silhouette	Maximum value of the index
duda	Smallest number of clusters such that index > criticalValue
pseudot2	Smallest number of clusters such that index < criticalValue
beale	Number of clusters such that critical value >= alpha
ratkowsky	Maximum value of the index
ball	Maximum difference between hierarchy levels of the index
ptbiserial	Maximum value of the index
frey	Cluster level before index value < 1.00
mcclain	Minimum value of the index
dunn	Maximum value of the index
hubert	Graphical method
sdindex	Minimum value of the index
dindex	Graphical method
sdbw	Minimum value of the index

Source: [13].

Stage 4. Direct clustering

The most widely used optimization criterion for clustering is the clustering error criterion, which for each point calculates its square distance from the corresponding center of the cluster, and then summarizes these distances for all points in the data set. A popular clustering method that minimizes clustering error is the K-mean algorithm [24], which belongs to Partition-based methods [31] and has demonstrated its practical effectiveness in many cases [4]. The K-mean clustering technique is described in [25; 19; 4; 9; 1; 40; 5].

If we have a set of m data points $X = \{x_i | i = 1, \dots, m\}$, where each of them is an n-dimensional vector, the K-means clustering algorithm allows to divide m data points into k clusters C={c_1,c_2,…,c_k }, in order to minimize the objective function J (V, X) of dissimilarity, which is the intracluster sum of squares. The objective function J based on the Euclidean distance between the vector of the data point xi in the cluster j and the corresponding center of the cluster vj is defined as:

$$J(X,V) = \sum_{j=1}^{k} J_i(x_i, v_j) = \sum_{j=1}^{k}(\sum_{i=1}^{m} u_{ij}.d^2(x_i, v_j)) \quad (3)$$

where, $J_i(x_i, v_j) = \sum_{i=1}^{m} u_{ij}.d^2(x_i, v_j)$ is the target function within the cluster c_i, $u_{ij} = 1$, if $x_i \in c_j$, in another case $u_{ij} = 1$.

$d^2(x_i, v_j)$ is the distance between xi and vj:

$$d^2(x_i, v_j) = \left\| \sum_{k=1}^{n} x_k^i - v_k^j \right\|^2 \quad (4)$$

where, n – the number of measurements of each data point;

x_k^i – the value k-measurement xi;

v_k^j – the value k-measurement vj.

Distributed clusters are defined by $m \times k$ binary membership matrix U, in which the element uij is equal to 1, if the data point xi belongs to the cluster j and 0 – otherwise. Once the centers of the cluster $V = \{v_1, v_2, \dots, v_k\}$ are fixed, the membership function uij, which minimizes (3), can be obtained as follows:

$$u_{ij} = \begin{cases} 1; if\ d^2(x_i, v_j) \le d^2(x_i, v_{j^*}) j \ne j^*, \forall j^* = 1, \dots, k \\ 0; in\ another\ case \end{cases} \quad (5)$$

Once the membership matrix $U = [u_{ij}]$ is fixed, the optimal center vi, which minimizes (3), is the average value of all vectors of data points in the cluster j. It can be calculated using:

$$v_j = \frac{1}{|c_j|} \sum_{i, x_i \in c_j}^{m} x_i \quad (6)$$

where, $|c_j|$ – cluster size cj, $|c_j| = \sum_{i=1}^{m} u_{ij}$;

Given the initial set of k means or centers of the cluster, $V = \{v_1, v_2, \dots, v_k\}$, the algorithm is performed by alternating two steps: 1) purpose – assigned to each data point of the cluster with the nearest center; 2) update – the center of the cluster is updated as the average of all data points in this cluster.

Step 5. Validation of clusters.

Despite the same data set, different clustering algorithms can potentially generate very different clusters [41; 32]. Validation makes it possible to answer the question of the acceptability of the configuration of the clusters obtained as a result of the analysis, to solve the tasks.

One approach to validating clusters is to use internal criteria. It makes it possible to evaluate the results of the clustering algorithm using information that includes the vectors of the data sets themselves. The use of specialized software facilitates calculations and allows you to present the results of the analysis in a graphical and understandable informative form. An excellent alternative to many commercial software products in this area is the freely distributable R software environment, which is a dynamically evolving general-purpose statistical

platform [14]. In the future, the software environment R will be used by us for statistical processing of data on the activities of charitable organizations in Ukraine.

