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Application of hierarchical clustering on principal components to evaluate the performance of justice system by judicial indicators

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Abstract: The performance of justice systems is measured by empirical indicators in both developing and developed countries. The findings of existing indicator initiatives have historically been based on surveys of experts, document reviews, administrative data, or public surveys. In this paper, Principal Component Analysis (PCA) and Cluster Analysis (CA) methods were combined to resolve the problem of evaluating multiple indicators. Using PCA, this method standardizes, reduces dimensions, and decorrelates multiple indicators of evaluation of justice systems and abstracts the principal components. Then, CA is used to assign individuals (observations) to homogeneous clusters (classes). Typically, hierarchical clustering on principal components (HCPC) is employed to classify civil branches of a trial court in Iran to create a comprehensive evaluation. By applying the multivariate statistical method to data, three principal components are identified and interpreted. A hierarchical clustering algorithm is then applied, which divides the data into three clusters based on dissimilarity. These groups of the civil branches were identified based on nine judicial performance indicators. It allows policymakers and reformers to measure the performance of each branch individually, and track their progress in reducing backlogs and delays separately. As shown by the practical example, these methods are effective across justice units

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1 Introduction

A wide range of data is collected on different aspects of the justice system, which can be summarized and communicated using justice indicators. They are useful for assessing performance, drawing attention to problems, establishing benchmarks, monitoring progress, and evaluating the effectiveness of policies or changes. The use of indicators and other monitoring and evaluation mechanisms is critical to ensuring transparency and accountability in justice. They also enable policymakers and reformers to obtain valuable feedback Dandurand et al. (2015).

Since evaluating the operating state of an individual unit is a complex decision system that involves multiple factors and indicators Luo et al. (2012), and there is a correlation at each indicator, this will increase the difficulty of the analysis. In order to evaluate the characteristics of unites, univariate analyses are limited, as they evaluate each variable individually, whereas multivariate analyses take into account the correlations between variables for a more complete interpretation of the information extracted from a data set.

On the basis of principal component analysis (PCA), hierarchical clustering was performed on the data to identify clusters of civil branches of an Iranian trial court based on judicial performance indicators. PCA approach concentrates the information and simplifies the structure of the indicators, making the process simple, intuitive, and effective (Anderson (1962); Wolfgang and Leopold (2003)). It can be used to compress a high-dimensional data set into a low-dimensional data set Santos et al. (2019). Thus, it is able to monitor unperceived components in addition to univariate evaluation of individual features Ribeiro et al. (2018). This multivariate statistical technique was initiated by Pearson Pearson (1901) and developed by Hotelling (1933).

For developing inbuilt classification systems, hierarchical clustering has been a powerful tool Murtagh and Contreras (2011). One of its highly desirable properties is that the optimal number of clusters "K" does not need to be specified in advance, as in other non-nested clustering techniques such as K-Means, etc. Hierarchical methods, on the other hand, produce a unique nested hierarchy of clusters from which a partition for any "number of clusters" can be obtained. Consequently, hierarchical clustering provides an excellent framework for exploring relationships between clusters. The success of hierarchical clustering in a procedure is also due to dendrograms, an extremely insightful binary tree visualization of clustering Kimes et al. (2017). The analysis is performed in the R environment for statistical computing and visualization. It is free, runs on most operating systems, and contains valuable contributions from leading computational experts in the field Ihaka and Gentleman (1996).

Overall, each variable used in this study was examined to determine whether similar characteristics of the analyzed performance could form groups and whether these characteristics could be discriminatory in forming groups with homogeneity within and heterogeneity between them Ventura et al. (2012). Based on Kaiser's rule Kaiser (1960), the number of principal components to be retained (i.e., the number of variables required to explain variation in judicial performance) was determined by eigenvalues (variances) greater than 1. Accordingly, only components with eigenvalues greater than 1 were considered significant, while all components with eigenvalues less than 1 were discarded. Pearson's correlation was used to analyze the relationship between the original variables and the principal components. To confirm the results of the cluster analysis, we used the nonparametric Kruskal-Wallis test. Dunn's (1964) post-hoc test was also used to identify the variables that contributed to the differentiation of the groups ($p < 0.05$), with Bonferroni corrections applied to the $p-$values. To confirm the most important variables within each group, the hierarchical clustering by principal components (HCPC) method was also used Husson et al. (2010).

