“State policy of preventing crimes against a person: Which best practices should be used by Azerbaijan?”

AUTHORS	Zamina Aliyeva
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Zamina Aliyeva (Azerbaijan)

STATE POLICY OF PREVENTING CRIMES AGAINST A PERSON: WHICH BEST PRACTICES SHOULD BE USED BY AZERBAIJAN?

Abstract

State policy of prevention, detection, termination, disclosure, and investigation of crimes against a person in Azerbaijan should be based on other countries' best practices and experience. The choice of countries to be followed by Azerbaijan should be very well-founded, given that the dynamics of crimes against a person depend significantly on many social and economic determinants: income inequality, the dominance of the rule of law in the country, the level of literacy and financial literacy of citizens, or racial diversity.

50 countries are clustered according to the similarity of trends regarding the dependence of crimes against persons on these socio-economic determinants. Clustering is based on data of 2021 from the World Bank, World Population Review, UNODC, and WGI (the selection of countries is due to the availability of comparable statistical information, the choice of year – to the availability of the most up-to-date data). Clustering was carried out using two methods (DBSCAN and K-Means) to ensure the adequacy of the calculations. Clustering is performed for 3 combinations: 1) by the entire set of crimes and their determinants; 2) by the specific type of crime and all types of determinants; 3) by the entire set of crimes and a specific socio-economic determinant. Albania, Jordan, Mongolia, Romania, and Serbia were most often in the same cluster with Azerbaijan. Therefore, the best experience and best practices of these countries can be used by the state regulatory bodies of Azerbaijan in developing state policy on preventing crimes against the person.

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Zamina Aliyeva, Ph.D. Student, Researcher, Department of Criminal Law, Faculty of Law, Baku State University, Azerbaijan.

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INTRODUCTION

State management to reduce crimes against persons is based on international agreements that establish uniform rules and standards for combating these types of crimes and provide for the unification of separate legislative and legal norms (this allows for effective investigation and disclosure of crimes committed on the territory of several countries), implementation of global cooperation of law enforcement agencies to exchange information, conduct joint operations and investigations, etc. For example, the European Convention on Combating Terrorism establishes uniform rules for combating terrorism, including responsibility for terrorist acts. The United Nations Convention against Transnational Organized Crime establishes uniform rules to combat organized crime, including human trafficking and drug and arms trafficking. The United Nations Convention against Corruption establishes uniform rules for combating corruption, including accountability for corrupt practices.

At the same time, state management, to reduce crimes against persons in each country, must consider that country's legal, socio-cultural, and socio-economic specificities. Copying those methods of state

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management that have proven successful in other countries will not give the desired result. Thus, for effective state management in this area, it is necessary to clearly outline the circle of countries' best practices, which can be applied given the similarity of the socio-economic context.

Any illegal actions involving other persons are recognized by international criminal law as crimes against the person. A crime against a person is always a criminal offense involving the use of force or the threat against another person. These crimes are generally considered the most serious types of crimes, and the penalties for them can be very severe. They are usually structured according to the following categories: fatal offenses, sexual offenses, and non-sexual offenses that do not result in death (Haque, 2022).

According to the Global Crime Index calculated by the Global Initiative against Transnational Organized Crime, among the 193 countries for which it is calculated, the highest crime rates are in the following: Myanmar (Index is 8.15), Colombia (7.75), Mexico (7.57), Paraguay (7.52), and Congo Dem. Rep. (7.35). Among the countries of the European Union, the highest crime rates according to this index are Italy (6.22), Serbia (6.22), Spain (5.90), France (5.82), and Greece (5.35). Among the countries with high GDP per capita, the highest crime rates are the United Arab Emirates (6.37), Qatar (5.45), the United States (5.67), and Germany (5.33). Thus, the problem of finding effective mechanisms to combat crimes against the person is relevant even for wealthy countries and those belonging to the European community.

Among the countries of Central Asia and the Caucasus, including Azerbaijan, countries with the highest crime rates according to this index are Tajikistan (5.45), Kyrgyzstan (5.32), Uzbekistan (4.95), Azerbaijan (4.8), Kazakhstan (4.47), and Turkmenistan (4.40). Given that Azerbaijan ranks 4th in the list of countries with the highest crime rate in its region, the problem of finding effective mechanisms to prevent crimes against the person and identifying the most important socio-economic determinants that can serve as their catalysts are of particular relevance.

Several socio-economic determinants influence the crime rate, including the level of security and social well-being in local communities, the dominance of social justice principles in society, and the effectiveness of public law enforcement agencies. Low living standards, education, culture, high poverty levels, unemployment, and inequality create a favorable environment for committing crimes against the person.

That is why each country developing its state management policy to reduce crimes against persons must clearly understand which countries' experience can be accepted as the best benchmarks given the obvious and latent similarities with these countries regarding the socio-economic context that determines this very type of crime.

1. LITERATURE REVIEW

The academic community has considerable experience in developing state management mechanisms to reduce crimes against persons, finding interconnections between the dynamics of crimes against the person and socio-economic factors that can either be its catalysts or inhibitors. Thus, Louis (2022) particularly described how mental health issues can affect the well-being of families, community development, and social and work environments. Fast (2021) empirically confirmed the hypothesis that an increase in the education level determines a decrease in crimes against the person. Kellermann et al. (1993) examined the relationship between keeping a firearm in the home and the risk of violent crime. Hussain (2022) systematized the root causes of crimes against the person, structured their types, and investigated current trends in scientific research on the theory of crime. Policastro et al. (2015) focused on investigating crimes committed against the elderly and finding similarities and differences in cases of criminal offenses. Breiding et al. (2015) conducted a national survey of the prevalence and characteristics of sexual

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violence in the United States. Vasilyeva et al. (2022a) proposed an approach for creating phase depictions of victims by structuring their personified characteristics. Yarovenko et al. (2023) analyzed the socio-economic profiles of countries where cybercrimes have become particularly widespread and described the profiles of the victims of these crimes. Aliyeva (2022), on the example of developing countries, examined the relationship between the dynamics of violent crimes and the regulatory interventions used by the state to prevent them. Klochko et al. (2020) proposed a crime prevention concept based on analyzing many regulatory documents. Gupta and Bhandari (2022) studied ethical decision-making models based on the dual process theory and their relationship with the commission of illegal and unethical actions. Bhandari (2023b) offered an in-depth understanding of the complex mechanisms of gender impact on the security of individuals and society. Cooper and Mujtaba (2022) proposed a new approach to assessing workplace discrimination.

