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Ranking and Visualizing Clusters of the US States by Adversity Childhood Experiences

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Abstract

Adverse Childhood Experiences (ACEs) refer to traumatic childhood events like emotional, physical, sexual abuse, and other forms of household dysfunction. ACEs are associated with biomarkers for chronic diseases resulting in early mortality and increased morbidity. According to the Centers for Disease Control and Prevention, ACEs are common: Around 61% of adults across 25 US states reported having experienced at least one type of ACE. Ranking and finding clusters of the US states on ACEs provide a better understanding of the situation and helps prevent or reduce the occurrence of ACEs. The paper aims to apply a Multiple Criteria Decision-Making Model called the *Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method* and calculate the overall 'Composite Index' to rank the states. Furthermore, the study uses the *K-Means Cluster algorithm* to identify and visualize clusters of states experiencing similar ACEs. The BRFSS 2019 data set was used for all analyses. The TOPSIS method suggested that Tennessee had the worst status of ACEs (ranked first) and North Dakota performed the best (ranked last). The elbow method determined that four clusters were present out of the 21 states. Many states ranked with the highest ACEs were clustered together: Tennessee, Florida, Pennsylvania, New Mexico, Delaware, Michigan. To better understand the current performance of the US regarding ACEs, it would be best to collect data from all states. Diagnostic studies, such as this study, can create the foundation for addressing and eradicating child maltreatment and ensuring healthy and nurturing childhoods.

Key Words: Adverse Childhood Experiences (ACEs), Ranking, Multiple-Criteria Decision-Making (MCDM), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Entropy Weight, Elbow method, K-Means Cluster.

AMS Classification: 62P15.

1. Introduction

The term "adverse childhood experiences" (ACEs) applies to any traumatic event an individual experienced starting at birth through the age of 17 years in an individual's life [1]. ACEs include different mental and physical traumas during childhood as follows:

1) being exposed to psychological, physical, and sexual violence and abuse,
2) experiencing neglect and imprisonment within a household or being separated from parents,
3) witnessing violence and substance, such as alcohol and drugs, abusive behaviors from caregivers or guardians, and
4) living or growing up with family member(s) who have untreated (or undiagnosed) mental issues.

These experiences create negative effects on a child’s health and well-being of a child and leave lasting impacts on education and quality of life [1, 3, 7, 12, 15]. Those who experienced ACE(s) will have a higher risk of having self-harm behaviors that can lead to injuries, STDs (from unprotected sexual activities), and maternal and child health in later life [9, 10, 19, 23]. ACEs are also associated with chronic diseases such as cancer, cardiovascular diseases, and diabetes [2, 6]. The toxic stress caused by ACEs affects an individual's brain development. Such individuals will be more likely to struggle with depression and financial hardship [8, 12, 13].

The health issues due to ACE exposure limits an individual's full potential in life and career. In fact, a study estimated that ACEs have created an economic burden ranging from $428 billion to $2.0 trillion in 2015 [4]. Another article used 2018–2019 data to rank the US states on ACEs [19]. This paper will also rank the US states regarding ACEs using a dataset in the same period but will use different criteria to better understand forms of violence against children.

This paper will determine which state is the worst regarding ACEs by ranking the 21 states using the 2019 Behavioral Risk Factor Surveillance System (BRFSS) data. A mathematical approach called "Multiple-Criteria Decision-Making" (MCDM) model [26] is used to rank the attributes with eight different ACE criteria. When no alternative shows an obvious dominance under the criteria, MCDM helps make meaningful integration of component indices to an overall index to rank all the alternatives from the best to the worst [11, 14, 16]. Although, there is always a trade-off in selecting one alternative over another. Therefore, a more advanced MCDM method called the "Technique for Order Preferences by Similarity to Ideal Solution" (TOPSIS) was introduced. In 1981, Hwang and Yoon [24] developed the TOPSIS method to help maximize the profit and minimize the harm by choosing the alternative with the shortest distance from the positive-ideal solution and the longest distance from the negative ideal solution [11, 24]. To eliminate the imprecision and uncertainty of the raw data, we calculated the entropy decision-weight to measure the relative importance among the criteria [20]. The entropy method is one of the most objective and efficient approaches, since its weights are not affected by the decision-maker's subjective judgments but rather by a statistical formulation [14].