This paper is divided into five sections. Section 2 and Section 3 contain a description of the data and materials and methods, respectively. With the aim of capturing the determinants of the judicial performance of the Iranian justice system, we used data from a judicial complex (EJC) consisting of 18 individuals (civil branches) described by 9 variables (selected indicators) to derive key measures of judicial performance. Section 4 is dedicated to the results and discussion. In this section, the successful clustering of judicial performance indicators by PCA is demonstrated. Then, hierarchical clustering based on principal component analysis is used to produce a comprehensive evaluation. The result of the evaluation proves that the paper evaluation method (HCPC) is effective. Section 5 briefly summarizes this study.

2 Data description

In Iran, the Judiciary Statistics and Information Technology Center publishes a report each month titled "Justice Performance Report", which uses two indices to evaluate the performance of the judicial branches: the administrative index and the judicial index.

According to the preface of the aforementioned April 2014 report states, "The comprehensive statistical system of the electronic justice plan is called SAJA". This system aims to identify all statistical needs at the different levels of the judiciary, as well as the environment outside the system. In addition, the judiciary collects its data in the court case management system known as SAMP. Here, the research object is about the 18 civil branches of the EJC in 2021-2022. The performance of the branches is measured by 20 indicators (11 for the calculation of the administrative score, 9 for the calculation of the judicial score). These variables can be measured using SAMP and have a greater impact on court efficiency. Descriptive statistics for the EJC performance assessment (by Judicial SAMP Score items) are presented in Table 1.

Table 1: Average, minimum, maximum, standard error values (EP) and coefficient of variation (CV) of the SAMP judicial variables of EJC branches.

Variable	Variable's Name	Average	Minimum	Maximum	EP	CV
X1	Time without action	-2681	-7252	-164	445.85	-70.54
X2	Judge's order to the branch	1339	0	7956	501.97	159.05
X3	Minutes of the proceedings	3067.03	0	9366.50	866.87	119.91
X4	Out of turn minutes	1232.03	0	7219	520.03	179.08
X5	Discretionary minutes	1263.06	0	9506	600.62	201.75
X6	Subsidiary Opinion	537	170	892	51.98	41.06
X7	Litigation of without detention	40630	17007	67615	3222.37	33.64
X8	Other closed files	927.2	444	2658	130.44	59.68
X9	Lawsuit without legal action	-278.9	-845	0	64.14	-97.58

The correlation coefficients between the indicators ranged from -0.62 to 0.65 for judicial SAMP score (Table 2). Holm's method revealed that these coefficients were significant ($p < 0.05$), except for variables $X1$, $X5$, and $X9$ ($p > 0.05$) in Table 2, which did not present significant correlations. Figure 1 visualize the correlation matrix using a correlation diagram.

Table 2: Pearson's correlation matrix, Kaiser-Meyer-Olkin (KMO) and Bartlett's test results for nine SAMP judicial indicators.

Variable	X1	X2	X3	X4	X5	X6	X7	X8	X9
X1	1.00								
X2	0.20	1.00							
X3	0.16	0.52	1.00						
X4	0.25	0.50	0.65	1.00					
X5	0.15	-0.28	-0.22	-0.14	1.00				
X6	0.13	-0.17	0.14	-0.00	0.17	1.00			
X7	0.33	0.46	0.53	0.54	0.08	0.51	1.00		
X8	-0.08	-0.15	-0.40	-0.24	0.18	-0.62	-0.55	1.00	
X9	0.38	0.37	0.35	0.32	0.33	0.07	0.34	-0.11	1.00
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy									0.651
Bartlett's Test of Sphericity Significance									0.036

Notes: KMO measure of sampling adequacy is 0.651 which is satisfactory and Bartlett's Testof Sphericity is 0.036, thus confirming the appropriateness of the dataset.