Furthermore, there are thorough scientific studies concerning the search for cause-and-effect relationships between social and economic parameters, which people consider as determinants of crimes against the person. In particular, such parameters are the level of income inequality of the population, the dominance of the rule of law in the country, the level of literacy and financial literacy of citizens, and racial diversity.

In particular, Vasilyeva et al. (2022b) and Turkebayeva et al. (2022) searched for causal links between economic development and income inequality. Vasilyeva et al. (2022c), modeling sustainable growth by determining the center of mass, identified the main determinants of the country's social, economic, and political development. Dluhopolskyi et al. (2023), Salju et al. (2023), and Surahman et al. (2023) identified the impact of the COVID-19 pandemic on digital financial literacy. Dluhopolskyi et al. (2023) created an integral digital financial literacy index. Kuzior et al. (2022) substantiated the relationship between financial literacy and formal education. Bhandari (2023a) reviewed the basic principles of research on people's relationships and their relationship with social stability in society. Didenko et al. (2023) summarized financial literacy problems and identified the key factors determining their occurrence. Lyeonov et al. (2021) answered whether there is convergence in the institutional quality of the social sector between countries based on two groups of indicators: QISS and the HDI. Isik (2022) conducted a comparative analysis of the financial literacy of young people in Bristol (UK) and Istanbul. Harshad (2022) investigated the impact of personal values on personal and public decision-making. Mujtaba and Kaifi (2023) reviewed general safety measures as required by the Occupational Safety and Health Administration (OSHA). Awojobi (2022) performed a comparative analysis of the level of inequality in Australia, Canada, and the United States. Moskalenko et al. (2022) developed an approach to comprehensively consider social, environmental, and economic determinants when choosing effective state management mechanisms.

The purpose of the study is to determine the list of countries whose best practices should be used by Azerbaijan in the implementation of state policy on the prevention, detection, termination, disclosure, and investigation of crimes against a person. The selection of these countries is based on the similarity of trends regarding the dependence of the number of crimes against the person (by their main types) on socio-economic determinants, in particular, the dominance of the rule of law in the country, the level of literacy and financial literacy of citizens, and racial diversity.

2. METHOD

To carry out a cluster analysis regarding crimes against the person and their determinants, the study summarized and grouped statistical data for 2021 (it is for this year that the most relevant data are available). Number of crimes against the person and corresponding statistical variables are as follows:

K1 – the number of intentional murders (per 100,000 people) (World Bank, n.d.a);

K2 – the number of sexual crimes in general (per 100,000 people) (UNODC, n.d.);

K3 – the number of rapes as a separate type of sexual crime (per 100,000 people) (UNODC, n.d.);

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K4 – the number of serious assaults (per 100,000 people) (UNODC, n.d.).

To characterize the socio-economic determinants that can be catalysts or inhibitors of the level of crimes against the person, we used the following:

K5 – the Gini coefficient (World Bank, n.d.b);

K6 – the compliance with the rule of law in the country (starting approximately from -2.5 (weak) to 2.5 (strong)) (Kaufmann & Kraay, 2023);

K7 – the level of racial diversity in the country (%) (World Population Review, n.d.a);

K8 – the literacy level of the population (%) (World Population Review, n.d.b);

K9 – the level of financial literacy (%) (Klapper et al., 2015).

Since the input sample includes variables with different units of measurement, they were cleaned and normalized for further use of these data in calculations. There are various normalization methods: Min-Max Scaling, Z-score normalization, normalization in linear regression, L2 normalization, logarithmic normalization, and Box-Cox normalization (Kharazishvili & Kwilinski, 2022). For standardization, which takes into account variables of the average trend of data changes and minimizes the impact of outliers, an alternative formula of logistic normalization is used, which has become widespread in data analysis and machine learning algorithms:

$$K = \frac{1}{1+e^{-3\frac{x_i - md}{mx - md}}}, \tag{1}$$

where K is the normalized value of input variables, x_i is the input value of a variable $(i = 1,\ldots,35)$, md is the median of a variable, and mx is the maximum value of an input variable.

To ensure the adequacy of the country cauterization, the study used two alternative methods: DBSCAN and K-means (calculations are implemented in R programming) (Dzwigol, 2023). DBSCAN is a method for spatial clustering of applications with noise based on density. It can be used to find arbitrary-shaped clusters with noise and outliers in the dataset. DBSCAN clustering algorithm uses two main parameters: neighborhood radius (eps) and the minimum number of points (MinPts). The eps parameter defines the radius in which the algorithm searches for neighbors for each point x. Thus, each point has its ∊-neighborhood. The MinPts parameter indicates the minimum number of neighbors a point should have in its ∊-neighborhood to be recognized as a core point.

Each point x in the data set can be a core point, a reachable point, or an outlier. If the number of neighbors of a point x is greater than or equal to the value of MinPts, then it is considered a core point. However, if the number of neighbors of a point x is less than MinPts but still in the ∊-neighborhood of some core point y, then it becomes a reachable point. Finally, if a point does not have enough neighbors and does not belong to the ∊-neighborhood of any core point, it is classified as a noise point or an outlier.

The method of determining the optimal value of the ∊-neighborhood is implemented in the DBSCAN library by the kNNdistplot function. Its main task is calculating the average distance from each point to its k-nearest neighbors. The value of k is specified as equal to MinPts. K-distances are then shown in ascending order. The main goal of this analysis is to determine the "knee" corresponding to the optimal parameter of the ∊-neighborhood (eps).

Thus, DBSCAN is an efficient algorithm that detects dense clusters of points in the data space and identifies points that do not belong to any clusters (outliers). Using eps and MinPts parameters allows one to control the clustering process and obtain clear and meaningful results (Ester et al., 1996).

The basic idea of K-means clustering is to group a data set into subgroups or "clusters" so that objects within each cluster are very similar and objects from different clusters are significantly different (Dzwigol, 2022).

The K-means algorithm works as follows:

1. Choose the number of clusters k to form. This can be a preset number or a selection based on specific criteria.

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2. Randomly initialize k centroids – the initial coordinates of the clusters.

3. Assign each object from the data to the nearest centroid (nearest cluster) based on the distance between them.

4. Calculate new centroids for each cluster, which are the averages or medians of objects in this cluster.

5. Repeat steps 3 and 4 until the centroids stabilize or reach maximum iterations.

6. When the centroids have maintained their position, the clustering is considered complete, and each data object will belong to one of the clusters.

