorial axis, and they are calculated according to the relation:

$$G_k(j) = \sqrt{\lambda_k} \cdot u_{kj} \quad (3)$$

where: λ_k is the own value appropriate to the k factorial axis;

u_{kj} are the coordinates of the eigenvector associated with the eigenvalue λ_k .

The coordinate values of the variables are presented in Table 6.

The values in Table 6 show the position of the variables on the factorial axes. For example, the variable **Pr** (daN) has a positive coordinate position on the first factorial axis (0.802) and a negative coordinate on the second factorial axis (-0.259); data will be plotted in the positive quadrant values of the first factorial axis and in the negative values quadrant of the second factorial axis. The high values of coordinate variables on the factorial axes listed that they are strongly correlated with that factorial.

For example, the variables **t** (cN/tex) and **g** (mm) are connected to the first factorial axis which indicates that these variables explain the significant differences between statistical units (there are significant differences between statistical units in terms of values obtained for these variables).

Table 6. The coordinates of the variables in the first three factorial axes.

Variable	Component		
	1	2	3
Pr(daN)	0,802	-0,259	-0,407
Cvu	0,406	0,847	0,047
t(cN/tex)	0,864	0,325	-0,184
g(mm)	-0,560	-0,487	0,608
M(g/m ²)	0,581	-0,094	0,707
Pa(m ³ /mm.min)	0,527	-0,731	-0,198
Kt(%)	0,470	0,192	0,617
R(mg.cm)	-0,580	0,475	0,104
Pz(%)	0,700	-0,092	0,388

Extraction Method: Principal Component Analysis.

However, between these two variables there is a reverse link because they have opposite sign coordinates and the statistical units with high values for the variable **t** (cN/tex) have lower values for the variable **g** (mm). The coordinates of variables in the factorial axes represent the coefficients of the linear equation of the relationship between variables. For example, for the data in Table 7, the first axis is a new variable defined by the linear combination of the initial variables, having the form:

$$F = 0,802 \text{ Pr} + 0,406 \text{ Cvu} + 0,864 \text{ t} - 0,560 \text{ g} + 0,581 \text{ M} + 0,527 \text{ Pa} + 0,470 \text{ Kt} - 0,580 \text{ R} + 0,700 \text{ Pz}$$

To identify the variables explaining the second factorial axis, choose those variables from Table 7 (Component 2 column) that have high coordinate values. Note that the formation of the second factorial axle is explained only by the variable **g** (mm).

From the analysis of the values of Table 7, it is noted that the variables **g** (mm), **M** (g/m²), and **Kt** (%) explain most the difference between the statistical units for the third factorial axle (column of the 3rd component), with values higher than 0.5.

3.8. The contribution of X_j variable at inertia of k axis (output for the Component Score Coefficient Matrix)

The contribution of a variable to the formation of a factorial axis is calculated with the relationship

$$CTR_k(j) = \frac{G_k(j)}{\lambda_k} \quad (4)$$

where: $G_k(j)$ is coordinate of the variable on k factorial axis;

λ_k is the appropriate own value corresponding to the k factorial axis.

Similarly to the interpretation of the values in Table 7, the high values of the contributions show the significant importance of the respective variable in differentiating the considered statistical units.

Table 7. Contributions of the variables to the inertia of the first three factorial axis.

Variable	Component		
	1	2	3
Pr(daN)	0,227	-0,133	-0,247
Cvu	0,115	0,436	0,028
t(cN/tex)	0,245	0,168	-0,111
g(mm)	-0,159	-0,251	0,368
M(g/m ²)	0,164	-0,049	0,428
Pa(m ³ /mm.min)	0,149	-0,376	-0,120
Kt(%)	0,133	0,099	0,374
R(mg.cm)	-0,164	0,245	0,063
Pz(%)	0,198	-0,047	0,235

Extraction Method: Principal Component Analysis

For the data from the Table 7, all variables contribute to the formation of the first factorial axis. For the second factorial axis, the variable that contributes to itself formation is **Cvu**; for the third factorial axis, the variables that contribute to this axis formation are: **g** (mm) and **M** (g/m²).