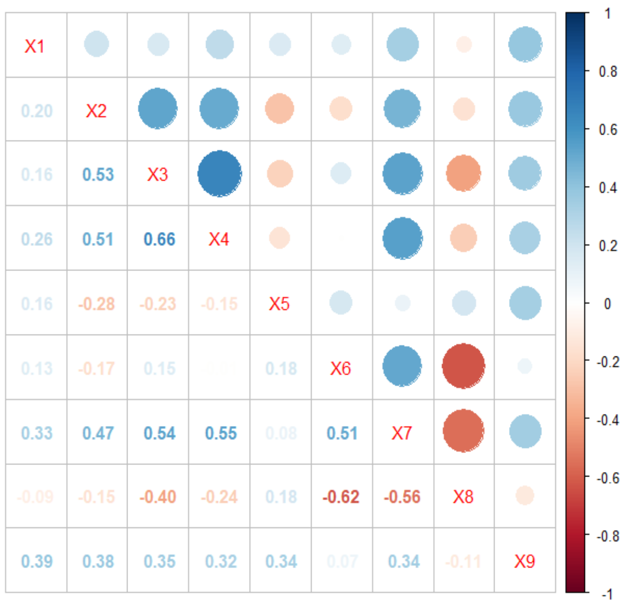


Figure 1: Visualize the correlation matrix for SAMP judicial indicators.

Note that correlation analysis is an important source for understanding the degree of association between two or more variables. It is also an essential prerequisite for use in multivariate analyses, since variables must have some degree of correlation in order to use PCA, for example.

3 Materials and methods

It is necessary to have justice indicators that measure how effectively, efficiently, and credibly a justice system is operating, and how sustainable it is. Among the variables of justice indicators, univariate analyses are limited, as they evaluate each variable individually, whereas multivariate analyses evaluate a set of characteristics concomitantly considering the correlations between variables, resulting in a more reliable interpretation of the information extracted from a data set. Multivariate analysis of the EJC branches allows to include in the analysis not only a single indicator but to select a few variables and to make an analysis with a group of the selected indicators. Setting up the variables is the first important step. The selection procedure is a critical aspect of a multivariate analysis, as the outcome will depend on the original dataset analyzed. In a multivariate analysis, the goal is to create relatively good isolated groups of EJC branches, where the branches in a specific cluster are similar to each other and differ from those in other groups. For cases of strong correlations, the most significant principal components were used instead of the original strongly correlated data set to perform a cluster analysis. As principal components are linearly independent, they can be used as inputs for cluster analysis.

3.1 Hierarchical clustering on principal components

PCA, hierarchical clustering, and K-means are three main multivariate data analysis methods combined in HCPC. An analysis of PCA reduces the dimensionality of data by extracting the most significant continuous variables. Cluster analysis is then performed as a noise removal step to ensure robust clustering of the PCA findings (Maugeri et al. (2021); Husson et al. (2010)). Lastly, the K-mean algorithm clusters them.

3.2 Layout and design of the study

All analyses were conducted using the R language for statistical computing Gardener (2012). In the first step, R was installed and loaded with the packages necessary for hierarchical clustering analysis. These packages included "FactoMineR" Lê et al. (2008) and "factoextra" Kassambara and Mundt (2017).

As part of the second step of analysis, features were extracted using PCA, which is frequently used to reveal hidden patterns in data. PCA is an unsupervised learning method that reduces ambiguity while preserving trends over time for large datasets. As our dataset contains variables that are correlated with one another, this was critical when working with it. Using PCA, a dataset is divided into principal components (PCs), which correspond to uncorrelated variables that maximize variance successively Lever et al. (2017). Setting $ncp = 3$ allowed us to analyze only the first three components. Due to the significance of these three components, the less significant components were ignored.

In the third step, hierarchical clustering was applied to selected principal components. Implementation of the hierarchical clustering on principal components method was done using the "FactoMineR" package. By applying the Ward criterion to the selected principal components, hierarchical clustering was computed. In the hierarchical clustering algorithm, the Ward criterion, which is based on multidimensional variance and similar to principal component analysis, was implemented Maugeri et al. (2021). In the initial partitioning, the hierarchical tree was split. K-means clustering was used to make the partitioning robust, and individuals and variables were used to characterize the clusters. Clustering is performed hierarchically on the basis of two principles: (i) proximity within a class (a small variability within each class) and (ii) distance between classes (a large variability between classes).

Having more classes makes homogeneity easier. A small number of classes, on the other hand, will lead to more variability within each class. Therefore, before reaching any strong conclusions based on this criterion, we consider the number of individuals and number of classes. Ward's method suggests a new way to do hierarchical clustering, based on the criterion for quality of a partition Szekely and Rizzo (2005).