The number of clusters, k, is a hyperparameter of the algorithm, and the right choice of k can affect the clustering quality. The analysis used the within-cluster sum of squares (WCSS) to determine the number of clusters. The number of clusters is determined by detecting the "elbow" on the graph, where the decrease of WCSS gets slower after adding another cluster. In other words, this is when the increase in clusters does not lead to such a strong decrease in the sum of the squares of the distances between the points and the cluster centroids as it was at the beginning.

3. RESULTS

The input statistical data of the study are presented in Table 1.

The same data, but normalized using formula (1), are shown in Table 2.

Table 3 shows the numerical characteristics of the normalized values obtained using the Statgraphics software. These results confirm the statistical significance of the feature space.

Table 1. Variables of the number of crimes against the person and the levels of their socio-economic determinants for different countries as of 2021

Source: World Bank (n.d.a, n.d.b), UNODC (n.d.), Kaufmann and Kraay (2023), World Population Review (n.d.a, n.d.b), Klapper et al. (2015).

Country	K1	K2	K3	K4	K5	K6	K7	K8	K9
Albania (ALB)	2.3120	4.7290	2.2769	5.7099	33.1	–0.26	0.21	0.98	31
Algeria (DZA)	1.5732	4.1016	1.7746	22.7082	27.60	–0.82	0.32	0.80	33
Argentina (ARG)	4.6227	83.6345	15.0055	340.5653	41.3	–0.46	0.00	0.98	28
Austria (AUT)	0.7285	48.8003	20.6342	40.4614	29.70	1.79	0.10	0.98	53
Azerbaijan (AZE)	1.9102	0.7466	0.1939	3.1902	33.7	–0.58	0.20	1.00	36
Belgium (BEL)	1.0765	83.9604	34.8967	500.4728	27.40	1.33	0.54	0.99	55
Belize (BLZ)	31.2476	29.2477	2.9998	251.2305	53.3	–0.78	0.64	0.83	33
Bosnia and Herzegovina (BIH)	0.9783	5.9310	0.6114	23.0820	33	–0.59	0.68	0.38	37
Chile (CHL)	3.6320	98.6755	21.8641	57.2969	44.4	0.91	0.08	0.97	41
Costa Rica (CRI)	11.4087	131.7046	35.5067	138.8448	48	0.45	0.06	0.98	35
Croatia (HRV)	0.8128	21.9451	11.1080	17.9058	30.40	0.30	0.21	0.99	44
Cyprus (CYP)	1.2860	5.0635	4.4206	14.3869	31.40	0.64	0.09	0.99	35
Czechia (CZE)	0.4472	15.1559	7.3544	35.2116	24.90	1.13	0.06	0.99	58
Denmark (DNK)	0.8028	108.3488	45.4030	32.1818	28.70	1.94	0.14	0.99	71
Dominican Republic (DMA)	10.5416	60.3173	11.8818	26.0122	43.7	–0.10	0.00	0.92	35
Ecuador (ECU)	14.0243	77.2008	33.8863	35.1955	45.4	–0.34	0.48	0.95	30
El Salvador (SLV)	18.1655	95.5470	40.5754	100.7100	38.6	–0.85	0.18	0.88	21
Estonia (EST)	1.9568	29.5778	13.9986	5.5693	30.40	–1.20	0.33	0.95	54
Eswatini (SWZ)	12.6649	90.6071	35.6395	30.0398	27.40	2.06	0.11	1.00	63
France (FRA)	1.1374	115.0245	52.5604	548.1839	31.6	1.29	0.38	0.99	52
Germany (DEU)	0.8332	50.1028	12.4807	146.6768	31.6	1.61	0.16	0.99	66
Ghana (GHA)	1.8366	5.6011	1.2548	155.1456	43.5	–0.08	0.65	0.77	32
Greece (GRC)	0.8521	3.0636	2.4796	11.3543	34.4	0.35	0.18	0.95	45
Guatemala (GTM)	19.9904	63.0492	39.8331	121.8447	48.3	–1.09	0.51	0.79	26
Honduras (HND)	38.3427	33.8479	18.4855	25.1889	48.9	–1.07	0.13	0.88	23
Ireland (IRL)	0.4412	58.5779	21.3375	96.6204	32.8	1.53	0.09	0.99	55
Jamaica (JAM)	52.1273	64.2573	16.3030	116.6321	35	–0.17	0.22	089	33

Table 1 (cont.). Variables of the number of crimes against the person and the levels of their socio-economic determinants for different countries as of 2021

Country	K1	K2	K3	K4	K5	K6	K7	K8	K9
Japan (JPN)	0.2287	4.5509	1.1139	14.5611	32.9	1.58	0.01	0.99	43
Jordan (JOR)	1.0226	9.7324	1.6236	5.8933	33.7	0.21	0.46	0.98	24
Kenya (KEN)	5.2749	15.4361	1.7753	42.1936	40.8	–0.39	0.81	0.78	38
Latvia (LVA)	3.0418	17.8770	9.1786	29.2969	35.6	0.98	0.52	1.00	48
Lithuania (LTU)	2.5837	5.2752	2.4402	4.5216	37.3	1.11	0.29	1.00	39
Luxembourg (LUX)	0.6257	54.4327	17.2058	85.7159	34.5	1.79	0.48	1.00	53
Malaysia (MYS)	0.7238	9.5580	4.0508	12.1017	41.1	0.56	0.59	0.95	36
Malta (MLT)	0.3797	26.1985	6.0750	32.4633	29.20	0.86	0.03	0.94	44
Mauritius (MUS)	2.6176	46.8083	2.7715	20.8636	36.8	0.87	0.44	0.91	39
Mongolia (MNG)	6.1533	16.1301	13.1132	11.0521	32.7	–0.23	0.31	0.98	41
Namibia (NAM)	12.4499	48.8113	47.7442	374.0884	59.1	0.36	0.55	0.91	27
Netherlands (NLD)	0.6514	26.0832	13.3701	26.1118	28.50	1.74	0.11	0.99	66
Norway (NOR)	0.5367	106.8846	45.7337	29.0763	27.00	1.95	0.06	1.00	71
Panama (PAN)	12.7319	152.8750	75.1275	107.8536	49.2	–0.25	0.22	0.95	27
Poland (POL)	0.7126	8.3900	1.5193	12.5693	29.70	0.44	0.15	1.00	42
Portugal (PRT)	0.7969	26.4234	3.8581	6.1127	33.8	1.13	0.05	0.95	26
Romania (ROU)	1.2624	12.1323	10.0887	0.9416	36	0.41	0.30	0.99	22
Serbia (SRB)	1.0553	9.0725	1.5760	72.1141	36.2	–0.09	0.46	0.98	38
Singapore (SGP)	0.1010	31.5600	6.6486	7.5407	45.9	1.86	0.39	0.97	59
Slovakia (SVK)	1.0096	10.8488	1.6888	20.7614	25.20	0.71	0.23	1.00	48
Slovenia (SVN)	0.4246	21.0908	2.5951	55.8646	24.20	1.03	0.15	1.00	44
Sweden (SWE)	1.0796	215.8956	88.9836	45.9822	28.80	1.73	0.06	0.99	71
Switzerland (CHE)	0.4832	35.0921	8.7098	7.5017	32.7	1.81	0.50	0.99	57