4 Results and Discussion

The results of normalization of data on the number of employees, charitable assistance received and maintenance costs in terms of individual charitable organizations of Ukraine are presented in table 3.

Table 3. Normalized values of the characteristics of charitable organizations of Ukraine

ID	Name of the charitable organization	Normalized values (dimensionless units):		
		number of employees	charitable assistance received	expenses for the maintenance of the organization
1	CO “Bright kids”	0.0149	0.000860	0.002810
2	CF “Kvitna”	0.0299	0.0109	0.0405
3	CF “Borys Kolesnikov Foundation”	0.0896	0.135	0.151
4	CO “Ukrainian forum of philanthropists”	0.0149	0.00948	0.0666
5	CO “Berezani Community Foundation”	0	0.00245	0.000670
6	CO “CF “Community unity”	0.0149	0.00205	0.00624
7	CO “CF “Svichado”	0.0448	0.0160	0.0253
8	CO “Nechitaylo family foundation”	0.0746	0.0390	0.0594
9	CO ICF “Everyone can”	0.0448	0.00626	0.0745
10	CF “Blagomay”	0.0448	0.0317	0.0346
11	CF “Pediatricians against cancer”	0.0299	0.00396	0.0203
12	A-UCF “Down syndrome”	0.104	0.0184	0.0265
13	WBF “Depol Ukraine”	1	0.0507	0.203
14	A-UCF “Association of Philanthropists of Ukraine”	0.0448	0	0
15	ICF “Caritas Ukraine”	0.955	1	1
16	CO ICF “Ukrainian Charity Exchange”	0.164	0.242	0.640
17	ICF “Life with a surplus”	0.104	0.0328	0.0902
18	ICF “Mission to Ukraine”	0.657	0.0602	0.303
19	CO “CF “Old people”	0.0448	0.00581	0.0289
20	CO “Zahoriy family foundation”	0.104	0.0441	0.109

Source: data of Reports on the use of income (profits) of the non-profit organization, provided on the website of the Ukrainian Forum of Philanthropists (https://rating.ufb.org.ua/) in free access standardized using the normalize function. Abbreviations: CO – charitable organization; CF – charitable foundation; A-UCF – All-Ukrainian Charitable Foundation; ICF – international charitable foundation

To visualize normalized data of large volumes, we use the popular graphical method “Cluster heat map” (Fig. 1).

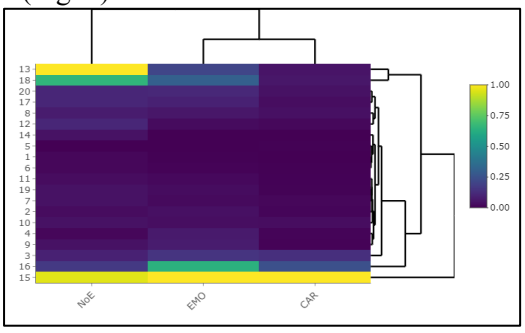

Fig. 1: Thermogram of normalized values of characteristics of activity of charitable organizations of Ukraine

NoE – number of full-time employees, standardized;

EMO – the amount of charitable assistance received, standardized;

CAR – the amount of expenses for the maintenance of the organization (administrative costs), standardized.

Source: data visualization using the heatmaply function of the R software environment

A cursory analysis of heat maps allows us to identify charitable organizations that could potentially serve as basic organizations for data segments: ICF “Caritas Ukraine” (ID 15) for all characteristics; WBF “Depol Ukraine” (ID 13) and

ICF "Mission to Ukraine" (ID 18) by the number of full-time employees and CO ICF "Ukrainian Charity Exchange" (ID 16) by the received charitable assistance. It is clear that ICF "Caritas Ukraine" (ID 15), which has the maximum value for all characteristics will form a separate cluster of charitable organizations in Ukraine.

To assess the suitability for clustering in the software environment R provides a function get_clust_tendency library factoextra. In relation to our task, the indicator H is calculated at the level of 0.8846554 (for 5 points that are randomly distributed in the data range of the original set), which is considered an acceptable value of the quality level of clustering.