The Ward method begins with the clustering where each individual represents a class. This implies that, within each class, there is no within-class variability, so the between-class variability equals the total inertia (total variance), which leads to a perfect partition. According to Ward's method, two classes, a and b, should be selected so that aggregating them minimizes the decrease in the between-class inertia Szekely and Rizzo (2005). In essence, the between-class inertia can only decrease when we aggregate two classes, and we want to minimize this decrease. The dendrogram resulting from hierarchical clustering was illustrated in the 4th step, using the "fviz_dend()" function in the factoextra package. Individuals on the principal component map were highlighted in the fifth step using the "fviz_cluster()" function of the "factoextra" package, based on the cluster to which they were assigned.

In the sixth step, the plot() function was used to create a three-dimensional plot combining hierarchical clustering with a factor map. The original data were created along with the cluster designations and quantitative features that best define each cluster. Key information about all clusters, including the "mean in category", the "overall mean", "$p-$value" and principal dimensions significantly associated with these clusters were calculated. Finally, a list of key individuals (civil branches of the courts) in each cluster was compiled.

4 Results and discussion

This section provides details of all analyzes performed as part of this study. Most of the analysis results have been presented as visualizations for ease of understanding. The main purpose of this analysis is to extract the hidden patterns in the data and visualize them in an appropriate way.

The circular diagram in Figure 2 represents the hierarchical clustering dendrogram using Ward's linkage and the Euclidean distance method for the 9 explanatory judicial variables considered in the analysis. The output of the hierarchical clustering algorithm on principal components resulted in a "factor map", a "hierarchical clustering on the factor map", and a "dendrogram". These visualizations can be seen in Figure 3 and Figure 4. The hierarchical cluster tree with three clusters in black, green and pink triangles is shown in Figure 4.

Figure 3 shows maps with identified clusters. Panel (a), in Figure 3, depicts the PCA plot showing EJC branches assigned to each of the tree clusters. Cluster 1 and 2 have coordinates on dimension 2, which explain 18.9% of the variance in the data.

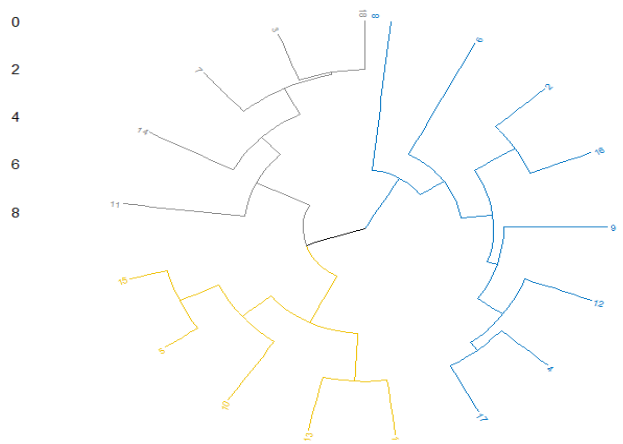


Figure 2: Circular dendrogram for 9 explanatory judicial variables.

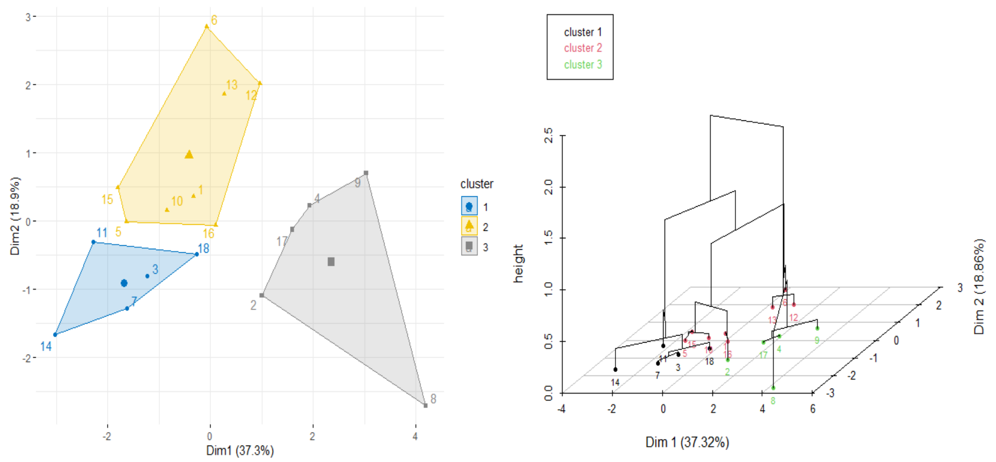


Figure 3: (a) the court branches assigned to each of the 3 clusters, (b) a combined plot of hierarchical clustering and PCA in a three-dimensional view.