Table 2. Normalized input data on the number of crimes against the person and the levels of their socio-economic determinants for different countries

Country	K1	K2	K3	K4	K5	K6	K7	K8	K9
ALB	0.5164	0.4020	0.4210	0.4654	0.4823	0.1870	0.4933	0.3353	0.2951
DZA	0.5055	0.3996	0.4164	0.4899	0.3273	0.0723	0.6277	0.0000	0.3368
ARG	0.5502	0.7052	0.5421	0.8580	0.7105	0.1337	0.2539	0.5319	0.2384
AUT	0.4931	0.5773	0.5949	0.5156	0.3840	0.9226	0.3596	0.4981	0.7787
AZE	0.5105	0.3867	0.4017	0.4618	0.5000	0.1086	0.4865	0.9379	0.4044
BEL	0.4982	0.7063	0.7171	0.9384	0.3221	0.8301	0.8362	0.8170	0.8102
BLZ	0.8545	0.4993	0.4278	0.7828	0.9101	0.0774	0.8971	0.0000	0.3368
BIH	0.4967	0.4067	0.4056	0.4905	0.4793	0.1070	0.9147	0.0000	0.4279
CHL	0.5358	0.7529	0.6062	0.5399	0.7797	0.6881	0.3345	0.1123	0.5242
CRI	0.6460	0.8383	0.7218	0.6529	0.8441	0.4744	0.3135	0.3696	0.3813
HRV	0.4943	0.4700	0.5049	0.4830	0.4038	0.4035	0.4953	0.8701	0.5956
CYP	0.5013	0.4033	0.4412	0.4779	0.4325	0.5635	0.3525	0.8301	0.3813
CZE	0.4889	0.4429	0.4690	0.5080	0.2613	0.7685	0.3146	0.8170	0.8509
DNK	0.4942	0.7807	0.7912	0.5036	0.3565	0.9408	0.4106	0.8170	0.9526
DMA	0.6342	0.6218	0.5123	0.4947	0.7651	0.2385	0.2539	0.0002	0.3813
ECU	0.6804	0.6833	0.7092	0.5080	0.7993	0.1637	0.7927	0.0053	0.2753
SLV	0.7309	0.7434	0.7590	0.6013	0.6408	0.0683	0.4550	0.0000	0.1372
EST	0.5111	0.5007	0.5325	0.4652	0.4038	0.0360	0.6367	0.0145	0.7949
SWZ	0.6627	0.7280	0.7228	0.5005	0.3221	0.9526	0.3742	0.9526	0.9025
FRA	0.4991	0.7986	0.8329	0.9526	0.4383	0.8198	0.6978	0.8170	0.7616
DEU	0.4946	0.5825	0.5180	0.6631	0.4383	0.8940	0.4356	0.8170	0.9253
GHA	0.5094	0.4054	0.4115	0.6739	0.7609	0.2439	0.9001	0.0000	0.3156
GRC	0.4949	0.3956	0.4229	0.4735	0.5207	0.4257	0.4534	0.0166	0.6187
GTM	0.7516	0.6321	0.7538	0.6303	0.8487	0.0437	0.8173	0.0000	0.2051
HND	0.8992	0.5178	0.5749	0.4935	0.8576	0.0454	0.3898	0.0000	0.1618
IRL	0.4888	0.6152	0.6013	0.5956	0.4735	0.8788	0.3452	0.8170	0.8102
JAM	0.9526	0.6366	0.5544	0.6232	0.5383	0.2143	0.5087	0.0000	0.3368

Table 2 (cont.). Normalized input data on the number of crimes against the person and the levels of their socio-economic determinants for different countries

Country	K1	K2	K3	K4	K5	K6	K7	K8	K9
JPN	0.4857	0.4013	0.4102	0.4782	0.4764	0.8885	0.2654	0.8170	0.5721
JOR	0.4974	0.4215	0.4150	0.4657	0.5000	0.3626	0.7719	0.5019	0.1753
KEN	0.5597	0.4440	0.4164	0.5181	0.6982	0.1507	0.9526	0.0000	0.4518
LVA	0.5271	0.4537	0.4864	0.4995	0.5559	0.7151	0.8215	0.9445	0.6844
LTU	0.5204	0.4041	0.4226	0.4637	0.6047	0.7629	0.5949	0.9387	0.4758
LUX	0.4915	0.5993	0.5629	0.5804	0.5236	0.9225	0.7912	0.9526	0.7787
MYS	0.4930	0.4208	0.4377	0.4746	0.7056	0.5256	0.8681	0.0063	0.4044
MLT	0.4879	0.4871	0.4568	0.5040	0.3702	0.6670	0.2829	0.0027	0.5956
MUS	0.5209	0.5695	0.4257	0.4873	0.5905	0.6708	0.7530	0.0000	0.4758
MNG	0.5724	0.4468	0.5240	0.4731	0.4705	0.1962	0.6189	0.6339	0.5242
NAM	0.6599	0.5774	0.8056	0.8800	0.9526	0.4316	0.8448	0.0000	0.2213
NLD	0.4919	0.4866	0.5265	0.4949	0.3511	0.9157	0.3665	0.8170	0.9253
NOR	0.4902	0.7767	0.7933	0.4991	0.3119	0.9422	0.3132	0.9526	0.9526
PAN	0.6636	0.8793	0.9220	0.6112	0.8618	0.1895	0.5047	0.0114	0.2213
POL	0.4928	0.4162	0.4140	0.4753	0.3840	0.4709	0.4209	0.9361	0.5482
PRT	0.4941	0.4880	0.4359	0.4660	0.5030	0.7710	0.2993	0.0204	0.2051
ROU	0.5009	0.4309	0.4951	0.4585	0.5675	0.4532	0.6038	0.7568	0.1491
SRB	0.4979	0.4189	0.4145	0.5611	0.5733	0.2401	0.7733	0.4981	0.4518
SGP	0.4838	0.5086	0.4623	0.4680	0.8086	0.9317	0.7039	0.1350	0.8628
SVK	0.4972	0.4259	0.4156	0.4871	0.2682	0.5958	0.5214	0.9167	0.6844
SVN	0.4886	0.4666	0.4240	0.5378	0.2456	0.7339	0.4154	0.9285	0.5956
SWE	0.4982	0.9526	0.9526	0.5236	0.3592	0.9148	0.3134	0.8170	0.9526
CHE	0.4894	0.5228	0.4819	0.4680	0.4705	0.9254	0.8056	0.8170	0.8382