In Section 2, we introduce the dataset and the details of the computational algorithm underlying TOPSIS method in a theoretical framework and the K-means algorithm. Section 3 includes our findings, and we conclude the paper in Section 4.

2. Material and Methods

2.1 Data Source

Administered by the Centers for Disease Control and Prevention (CDC), the Behavioral Risk Factor Surveillance System (BRFSS) conducted a cross-sectional phone survey of non-institutionalized adults aged 18 and older. Public health officials collect information on health-related risk behaviors, chronic health conditions, health care access, and use of preventive services in non-institutionalized adults aged ≥ 18 years. The BRFSS 2019 dataset was used for analysis and had 418,268 adult participants residing in all 50 states and US territories.

Among participants who completed the 2019 BRFSS interview, 149,801 individuals aged ≥ 18 years from twenty-one states (Alabama, Delaware, Florida, Indiana, Iowa, Kansas, Michigan, Mississippi, Missouri, New Mexico, New York, North Dakota, Ohio, Oklahoma, Pennsylvania, Rhode Island, South Carolina, Tennessee, Virginia, West Virginia, Wisconsin) answered the optional ACE module. The ACE module is an 11item survey (see Table 1) where respondents are asked if they experienced various adverse events during their childhood (prior to age 18 years).

For analyses investigating the influence of specific types of adverse events, questions were categorized by components into eight categories: physical abuse, emotional abuse, sexual abuse, mental illness in the household, substance abuse, incarcerated household member, parental separation, and intimate partner violence, which is shown in Table 1.

Table 1: Categories of adverse childhood experience events

Question#	Question text	ACE category
M22.01	Now, looking back before you were 18 years of age- Did you live with anyone who was depressed, mentally ill, or suicidal?	Mental illness in the HH
M22.02	Did you live with anyone who was a problem drinker or alcoholic?	Substance abuse in the HH
M22.03	Did you live with anyone who used illegal street drugs or who abused prescription medications?	Substance abuse in the HH
M22.04	Did you live with anyone who served time or was sentenced to serve time in a prison, jail, or other correctional facility?	Incarcerated HH member
M22.05	Were your parents separated or divorced?	Parental separation
M22.06	How often did your parents or adults in your home ever slap, hit, kick, punch or beat each other up? Was it…	Intimate partner violence
M22.07	Not including spanking, (before age 18), how often did a parent or adult in your home ever hit, beat, kick, or physically hurt you in any way? Was it…	Physical abuse
M22.08	How often did a parent or adult in your home ever swear at you, insult you, or put you down? Was it…	Emotional abuse
M22.09	How often did anyone at least 5 years older than you or an adult, ever touch you sexually? Was it…	Sexual abuse
M22.10	How often did anyone at least 5 years older than you or an adult, try to make you touch them sexually? Was it…	Sexual abuse
M22.11	How often did anyone at least 5 years older than you or an adult, force you to have sex? Was it…	Sexual abuse

We use the following dataset in Table 2 to rank the 21 US states based on eight variables. The original data include the counts of 'Yes'/'No' and the total responses. We calculated the percentages of 'Yes' out of the total number of responses for each criterion for each state since we were interested in ranking the states using the TOPSIS-MCDM method. The proportions generated from the original data are shown in Table 3 below.

2.2 The TOPSIS method

We represent each data point in Table 3 by $X = (x_{ij})$, the positive-valued score matrix (or the decision matrix) of order $m \times n$. The matrix X represents the twenty-one states as m rows (m=21) and the eight criteria (eight ACEs listed in Table 3) as n columns (n=8.) The assumption that the score for a particular state does not exceed those of all other states in the data ensures that each state is adjudged the best with respect to some evaluation criterion. The study's objective is the overall ranking of all states by considering their performance across all criteria. Hence, we must ensure that all the scores for the evaluation criteria have a consistent interpretation that 'min-to-max' agrees with 'best-to-worst.'