Cluster 3 has coordinates on dimension 1, which explain 37.3% of the variance. Panel (b) shows a combined plot of hierarchical clustering and PCA in a three-dimensional view. Figure 4 which shows the hierarchical cluster tree showing the cluster dendrogram dividing the EJC branches into 3 clusters along with a graphical output showing the loss of inertia. Cluster 1 is enclosed in the black rectangle, whereas the pink and green rectangles encloses the areas coming under Cluster 2 and Cluster 3, respectively. In this figure, at the first bar in the graph, we see that there is a large loss in inertia when passing from two classes to one, which means that it is not a good option to group them together. In the same way, we see that there is a loss of inertia when passing from three classes to two. In contrast, there is very little loss of inertia when passing from four classes to three.

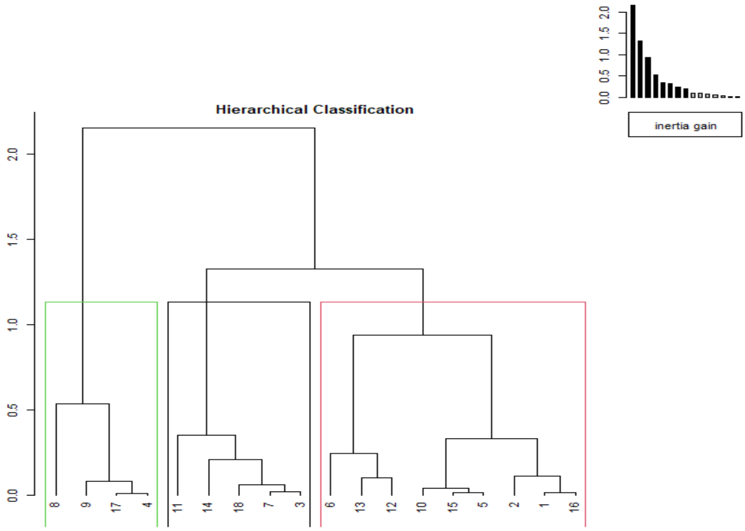


Figure 4: Cluster dendrogram dividing the EJC branches into 3 clusters, showing the loss of inertia.

Eigenvalues obtained through PCA are used to determine the number of PCs to keep, such that the most significant features are retained, and the trivial ones are ignored. The eigenvalues presented in Table 3 show that a total of three PCs were obtained. The eigenvalue of the first principal component explained 37.32% of the variation, while 18.86% of the variation is explained by the second eigenvalue. The third eigenvalue explained 16.67% of the variance. The cumulative percentage explained is calculated by adding the running total of the successive proportions of variation explained by each principal component; results can be observed in Table 3.

Table 3: Three principal components with their corresponding eigenvalues, percentage of variance and cumulative percentage of variance for each principal component.

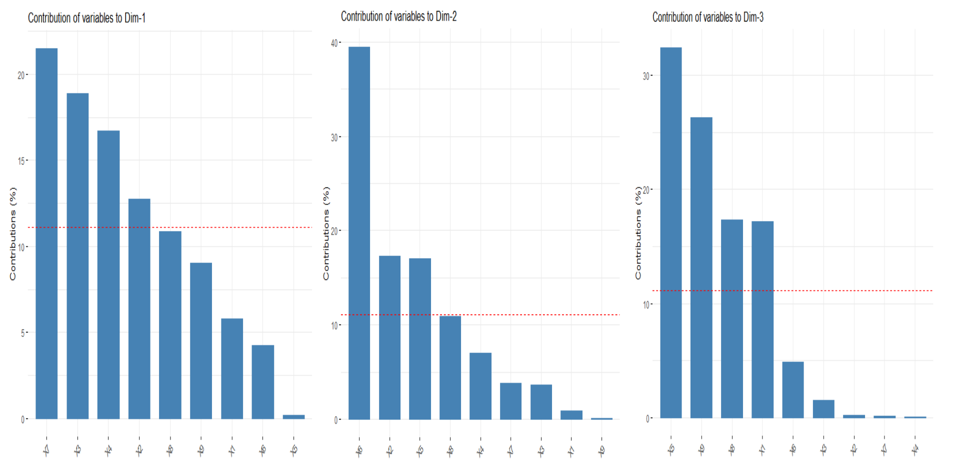
Principal Component	Eigenvalue	Total Variance (%)	Accumulated Variance (%)
PC1	3.3583900	37.315445	37.31544
PC2	1.6970643	18.856270	56.17171
PC3	1.5002547	16.669497	72.84121
PC4	0.7217379	8.019310	80.86052
PC5	0.5580466	6.200517	87.06104
PC6	0.4678144	5.197938	92.25898
PC7	0.2976201	3.306890	95.56587
PC8	0.2417719	2.686354	98.25222
PC9	0.1573001	1.747779	100.00000