Thus, using the rule of simple majority, it was found that the optimal number of clusters for the segmentation of charitable organizations of Ukraine – 4 (Table 4).

Table 4. Positioning methods for establishing the optimal number of clusters

Method of determination	The optimal number of clusters					
	2	3	4	5	6	8
Maximum value of the index	–	ratkowsky	kl, ccc, silhouette, ptbiserial, dunn	ch	–	–
Maximum difference between hierarchy levels of the index	–	scott, trcovw, ball	hartigan	–	–	friedman
Maximum value of second differences between levels of the index	–	marriot, tracew	–	–	–	–
Number of clusters such that critical value >= alpha	beale	–	–	–	–	–
Smallest number of clusters such that index > criticalValue	duda	–	–	–	–	–
Smallest number of clusters such that index < criticalValue	–	–	pseudot2	–	–	–
Minimum value of the index	cindex	–	db, mcclain, sdindex	–	sdbw	–
Minimum value of second differences between levels	–	–	rubin	–	–	–
Cluster level before index value < 1.001	–	–	–	–	–	–
Graphical method	–	–	hubert, dindex	–	–	–
Total	3	6	13	1	1	1

Note: failed to obtain reliable data to establish the optimal number of clusters by the frey method
Source: summarized by the authors

The optimality of the four-cluster division of charitable organizations of Ukraine is confirmed both by methods focused on maximizing the assessment (kl, ccc, silhouette, ptbiserial, dunn) and on its minimization (db, mcclain, sdindex), as well as graphic methods (hubert, dindex).

In the four-cluster model of segmentation of charitable organizations (Fig. 2) identified: cluster 1 (WBF "Depol Ukraine" – ID 13 and ICF "Mission to Ukraine" – ID 18); cluster 2 (ICF "Caritas Ukraine" – ID 15); cluster 3 (CO ICF "Ukrainian Charity Exchange" – ID 16); cluster 4 (other charitable organizations of Ukraine).

In the five-cluster segmentation model (Fig. 3) in a separate group from the cluster "Others" are: CF "Borys Kolesnikov Foundation" (ID 3), ICF "Life with a surplus" (ID 17) and CO "Zahoriy family foundation" (ID 20).

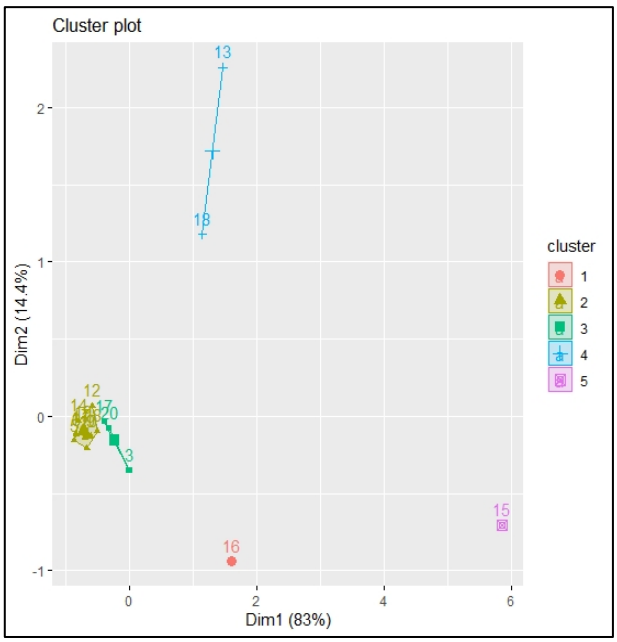

Fig. 2: Visual representation of clusters of charitable organizations of Ukraine (number of clusters – 5)