The TOPSIS method evaluates the following decision matrix shown in Table 3, which has m alternatives $A_1,\ A_2, \dots, A_m$ (21 US states) associated with n attributes or criteria $C_1,\ C_2, \dots, C_n$ (eight ACEs). Here, x_{ij} is the numerical outcome of the i^{th} alternative for the j^{th} criterion, and w_j is the weight of criterion C_j, indicating its relative importance among all evaluation criteria.

Table 4: Decision matrix in MCDM

Alternatives	Criteria (Weights	C_1 w_1	C_2 w_2	C_3 w_3	$\cdots$ $\cdots$	C_n w_n)
A_1		x_{11}	x_{12}	x_{13}	$\cdots$	x_{1n}
A_2		x_{21}	x_{22}	x_{23}	$\cdots$	x_{2n}
A_3		x_{31}	x_{32}	x_{33}	$\cdots$	x_{3n}
$\vdots$		$\vdots$				
A_m		x_{m1}	x_{m2}	x_{m3}	$\cdots$	x_{mn}

The following steps are used to calculate the entropy weight w_j:

Step 1. *Converting the decision matrix to the normalized mode:*

We computed the entropy value for the j^{th} criterion by normalizing each value in the decision matrix as p_{ij} using Equation 1 below:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad \text{for } i = 1,2,3,\dots,m \text{ and } j = 1,2,3,\dots,n \tag{1}$$

Step 2. *Calculating the entropy and degree of diversity for each criterion of the dataset:*

The entropy e_j of the corresponding j^{th} criterion is calculated as follows:

$$e_j = -\alpha \sum_{i=1}^{m} p_{ij}\, ln(p_{ij}) \quad \text{for } j = 1,2,3,\dots,n \tag{2}$$

In Equation (2), α represents a constant: $\alpha = {}^{1}/_{\ln(m)}$, which guarantees that $0 \le e_j \le 1$.

Next, the degree of diversity d_j relative to the corresponding anchor value (unity) is calculated by subtracting the entropy e_j from 1:

$$d_j = 1 - e_j \qquad \text{for } j = 1, 2, 3, \ldots, n \tag{3}$$

Step 3. *Defining criteria weights:*

The entropy weight vector, $W = (w_1, w_2, \ldots, w_n)$, is calculated as:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \qquad \text{for } j = 1, 2, 3, \ldots, n \tag{4}$$

Once the weights are calculated using the entropy method, these weights are then incorporated into the TOPSIS method to calculate the overall score. The algorithm of this technique is summarized as follows:

i) Construct the normalized decision matrix R:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad \text{for } i = 1, 2, 3, \ldots, n \text{ and } j = 1, 2, 3, \ldots, n \tag{5}$$

ii) Construct the weighted normalized decision matrix V:

$$v_{ij} = r_{ij} \times w_j \qquad \text{for } i = 1, 2, 3, \ldots, m \text{ and } j = 1, 2, 3, \ldots, n \tag{6}$$

iii) Determine the "Positive-ideal Row" (IDR) as the one with the smallest observed value for each column:

$$IDR = (\min v_{i1}, \min v_{i2}, \ldots, \min v_{in}) = (v_1^+, v_2^+, \ldots, v_n^+) \text{ for } i = 1, 2, 3, \ldots, n \tag{7a}$$

Similarly, the “Negative-ideal Row” (NIR) as the one with the largest observed value for each column:

$$NIR = (\max v_{i1}, \max v_{i2}, \ldots, \max v_{in}) = (v_1^-, v_2^-, \ldots, v_n^-) \text{ for } i = 1, 2, 3, \ldots, n \tag{7b}$$

iv) Calculate the Euclidean distance, d_i^+ for i = 1, 2, 3, …, m, of each alternative from the positive ideal row:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \qquad \text{for } i = 1, 2, 3, \ldots, m \tag{8a}$$

Similarly, we determined the Euclidean distance, d_i^- for i = 1, 2, 3, …, m, of each alternative from the negative ideal row:

$$d_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \qquad \text{for } i = 1, 2, 3, \ldots, m \tag{8b}$$