The covariance matrix is symmetric, and symmetric matrices include orthogonal eigenvectors; the PCA produced orthogonal components (Husson et al. (2010); Abdi and Williams (2010); Wold et al. (1987)). The first principal component of the data is the eigenvector with the highest eigenvalue 3.3583900; this component explains the most variation in the data, making it the most significant component. Similarly, the eigenvector with the second largest eigenvalue, 1.6970643, became the second principal component, and the third component became significant as well. However, the fourth principal component explained almost law variance. As a result, this feature was not examined further.

In the present study, the highest weighting coefficients (autovectors) and contributions (Figure 5a), for Table 4 represented by: $X7(0.849)$, $X3(0.797)$, $X4(0.749)$ and $X2(0.654)$. As a result, $X7$ is an important indicator of the judicial SAMP score offered to the EJC branches. Similarly, in PC2 the variables of major autovectors and contributions were $X6(0.818)$, $X2(-0.541)$ and $X5(0.537)$ which explained 18.86% of the total variance (Figure 5b). Further, $X5$ presented an autovector of 0.697 in the PC3, $X9$ (0.628), $X8(0.510)$ and $X1(0.508)$ explaining 16.67% of the total variation of the data (Figure 5c). X5 content proved to be the component with the highest variability of the judicial SAMP score analyzed EJC branches.

Table 4: Autovectors for the nine descriptive variables of EJC.

Variable	PC1	PC2	PC3
X1	0.441	0.123	0.508
X2	0.654	-0.541	0.055
X3	0.797	-0.249	-0.151
X4	0.749	-0.345	0.027
X5	-0.082	0.537	0.697
X6	0.378	0.818	-0.271
X7	0.849	0.255	-0.045
X8	-0.605	-0.430	0.510
X9	0.551	0.028	0.628



(a) The first component (b) The second component (c) The third component

Figure 5: The main components (PC1, PC2 and PC3) contributions for SAMP judicial indicators.

PCA used a projection diagram (Figure 6) to evaluate the behavior of variables based on correlations inherent to the distribution of the components, as well as a function of the angle formed by the vectors. When the angle between the variables (vectors) is close to zero, the correlation is very high and positive and will be close; when the angle is close to 180°, the correlation is very high and negative and will be more distant; when the angle is 90°, the correlation is less Bodenmüller et al. (2020).

According to the judicial score indicators, a strong correlation could be observed between the contents of $X7, X1, X9, X3, X4$ and $X6$, characterizing the EJC branches performance and these variables were close to axis 1 and in the same quadrant (1), except for $X3$, $X4$ and $X2$ which appeared in the quadrant (4). Therefore, we can verify that the variables with the greatest length vectors were the most important. In addition, the angle formed between the variables was less than 45°, indicating a strong relationship between those characteristics. The inverse situation was observed for $X8$, which formed an angle close to 180° and appeared in opposite quadrants, presenting a strong negative (positive) correlation. In the graph, different colors are used to represent the correlations between the analyzed characteristics within a component, the colors orange and blue represent positive and negative correlations respectively.

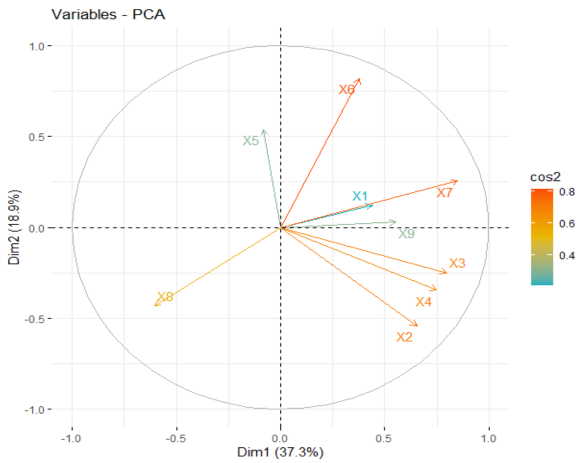


Figure 6: Projection of judicial performance variables for EJC branches in the main components (PC1, PC2).