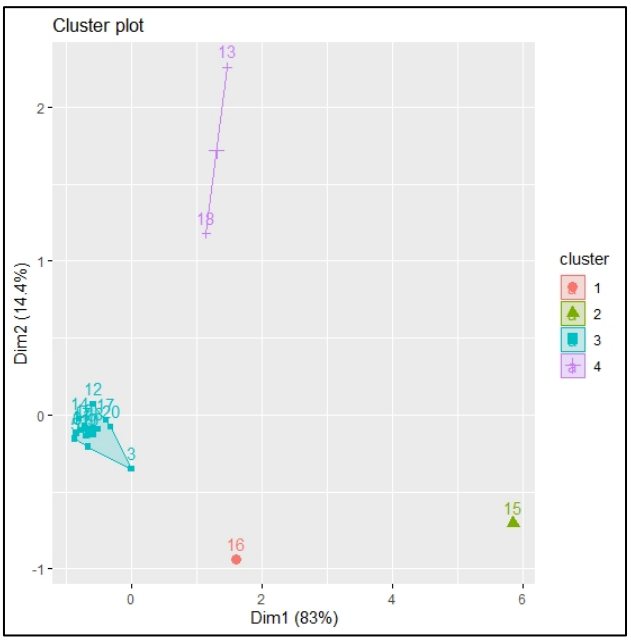

Fig. 3: Visual representation of clusters of charitable organizations of Ukraine (number of clusters – 4)

Source: data visualization using the fviz_cluster function of the R software environment

Assessment of the validity of the created clusters of charitable organizations of Ukraine requires the calculation of a number of indices, summarized in table 5.

Table 5. Assessment of the validity of clusters of charitable organizations of Ukraine

Evaluation indicator	Indicator value		The model for which the indicator is the best	
	for a four-cluster model	for the five-cluster model	four-cluster	five-cluster
Internal measures				
Connectivity	9.7159	11.7159	+	
Silhouette coefficient	0.7598	0.6916	+	
Dunn's index	1.6493	1.3303	+	
Stability measures				
Average proportion of non-overlap (APN)	0.0479	0.0896	+	
Average distance (AD)	0.4025	0.3176		+
Average distance between means (ADM)	0.1713	0.1448		+
Figure of merit (FOM)	0.4286	0.3860		+

Source: generalized by the authors based on calculations using the clValid function of the R software environment

We see that the four-cluster model demonstrates high validity, surpassing the fifth-cluster model in terms of internal assessment and slightly behind the three indicators of stability assessment (AD, ADM and FOM).

5 Conclusions

The cluster analysis showed the existence of 4 fairly clear clusters into which charitable organizations of Ukraine can be united.

The first two clusters (ICF "Caritas Ukraine" and CO ICF "Ukrainian Charity Exchange") are effective charitable organizations that have a good structure and ratio between borrowed and spent funds and, while the first, having significant

financial resources and permanently implementing joint projects with various government institutions, have relatively low flexibility in decision-making, others seek to compensate for average funding capacity, speed and consistency in responding to external challenges. The third cluster (WBF "Depol Ukraine" and ICF "Mission to Ukraine") includes organizations that do not fully use the available capacity to attract funding, and also need to improve the existing ratio between borrowed funds and money spent on their own needs. The fourth cluster (CO "Bright kids", CF "Kvitna", CF "Borys Kolesnikov Foundation", CO "Ukrainian forum of philanthropists", CO "Berezani Community Foundation", CO "CF "Community unity", CO "CF "Svichado", CO "Nechitaylo family foundation", CO ICF "Everyone can", CF "Blagomay", CF "Pediatricians against cancer", A-UCF "Down syndrome", A-UCF "Association of Philanthropists of Ukraine", ICF "Life with a surplus", CO "CF "Old people", CO "Zahoriy family foundation") includes a fairly wide range of small charitable organizations, mainly at the regional level, which have limited influence on the formation of state social policy, but are characterized by proximity to the final recipients. This cluster requires further division into smaller segments to establish the effectiveness of their activities. Such organizations are system-creating for the entire non-profit sector in Ukraine, their importance is manifested in the most rapid response to the needs of recipients through the implementation of small charitable projects. Their development in recent years has been caused by a violent volunteer movement related to hostilities in eastern Ukraine. 4th cluster organizations also require additional government support.

Limitations in our study are: the relatively small number of Ukrainian charities that currently provide official reporting in the public domain; frequent cases of improper attitude to the preparation of reports by charitable organizations on the use of income (profits) of a non-profit organization, which are the basic source of information for the implementation of the model presented in the study; The study deals exclusively with economic indicators of charitable organizations, which do not always correlate with the social purpose of their creation.

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