The distance measures used in Equations (8a) and (8b) are referred to as 'Euclidian distance' or ‘Euclidian Norm,’ denoted by L_2.

v) Calculate the relative closeness of alternatives to ideal solution by computing the ‘Composite Index [CI]’ as follows:

$$CI_i = \frac{d_i^+}{d_i^- + d_i^+} \qquad \text{for } i = 1, 2, 3, \ldots, m \tag{9}$$

In Equation (9), $0 \leq CI_i \leq 1$. These composite indices are used for the final ranking of the states, with the rule being: max–to–min for ranks 1–to–m. The results of the algorithm are included in the section hereafter.

Table 2: Original data including the number of responses to eight types of ACEs in 21 states in 2019

State	Physical abuse			Emotional abuse			Sexual abuse			Mental abuse			Substance abuse			Incarcerated abuse			Parent separation			Intimate parent violence		
	Yes	No	n	Yes	No	n	Yes	No	n	Yes	No	n	Yes	No	n	Yes	No	n	Yes	No	n	Yes	No	n
Alabama	107	474	581	159	420	579	766	497	573	943	490	584	155	428	584	417	545	587	164	420	584	918	486	578
Delaware	913	216	308	105	200	305	392	266	306	484	263	312	799	231	311	215	291	313	804	231	311	533	255	308
Florida	330	936	126	389	870	126	176	107	124	193	108	128	351	927	127	102	118	128	380	896	127	215	104	125
Indiana	174	560	734	235	498	733	931	634	727	117	625	742	177	564	742	485	697	745	176	562	739	114	620	734
Iowa	179	641	821	277	539	816	903	725	816	143	681	824	202	620	823	544	775	829	169	657	827	119	698	817
Kansas	107	368	475	158	312	471	648	404	469	873	390	477	118	359	477	293	451	480	113	365	478	622	411	473
Michigan	231	703	934	326	597	923	123	798	921	177	763	941	264	673	937	659	878	944	233	710	943	149	782	931
Mississipp	732	380	453	107	344	451	510	400	451	602	394	454	111	343	454	345	424	459	124	332	456	717	375	447
Missouri	136	484	620	190	426	616	781	536	614	109	514	624	163	460	623	494	577	626	163	461	625	915	524	615
New	138	374	513	174	337	511	770	431	508	958	419	515	158	355	514	368	481	518	125	391	517	927	419	511
New York	977	282	379	117	259	377	424	334	376	527	332	384	801	302	382	140	372	386	899	293	383	551	322	377
North	917	412	504	140	360	500	454	455	501	641	444	508	113	393	507	245	485	510	734	435	509	564	446	502
Ohio	179	594	773	245	521	766	898	671	760	121	656	778	194	583	778	509	731	782	178	599	777	120	646	767
Oklahoma	498	195	245	730	169	242	351	207	242	454	200	245	672	177	244	192	226	246	721	173	245	425	197	240
Pennsylva	135	408	543	191	350	541	622	475	538	104	441	546	149	396	546	444	504	549	138	409	547	848	456	541
Rhode	129	362	492	168	321	490	632	423	486	891	406	495	133	360	494	206	476	497	115	381	496	749	415	490
South	134	466	601	179	418	597	749	520	595	977	506	604	160	444	604	445	563	607	147	456	603	996	496	596
Tennessee	110	361	472	149	321	470	684	400	468	860	391	477	134	342	477	414	437	478	138	338	476	851	386	471
Virginia	167	631	799	241	552	794	955	694	790	128	676	805	211	593	804	505	757	807	188	616	804	115	677	793
West	820	389	471	123	344	468	511	415	466	717	400	472	111	362	473	279	447	475	101	374	475	718	396	468
Wisconsin	101	299	401	143	256	400	429	356	399	628	345	408	101	304	406	204	389	409	766	328	404	555	345	400

Table 3: Percentage distribution of adult's responses who experienced different ACEs in 21 states in 2019.