It is common to use a graphical representation known as a scree plot to determine how many PCs should be retained. In a scree plot, each PC's eigenvalues are depicted in a simple line segment plot. A scree plot, on the other hand, serves as a diagnostic tool to determine if you need to run PCA on your data or not. The y-axis shows the eigenvalues, and the x-axis shows the number of factors. In scree plot, all components are selected just before the line flattens out, looking for the "elbow" in the curve. The curve always indicates a downward slope.

Visualize eigenvalues (scree plot) Show the percentage of variances explained by each principal component. In Figure 7, just PC 1,2, and 3 are enough to describe the data. These PCs have capture most of the information, then we can ignore the rest without losing anything important.

After applying hierarchical clustering on PCs, the combined plot of hierarchical clustering and PCA was created, which can be seen in Figure 4. The analysis of the clusters revealed that five EJC branches were assigned to Cluster 1 and Cluster 3, and

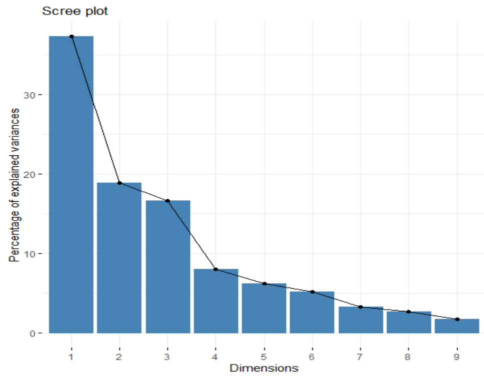


Figure 7: Scree plot for 9 judicial performance indicators.

eight EJC branches was assigned to Cluster 2.

Each cluster was found characterized by the variables (numerical characteristics) in our dataset. The numerical characteristics that best define each cluster are displayed in Table 5.

Table 5: The clusters characterized by the variables.

Clusters	Variables	V. test	Mean in Category	Overall Mean	Sd in Category	Overall Sd	P-Value
Cluster 1	X8	3.248	1.235	6.091e-17	1.069	0.972	0.001
	X3	-2.134	-0.81	6.167e-18	0.024	0.972	0.03
	X7	-2.355	-0.895	-1.214e-16	0.715	0.972	0.019
	X6	-2.976	-1.131	1.214e-17	0.333	0.972	0.003
Cluster 2	X6	2.289	0.603	1.214e-17	0.668	0.972	0.022
Cluster 3	X3	3.357	1.276	6.168e-18	0.476	0.972	0.001
	X4	2.857	1.086	-1.889e-17	1.288	0.972	0.004
	X2	2.705	1.028	-1.735e-18	1.253	0.972	0.007
	X7	2.111	0.802	-1.214e-16	0.724	0.972	0.035
	X9	1.991	0.757	8.842e-17	0.384	0.9718	0.0465

Table 5 shows quantitative variables significantly associated with clusters. When compared to other clusters, EJC branches in Cluster 1 had significantly higher average X8 with high score (mean in category). Similarly, EJC branches in Cluster 3 had a higher average number of judicial performance score(mean in category) as compared to other clusters. When compared to other clusters, EJC branches in Cluster 3 had a significantly higher average point prevalence rate of $X3$ (mean in category). Table 6 shows the principal dimensions belonging to each cluster. Table 6 output indicates that Cluster 1 has lower coordinates on dimension 1. Cluster 2 has high coordinates on dimension 2. Similarly, Cluster 3 has high coordinates on dimension 1.

Hierarchical clustering is based on an appropriate metric as a measure of distance between pairs of observations Erişŏglu and Sakallıŏglu (2010). Cursory scrutiny of the hierarchical clustering dendrogram, which serves as a summary of the distance matrix, reveals the similarities and differences between individuals in each cluster. From Figure 3, it can be observed that EJC branch “2” is closer to “1, 16” as compared to “8, 9,

Table 6: Clusters with their respective coordinates.