Table 3. Descriptive analysis

Variables	K1	K2	K3	K4	K5	K6	K7	K8	K9
Count	50	50	50	50	50	50	50	50	50
Average	0.5560	0.5526	0.5493	0.5544	0.5431	0.5136	0.5551	0.4556	0.5337
Median	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
Geometric mean	0.5470	0.5346	0.5313	0.5431	0.5105	0.3677	0.5131		0.4660
Harmonic mean	0.5398	0.5186	0.5158	0.5342	0.4795	0.2137	0.4734		0.3960
5% Trimmed mean	0.5402	0.5422	0.5370	0.5386	0.5382	0.5158	0.5511	0.4533	0.5320
5% Winsorized mean	0.5533	0.5499	0.5454	0.5519	0.5409	0.5136	0.5543	0.4556	0.5345
Variance	0.0126	0.0225	0.0231	0.0158	0.0368	0.1062	0.0472	0.1629	0.0658
Standard deviation	0.1122	0.1499	0.1521	0.1259	0.1920	0.3259	0.2172	0.4036	0.2564
Coeff. of variation	20.1%	27.1%	27.6%	22.7%	35.3%	63.4%	39.1%	88.5%	48.0%
Gini coefficient	0.0900	0.1502	0.1488	0.1068	0.2018	0.3659	0.2254	0.4892	0.2788
Standard error	0.0159	0.0212	0.0215	0.0178	0.0271	0.0461	0.0307	0.0571	0.0363
Geometric standard deviation	1.1889	1.2907	1.2890	1.2143	1.4304	2.6247	1.5019		1.7459
5% Winsorized sigma	0.1119	0.1548	0.1545	0.1282	0.2020	0.3538	0.2331	0.4391	0.2777
Mean absolute deviation	0.1314	0.2205	0.2112	0.1484	0.2922	0.8149	0.3537	0.3780	0.4631
MAD	0.0111	0.0940	0.0813	0.0320	0.1353	0.3164	0.1859	0.4370	0.2148
Sbi	0.0171	0.1516	0.1451	0.0563	0.1995	0.3365	0.2298	0.4173	0.2669
Minimum	0.4838	0.3867	0.4017	0.4585	0.2456	0.0360	0.2539	0.0000	0.1372
Maximum	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526	0.9526
Range	0.4688	0.5659	0.5508	0.4940	0.7069	0.9166	0.6987	0.9526	0.8154
Lower quartile	0.4931	0.4215	0.4229	0.4753	0.3840	0.1895	0.3596	0.0027	0.3368
Upper quartile	0.5597	0.6366	0.6062	0.5956	0.7056	0.8301	0.7733	0.8170	0.7787
Interquartile range	0.0667	0.2151	0.1832	0.1204	0.3215	0.6406	0.4137	0.8143	0.4419
1/6 sextile	0.4915	0.4067	0.4164	0.4680	0.3565	0.1337	0.3146	0.0000	0.2384
5/6 sextile	0.6599	0.7280	0.7228	0.6303	0.7797	0.9148	0.8173	0.9167	0.8382
Intersextile range	0.1683	0.3213	0.3064	0.1622	0.4232	0.7811	0.5028	0.9167	0.5998
Skewness	2.1321	0.8803	1.0766	1.9897	0.4927	–0.0600	0.2995	–0.0556	0.1760

Table 3 (cont.). Descriptive analysis

Variables	K1	K2	K3	K4	K5	K6	K7	K8	K9
Stnd. skewness	6.1547	2.5413	3.1078	5.7437	1.4223	–0.1732	0.8645	–0.1606	0.5082
Kurtosis	4.1027	–0.2118	0.0896	3.3232	–0.8244	–1.5670	–1.3437	–1.8527	–1.2468
Stnd. kurtosis	5.9218	–0.3057	0.1293	4.7967	–1.1899	–2.2618	–1.9394	–2.6741	–1.7995
Sum	27.7994	27.6309	27.4670	27.7183	27.1536	25.6800	27.7569	22.7810	26.6870
Sum of squares	16.0729	16.3701	16.2222	16.1424	16.5518	18.3936	17.7207	18.3619	17.4661

For K-Means clustering, the study created a scree plot (Figure 1).

According to the scree plot, the moment when the increase in clusters does not lead to such a strong decrease in the sum of squares of the distances between the points and the centroids of the clusters corresponds to the value 4, which is the optimal value of the number of clusters for constructing clusters by the K-Means method.

To ensure the adequacy and completeness of the analysis, clustering was carried out in three ways:

1) clustering by the entire set of crimes and their determinants;

2) clustering by the specific type of crime and all types of determinants;

3) clustering by all types of crime and a separate socio-economic determinant.

Clusters built on the entire set of crimes and their determinants by the K-Means method (the value of cluster number is 4) are shown in Figure 2.

The first cluster includes 12 countries: Austria, Belgium, Denmark, Eswatini, France, Germany, Ireland, Luxembourg, Netherlands, Norway, Sweden, and Switzerland.

The second cluster includes 22 countries: Algeria, Belize, Bosnia and Herzegovina, Chile, Costa Rica, Dominican Republic, Ecuador, El Salvador, Estonia, Ghana, Greece, Guatemala, Honduras, Jamaica, Kenya, Malaysia, Malta, Mauritius, Namibia, Panama, Portugal, and Singapore.

Source: RStudio software.