State	Physical abuse	Emotional abuse	Sexual abuse	Mental abuse	Substance abuse	Incarcerated abuse	Parent separation	Intimate parent
Alabama	18.46	27.45	13.35	16.13	26.59	7.10	28.08	15.87
Delaware	29.64	34.46	12.81	15.51	25.64	6.87	25.79	17.29
Florida	26.11	30.91	14.15	15.08	27.46	7.97	29.82	17.12
Indiana	23.73	32.06	12.80	15.82	23.94	6.50	23.87	15.56
Iowa	21.88	33.99	11.07	17.41	24.61	6.56	20.54	14.66
Kansas	22.54	33.60	13.80	18.29	24.69	6.10	23.74	13.13
Michigan	24.73	35.36	13.36	18.84	28.17	6.98	24.71	16.01
Mississippi	16.14	23.73	11.31	13.23	24.58	7.51	27.27	16.03
Missouri	21.99	30.93	12.72	17.61	26.18	7.88	26.16	14.86
New Mexico	27.05	34.11	15.15	18.60	30.83	7.10	24.33	18.12
New York	25.72	31.19	11.25	13.70	20.92	3.62	23.47	14.61
North	18.18	28.09	9.06	12.60	22.43	4.80	14.41	11.21
Ohio	23.14	32.00	11.80	15.66	25.01	6.50	22.93	15.70
Oklahoma	20.33	30.08	14.47	18.48	27.47	7.80	29.34	17.69
Pennsylvania	24.87	35.26	11.56	19.21	27.38	8.09	25.22	15.66
Rhode Island	26.35	34.36	12.99	17.97	27.04	4.14	23.19	15.27
South	22.34	30.05	12.58	16.16	26.53	7.32	24.49	16.71
Tennessee	23.44	31.74	14.60	18.02	28.19	8.64	29.01	18.06
Virginia	20.95	30.44	12.08	15.99	26.24	6.25	23.46	14.60
West	17.38	26.33	10.95	15.18	23.47	5.86	21.34	15.34
Wisconsin	25.39	35.94	10.73	15.38	25.06	4.98	18.93	13.85

2.3 The K-Means Clustering

K-means clustering algorithm [25], an unsupervised machine learning method, was used to group states which were experiencing similar ACEs. This method orders the data points by finding relationships automatically, without human intervention. In terms of the actual process of K-means, the data points are grouped by their similarities where the distance between the groups is maximized and the distance between points within a group is minimized. It is used in a variety of fields, such as healthcare, banking, retail, media, etc. The algorithm is as follows:

1. Choose the number of clusters K.
2. Select at random K points called centroids.
3. Assign each data point to the closest centroid thereby forming K clusters.
4. Compute and place the new centroid of each cluster.
5. Reassign each data point to the nearest new centroid.

To determine the optimal number of clusters in K-means clustering, the elbow method [23] was used.

3. Findings

We considered the data in Table 3 as the decision matrix to apply the entropy method and the TOPSIS-MCDM technique to rank the states. Following the steps in the previous section, we calculated the entropy e_j, the degree of diversity d_j, and the weight w_j for all eight criteria and included the results in Table 5.

After calculating the criteria weights, we proceeded to calculate distances d_i^+ and d_i^- from the positive and negative ideal solution to each alternative. We utilized the entropy weights in Table 5 to determine necessary values in the TOPSIS technique to reach the measures of the distances for each state. The final score or the 'Composite Index [CI]' was calculated using Equation (9). The rankings of the 21 states are based on the descending order of their TOPSIS score CI_i, since we were interested in which states are the worst regarding ACEs. The results of the distances, TOPSIS scores, and rankings presented in Table 6 show that out of the 21 states, Tennessee had the worst ACEs, with Florida being a close second. North Dakota had the most positive performance regarding ACEs.

Table 5: The entropy (e_j), degree of diversity (d_j), and criteria weight (w_j) for each evaluation criterion of ACEs.

Indices	Physical abuse	Emotional Abuse	Sexual abuse	Mental abuse	Substance abuse	Incarcerated abuse	Parent separation	Intimate parent violence
e_j	0.9964	0.9983	0.9977	0.9979	0.9989	0.9933	0.9963	0.9982
d_j	0.0036	0.0017	0.0023	0.0021	0.0011	0.0067	0.0037	0.0018
w_j	0.1569	0.0716	0.1003	0.0920	0.0495	0.2916	0.1585	0.0796

Table 6: Result of the distances d_i^+ and d_i^-, final TOPSIS scores, and the rankings.