Clusters	Variables	V. test	Mean in Category	Overall Mean	Sd in Category	Overall Sd	P-Value
Cluster 1	Dim.3	2.0414	0.978	-3.968e-17	1.087	1.225	0.041
	Dim.1	-2.353	-1.687	-4.626e-17	0.935	1.833	0.019
Cluster 2	Dim. 2	2.692	0.951	1.667e-16	1.045	1.303	0.007
Cluster 3	Dim. 1	3.284	2.353	-4.626e-17	1.132	1.833	0.001

4, 17". The individuals lying on the same unit of the hierarchical dendrogram tree are closer to one another and closest to their respective clusters' centers. The same phenomena are displayed in Table 7, denoted as paragons. The top five individuals as the regions closest to the cluster center are presented for each cluster. The individuals in each cluster obtained in Figure 4 are similar to the individuals shown in Table 7 as paragons of each cluster. EJC branch "3, 7, 11, 14, 18" belongs to Cluster 1 and is the closest to the center of the first cluster. EJC branch "1, 5, 10, 13, 16" belongs to Cluster 2 and is the closest to the center of the second cluster. EJC branch "2, 4, 8, 9, 17" belongs to Cluster 3 and is closest to the center of the third cluster (see Table 7). The individuals, based on the dissimilarity matrix, have been separated into different clusters, and the individuals belonging to one cluster are at a farther distance from the individuals belonging to another cluster. The phenomenon is expressed in Table 7. Thus, these court branches were the most important ones characterized by high judicial performance score. These court branches should be given greater priority while implementing adequate reform in the future.

Table 7: Each cluster's most important variables, closest to their respective cluster centers.

Clusters	Court Branches	Paragons
Cluster 1	7	0.4149238
	3	0.8798506
	18	1.4922195
	14	1.8237490
	11	2.2481085
Cluster 2	1	0.6183443
	16	1.1859279
	13	1.3220244
	5	1.6551833
	10	1.6998633
Cluster 3	4	0.9396393
	17	1.0442786
	9	1.4678501
	2	1.7547585
	8	2.8218436

Table 8 displays the distances between EJC branches in one cluster and EJC branches in other clusters. EJC branch "11, 14, 7, 3, 18" belongs to Cluster 1 and is far away from the centers of Clusters 2 and 3. EJC branch "6, 13, 10, 15, 12" belongs to Cluster 2 and is far away from the centers of Clusters 1 and 3. Similarly, EJC branch "8, 9, 4, 17, 2" belongs to Cluster 3 and is far away from the centers of Clusters 1 and 2.

Table 8: Dissimilarity matrix separated the individuals.

Clusters	Court Branches	Distance
Cluster 1	11	4.317831
	14	3.752673
	7	2.928004
	3	2.121412
	18	2.018444
Cluster 2	6	4.193934
	13	3.481620
	10	3.326223
	15	3.044014
	12	2.997662
Cluster 3	8	5.975218
	9	3.515840
	4	2.584119
	17	2.576383
	2	2.522028

Discussion and conclusions

Justice indicators have been developed and used numerous times over the last decade. In different contexts, they were driven by different goals, took different forms, had different scopes, used different methods, and were managed differently Dandurand et al. (2015). In the present paper, we used the HCPC method to provide an effective evaluation of judicial performance indicators in the justice systems. This method has been used in many researches in different fields (Koh et al. (2022), Abreu et al. (2020), Combes and Azéma (2010), Penkova (2017), Shang and Wang (2015)), but it has not been used before in this field. By employing principal component analysis to identify the major judicial indicators affecting the operation state of a court branches, the comprehensive evaluation index system was considered. The principal components were then extracted as new data matrices for clustering, which eliminates the need for subjective selection of cluster variables. Finally, using the principal component score to quantify the pros and cons of each factor, the final evaluation results accurately reflect the overall operating state of the court. Calculation results show that, when there is a strong linear association between the indicators, the most significant principal components are used, rather than the original strongly correlated dataset. Nine indicators were used to group 18 civil branches based on their similarity. Based on judicial score indicators, those branches were divided into three subgroups at the end of the study. Overall, the paper method (HCPC) could give guidance unite state comparisons among different justice institutions and launching competition among different levels of judicial institutions. This method could produce acceptable clustering based on a set of justice performance indicators. It involves determining the distance between each pair of objects based on the study's indicators, and then grouping units that are close enough together. A primary benefit of this method in judicial context is that it uses a clustering approach to investigate PCA results, resulting in a better cluster arrangement. The effectiveness of the reforms of the judiciary system must be evaluated by distinguishing between different clusters of judicial performance scores. Delineating the demarcation may also aid in directing future countermeasures, which should be implemented in accordance with unite conditions. Furthermore, making appropriate modifications to our strategy might help us deal with emergencies in the future.

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