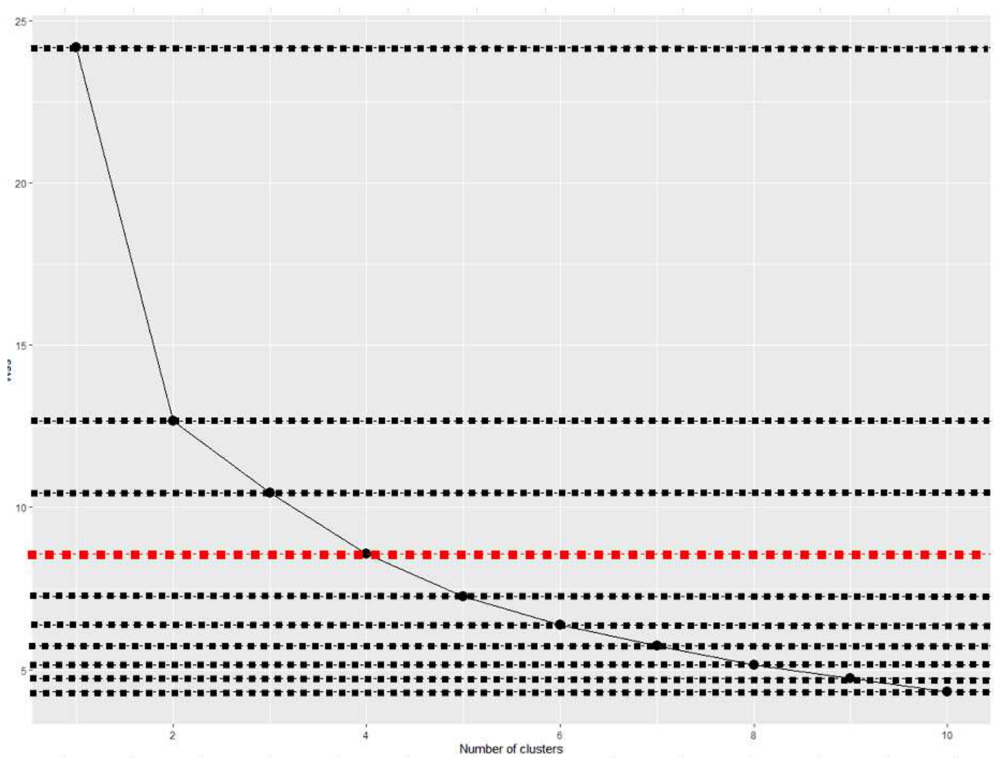

Figure 1. Scree plot

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Source: RStudio software.

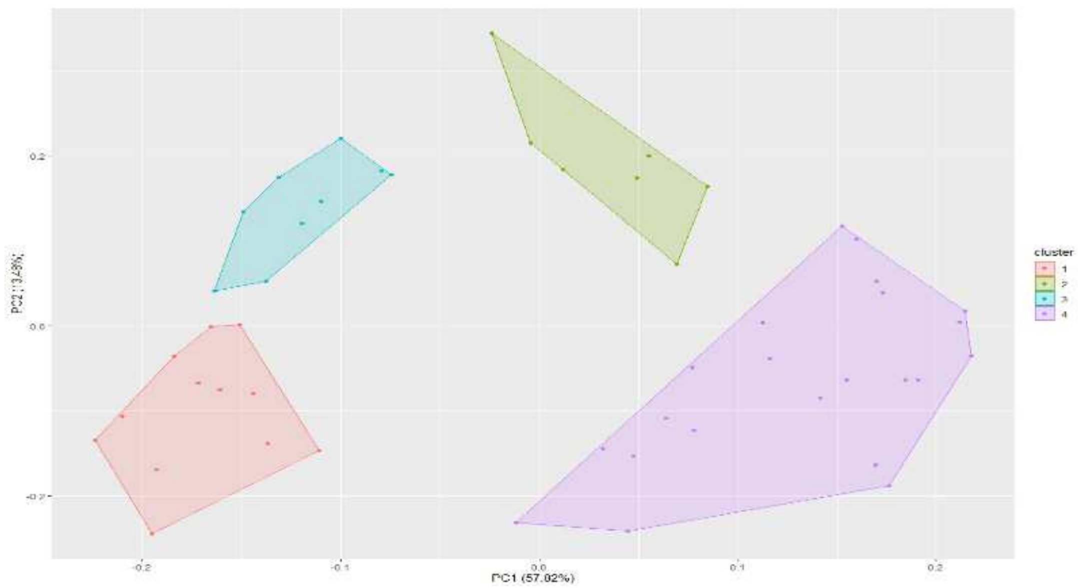

Figure 2. Clusters built on the entire set of crimes and their determinants by the K-Means method

The third cluster comprises seven countries: Albania, Argentina, Azerbaijan, Jordan, Mongolia, Romania, and Serbia.

The fourth cluster includes nine countries: Croatia, Cyprus, Czechia, Japan, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia.

Based on this set of variables, for the entire set of crimes and their socio-economic determinants specifically, the analysis also carried out clustering using the DBSCAN method (Figure 3).

From the first part of Figure 3, it can be seen that the optimal value of the ϵ-neighborhood (eps) is approximately at a distance of 0.45 for the entire K1-K9 data set.

The second part of Figure 3 shows information about the cluster distribution. The first cluster covers 39 countries: Albania, Algeria, Austria, Azerbaijan, Belize, Bosnia and Herzegovina, Croatia, Cyprus, Czechia, Denmark, Dominican Republic, Ecuador, El Salvador, Eswatini, Germany, Ghana, Guatemala, Honduras, Ireland, Jamaica, Japan, Jordan, Kenya, Latvia, Lithuania, Luxembourg, Malaysia, Mauritius, Mongolia, Netherlands, Norway, Panama, Poland, Romania, Serbia, Slovakia, Slovenia, Sweden, and Switzerland.

Source: RStudio software.