States	$d(i)^-$	$d(i)^+$	$CI(i)$	Rank
Alabama	0.0005	0.0016	0.7433	10
Delaware	0.0004	0.0017	0.8286	7
Florida	0.0001	0.0025	0.9601	2
Indiana	0.0006	0.0011	0.6523	12
Iowa	0.0008	0.0010	0.5666	14
Kansas	0.0008	0.0010	0.5420	15
Michigan	0.0004	0.0016	0.8090	9
Mississippi	0.0007	0.0017	0.7202	11
Missouri	0.0003	0.0021	0.8921	5
New Mexico	0.0003	0.0018	0.8616	6
New York	0.0025	0.0004	0.1403	20
North Dakota	0.0023	0.0001	0.0559	21
Ohio	0.0007	0.0011	0.6170	13
Oklahoma	0.0003	0.0023	0.8942	4
Pennsylvania	0.0002	0.0023	0.9326	3
Rhode Island	0.0020	0.0005	0.2190	19
South Carolina	0.0004	0.0016	0.8112	8
Tennessee	0.0001	0.0030	0.9697	1
Virginia	0.0008	0.0009	0.5221	16
West Virginia	0.0013	0.0006	0.3159	17
Wisconsin	0.0016	0.0005	0.2246	18

Various methods are available to choose the optimal number of clusters (K^*) by searching through proposed values K=1, 2, …, 10. The Gap statistic method [22] shows K^*=1, the Silhouette method [18] suggests K^*=2, and the Elbow method [22] recommends K^*=4. To discriminate the states sufficiently, we have adopted the Elbow method and show in Figure 1 the total within-cluster sum of squares for K=1, 2, …, 10.

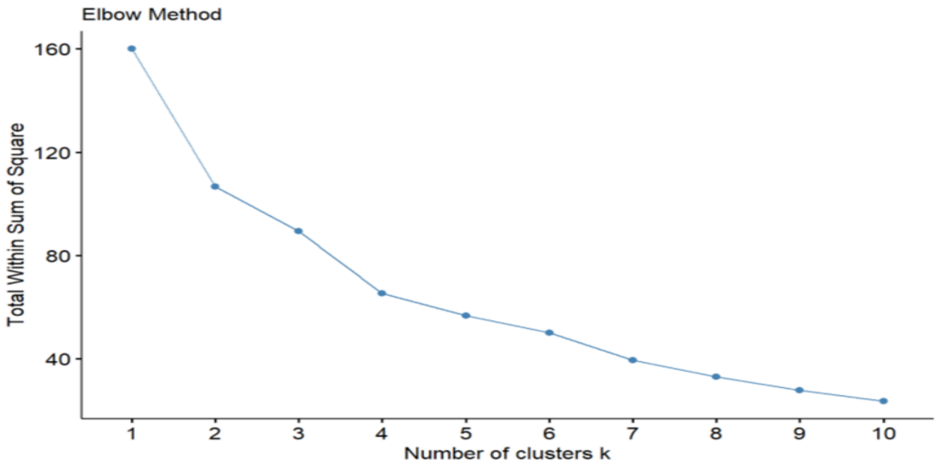

Figure 1: Elbow method recommends four clusters to be considered.

The elbow chart begins to flatten around *K*=4; therefore, we have chosen to use *K**=4 clusters. The following graphs visualizes the four clusters, along with a table that lists the states in the data, as well as their corresponding cluster group. The horizontal and the vertical dimensions in Figure 2 are the two largest principal components (PCA1 and PCA2) obtained from the weighted normalized decision matrix given in Equation (5). For details, see the annotation of R function fviz_cluster(). Table 7 summarizes the states within the four clusters.