3.9. The graphical representation

The representation of the variable points in the first two factorial axes is shown in figure 2.

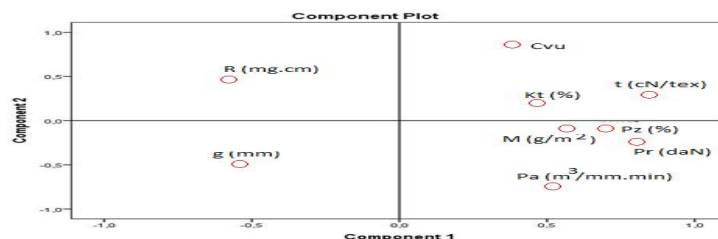


Figure 2. Position of the variables on the first two factorial axes.

The first factorial axis represented on the horizontal shows that between the variables M (g/m^2), Pz (%), Kt (%), Pr (daN) and t (cN/tex) there is a strong direct connection and between the variables M (g/m^2), Pz (%) and the variable R (mg.cm) there is a reverse link. The representative variables for the second factorial axis, represented on the vertical, are Cvu and Pa ($\text{m}^3/\text{mm.min}$): between them there is a reverse link.

For the interpretation of the third factorial axis, it is possible representing of the variable points in three-dimensional space (figure 3). Because it is difficult to interpret the variables in the graph of figure 3, the coordinate values of variables on the third factorial axis were analyzed according to the values obtained in table 7. The graphical representation of the variety of fabrics from those five groups, on the first two factorial axes, is shown in Figure 4.

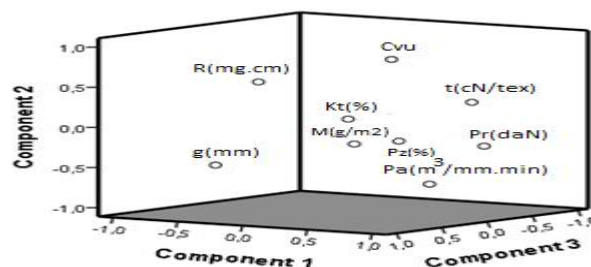


Figure 3. The representation of the variables in the first three-factorial axis system.

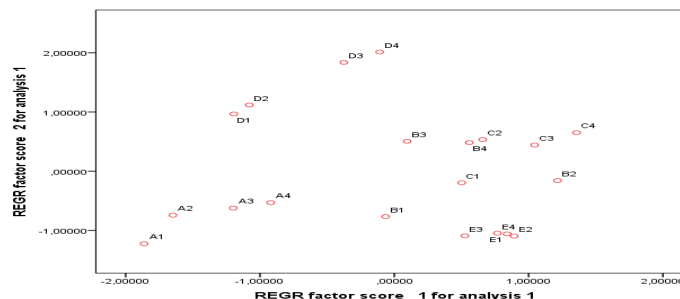


Figure 4. Position of the assortments of fabrics on the first two factorial axes.

4. Conclusions

The first factorial axis highlights two groups of types of fabrics: The first group is made up of the articles B2 and C4 (with an extreme position to the right of the graph in figure 4) and the second group of articles A1 and A2 (with an extreme position to the left of the graph). The items from the first group are characterized by higher values than average for the following characteristics: breaking force, tenacity, weight, air permeability, degree of compactness and porosity of woven fabrics, because the percentage of polyester fibers in the composition of yarns, as opposed to the items of the second group, the articles A1 and A2, where the yarns are only made of wool fibers. The second factorial axis highlights the D4 item, which is characterized by high values of the degree of compactness, stiffness and porosity of the fabric as opposed to articles E2 and E1 where the volumetric filling coefficient, thickness, weight, degree of compactness, stiffness and porosity of the fabrics are below the average. By applying the PCA mathematical model it was obtained the controlled decrease of the number of variables (columns) of the data matrix, at both components, which contain information about each group/types of fabrics.

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