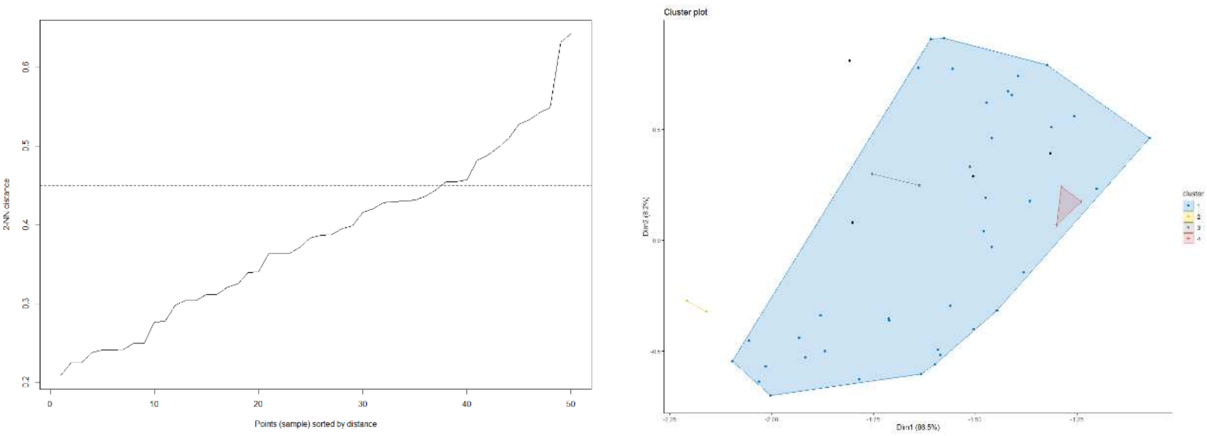

Figure 3. Results of clustering by the entire set of crimes and their socio-economic determinants using the DBSCAN method

The second cluster includes two countries: Belgium and France. The third cluster consists of two countries: Chile and Costa Rica. The fourth cluster comprises three countries: Greece, Malta, and Portugal. This clustering method distributes as outliers the following four countries: Argentina, Estonia, Namibia, and Singapore.

Considering the clusters formed by the K-Means and DBSCAN methods, it should be noted that Azerbaijan was consistently in the same cluster as Albania, Jordan, Mongolia, Romania, and Serbia when applying each method.

Next, the study carried out a cluster analysis for specific types of crime and their socio-economic determinants using the K-Means and DBSCAN methods (Table 4).

The results of clustering by the K-Means and DBSCAN methods for specific types of crime and all types of their socio-economic determinants show that Azerbaijan was most often in the same clusters as Albania, Jordan, Mongolia, Romania, Serbia, and Argentina.

Table 5 shows the clustering results by all types of crime and a specific socio-economic determinant.

According to the results of clustering by all types of crime and a specific socio-economic determinant using the K-Means and DBSCAN method, Azerbaijan is most often in the same cluster as Romania, Albania, Jordan, Lithuania, Mongolia, Serbia, Croatia, and Poland.

Thus, according to the result of clustering by both chosen methods, Azerbaijan is most often in the same clusters as

1) Albania, Jordan, Mongolia, Romania, and Serbia (when clustering by the entire set of crimes and their determinants);
2. Albania, Jordan, Mongolia, Romania, Serbia, and Argentina (when clustering by the specific types of crime and all types of determinants);
3. Romania, Albania, Jordan, Lithuania, Mongolia, Serbia, Croatia, and Poland (when clustering by the entire set of crimes and a specific socio-economic determinant).

Based on this, one can argue that in improving the policy of state prevention of crimes against the person in Azerbaijan, this country should focus on the best practices and benchmarks used primarily in the countries mentioned above.

Table 4. The results of clustering by specific type of crime and all types of their socio-economic determinants (K-Means and DBSCAN methods)

Clustering by variables: "Type of crime – number of intentional murders (K1) – all determinants (K5, K6, K7, K8, K9)"											
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method							
1	2	3	4	0 (outliners)	1	2	3	4	5	6	7
AUT CZE DNK SWZ DEU IRL JPN NLD NOR SVK SVN SWE	BEL FRA LVA LTU LUX SGP CHE	DZA BLZ BIH CHL DMA ECU SLV EST GHA GRC GTM HND JAM KEN MYS MLT MUS NAM PAN PRT	ALB ARG AZE CRI HRV CYP JOR MNG POL ROU SRB	ALB ARG AZE CHL CRI EST JAM PRT SGP	DZA BLZ BIH DMA ECU SLV GHA GTM HND KEN MYS MUS NAM PAN	AUT BEL HRV CYP CZE DNK SWZ FRA DEU IRL JPN LVA LTU LUX NLD NOR POL SVK SVN SWE CHE	GRC MLT	JOR MNG ROU SRB			

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Table 4 (cont.). The results of clustering by specific type of crime and all types of their socio-economic determinants (K-Means and DBSCAN methods)

Clustering by variables: "Type of crime – number of sexual crimes in general (K2) – all determinants (K5, K6, K7, K8, K9)"											
Composition of clusters by K-Means method				**Composition of clusters by DBSCAN method**							
1	**2**	**3**	**4**	**0 (outliners)**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
AUT BEL CZE DNK SWZ FRA DEU IRL LUX NLD NOR SWE CHE	DZA BLZ BIH CHL CRI DMA ECU SLV EST GHA GRC GTM HND JAM KEN MYS MLT MUS NAM PAN PRT SGP	ALB ARG AZE JOR MNG ROU SRB	HRV CYP JPN LVA LTU POL SVK SVN	ARG EST PRT SGP	ALB AUT AZE BEL HRV CYP CZE DNK SWZ FRA DEU IRL JPN JOR LVA LTU LUX MNG NLD NOR POL ROU SRB SVK SVN SWE CHE	DZA BLZ BIH DMA ECU SLV GHA GTM HND JAM KEN MYS MUS NAM PAN	CHL CRI	GRC MLT	LVA LTU LUX CHE		

Clustering by variables: "Type of crime – number of rapes as a separate type of sexual crime (K3) – all determinants (K5, K6, K7, K8, K9)"											
Composition of clusters by K-Means method				**Composition of clusters by DBSCAN method**							
1	**2**	**3**	**4**	**0 (outliners)**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
BEL FRA LVA LTU LUX SGP CHE	DZA BLZ BIH CHL CRI DMA ECU SLV EST GHA GRC GTM HND JAM KEN MYS MLT MUS NAM PAN PRT	ALB ARG AZE HRV CYP JOR MNG POL ROU SRB	AUT CZE DNK SWZ DEU IRL JPN NLD NOR SVK SVN SWE	ALB ARG AZE CHL CRI EST PRT SGP	DZA BLZ BIH DMA ECU SLV GHA GTM HND JAM KEN MYS MUS NAM PAN	AUT HRV CYP CZE DNK SWZ DEU IRL JPN NLD NOR POL SVK SVN SWE	BEL FRA LVA LTU LUX CHE	GRC MLT	JOR MNG ROU SRB		

Table 4 (cont.). The results of clustering by specific type of crime and all types of their socio-economic determinants (K-Means and DBSCAN methods)