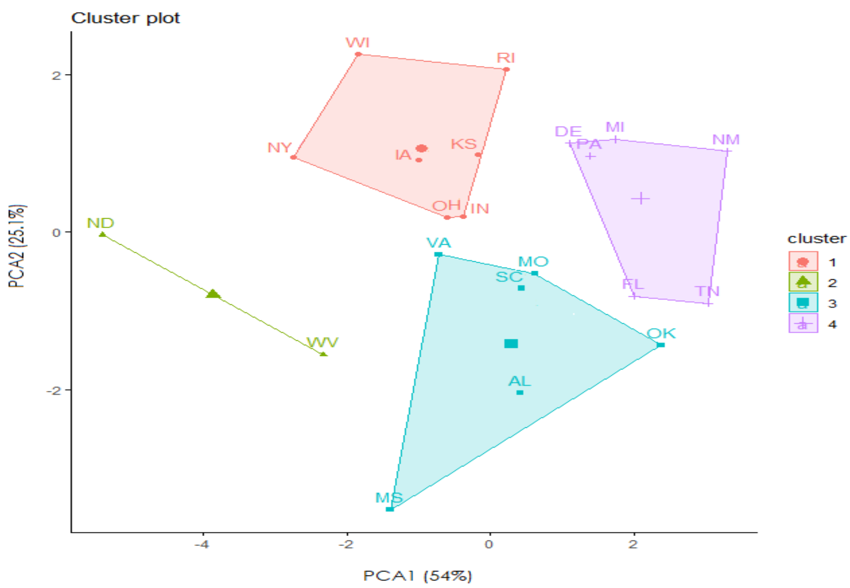

Figure 2: Cluster analysis visualizes the four clusters of states.

Table 7: States within each cluster.

Cluster #1	Cluster #2	Cluster #3	Cluster #4
Indiana (IN)	North Dakota (ND)	Alabama (AL)	Delaware (DE)
Iowa (IA)	West Virginia (WV)	Mississippi (MS)	Florida (FL)
Kansas (KS)		Missouri(MO)	Michigan (MI)
Ohio (OH)		Oklahoma (OK)	New Mexico (NM)
New York (NY)		South Carolina (SC)	Pennsylvania (PA)
Rhode Island (RI)		Virginia (VA)	Tennessee (TN)
Wisconsin (WI)			

The results indicated that many states ranked worst on ACEs found in the TOPSIS method were also observed in the same cluster. For example, of the 11 states ranked worst on ACEs in the TOPSIS method, six fell in Cluster 4 (which contains no other state) and the remaining five states fell in Cluster 3 (which contains only one more state, Virginia, ranking 16).

4. Discussion

The 21 US states were ranked based on their evaluation regarding ACEs from the worst to the least negative by applying the TOPSIS-MCDM technique to the 2019 data. The TOPSIS method helped calculate each state's overall score since the rankings are not the same under different criteria. The K-means analysis was used to find clusters of states based on ACEs. The findings show that Tennessee had the worst status of ACEs, while North Dakota performed the best among the 21 states.

Referring to an article also ranking the US states published in 2018 [20], we expected to find Tennessee, New Mexico, and North Dakota to be among the worst performance group based on the 2019 BRFSS dataset. We found similar results for Tennessee and New Mexico—ranking 1 out of 21 and 6 out of 21, respectively, on the worst performance. However, our data set suggests that North Dakota observed the least occurrence of ACEs. This result suggests further research is needed to compare the two data sets and identify if North Dakota implemented some effective improvement measures to help improve their ACE performance.

Along with Tennessee, many other state governments need to take action to improve their situations. The CDC suggests several measures, such as educating parents and children to handle stress and emotions or strengthening economic supports to families [17]. All the other states within the US should also take similar measures to reduce and prevent the occurrence of ACEs as it is part of children's rights. Additionally, reducing victims of ACEs also helps with socio-economic performances. In this study, we only had access to the 2019 BRFSS dataset, which is likely insufficient: According to the CDC, ACEs should include two more criteria which are emotional and physical neglect [5]. To better understand the current performance of the US regarding ACEs, it would be best to collect data from all 50 states. We can also look at more historical data and analyze the performance over time to see any improvement or deterioration.

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