Clustering by variables: "Type of crime – number of serious assaults (K4) – all determinants (K5, K6, K7, K8, K9)"											
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method							
1	2	3	4	0 (outliners)	1	2	3	4	5	6	7
BEL FRA LVA LTU LUX SGP CHE	DZA BLZ BIH CHL DMA ECU SLV EST GHA GRC GTM HND JAM KEN MYS MLT MUS NAM PAN PRT	ALB ARG AZE CRI HRV CYP JOR MNG POL ROU SRB	AUT CZE DNK SWZ DEU IRL JPN NLD NOR SVK SVN SWE	ALB ARG AZE CHL CRI EST NAM PRT SGP	DZA BLZ BIH DMA ECU SLV GHA GTM HND JAM KEN PAN	AUT HRV CYP CZE DNK SWZ DEU IRL JPN NLD NOR POL SVK SVN SWE	BEL FRA	GRC MLT	JOR MNG ROU SRB	LVA LTU LUX CHE	MYS MUS

Table 5. Results of clustering by all types of crime and a specific socio-economic determinant (by K-Means and DBSCAN methods)

Clustering by variables: "Type of socio-economic determinants – the Gini coefficient (K5) – all types of crime (K1, K2, K3, K4)"										
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method						
1	2	3	4	0 (outliners)	1	2	3	4	5	6
BEL DNK SWZ FRA NOR SWE	ARG BLZ CHL CRI DMA ECU SLV GTM HND JAM NAM PAN	ALB AZE BIH GHA GRC JPN JOR KEN LVA LTU MYS MUS PRT ROU SRB SGP	DZA AUT HRV CYP CZE EST DEU IRL LUX MLT MNG NLD POL SVK SVN CHE	ARG BLZ CRI SLV HND JAM NAM PAN SWE	ALB DZA AUT AZE BIH HRV CYP CZE EST DEU GHA GRC IRL JPN JOR KEN LVA LTU LUX MYS MLT MUS MNG NLD POL PRT ROU SRB SGP SVK SVN CHE	BEL FRA	CHL DMA ECU GTM	DNK SWZ NOR		

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Table 5 (cont.). Results of clustering by all types of crime and a specific socio-economic determinant (by K-Means and DBSCAN methods)

Clustering by variables: "Type of socio-economic determinants – the compliance with the rule of law (K6) – all types of crime (K1, K2, K3, K4)"										
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method						
1	2	3	4	0 (outliners)	1	2	3	4	5	6
AUT BEL CHL DNK SWZ FRA DEU IRL LUX NOR SWE	ARG BLZ CRI ECU SLV GTM HND JAM NAM PAN	ALB DZA AZE BIH HRV DMA EST GHA GRC JOR KEN MNG POL ROU SRB	CYP CZE JPN LVA LTU MYS MLT MUS NLD PRT SGP SVK SVN CHE	ARG BLZ CHL CRI HND JAM NAM PAN SWE	ALB DZA AUT AZE BIH HRV CYP CZE DMA EST DEU GHA GRC IRL JPN JOR KEN LVA LTU LUX MYS MLT MUS MNG NLD POL PRT ROU SRB SGP SVK SVN CHE	BEL FRA	DNK SWZ NOR	ECU SLV GTM		

4. DISCUSSION

The scientific community has conducted several studies using the clustering method to study the relationship between crimes and their determinants. In particular, Premasundari and Yamini (2019) used the soft Fuzzy C-Means clustering model for group analysis based on crime rate variables. In this model, each object can belong to several clusters simultaneously. The multiple clustering technique proposed by these authors is based on the USArrests data set. Instead, this study uses two clustering methods (K-Means and DBSCAN), which have different approaches to cluster formation. The K-Means method presupposes that each object belongs to a certain cluster, while when using the DBSCAN method, the object can be an outliner (noise), which allows one to clarify the composition of clusters significantly. In addition, Premasundari and Yamini (2019) made their empirical calculations on the example of different US states, while in this study, the sample of countries is significantly wider and covers 50 countries of the world.

Uittenbogaard and Ceccato (2011) carried out the geographic clustering of offenses over time using Kulldorff's scan test. As source data, these scientists used crime records of Stockholm city. Unlike Kulldorff's scan test, which sufficiently rigorously identifies statistically significant clusters, the K-Means clustering method allows for the detection of clusters in data sets with noise and degenerate clusters, and the DBSCAN method provides an opportunity to detect clusters in data sets with different cluster densities (for example, for geographic data).

Table 5 (cont.). Results of clustering by all types of crime and a specific socio-economic determinant (by K-Means and DBSCAN methods)

Clustering by variables: "Type of socio-economic determinants – the level of racial diversity (K7) – all types of crime (K1, K2, K3, K4)"										
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method						
1	2	3	4	0 (outliners)	1	2	3	4	5	6
BEL BLZ BIH ECU GHA GTM KEN LVA LUX MYS MUS NAM SRB CHE	ARG CHL CRI DNK SLV SWZ FRA JAM NOR PAN SWE	AUT CYP CZE DMA DEU HND IRL JPN MLT NLD POL PRT SVN	ALB DZA AZE HRV EST GRC JOR LTU MNG ROU SGP SVK	ARG BLZ NAM PAN SWE	ALB DZA AUT AZE BIH CHL CRI HRV CYP CZE DNK DMA SLV EST SWZ DEU GHA GRC IRL JPN JOR KEN LVA LTU LUX MYS MLT MUS MNG NLD NOR POL PRT ROU SRB SGP SVK SVN CHE	BEL FRA	ECU GTM	HND JAM		

Rasoul et al. (2015) performed a classification of crimes based on the occurrence frequency during different years. The study used a model of intelligent data analysis, which made it possible to identify patterns of occurrence of various crimes on real data from 1990 to 2011. Rasoul et al. (2015) applied weighted features for functions to obtain statistically significant variables. In contrast, this study used a scree plot to choose the number of clusters using the K-Means method. That allows one to visually record the moment when the increase in clusters does not lead to a strong decrease in the sum of the squares of the distances between the points and the centroids of the clusters, corresponding to the optimal number of clusters. When applying the DBSCAN method, the kNNdistplot function is used, which creates a graph of the average distance from each point to its nearest neighbors. Therefore, it can determine the "knee" point corresponding to the optimal parameter of the ϵ-neighborhood (eps).

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Table 5 (cont.). Results of clustering by all types of crime and a specific socio-economic determinant (by K-Means and DBSCAN methods)

Clustering by variables: "Type of socio-economic determinants – the literacy level (K8) – all types of crime (K1, K2, K3, K4)"										
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method						
1	2	3	4	0 (outliners)	1	2	3	4	5	6
ARG BEL CRI DNK SWZ FRA NOR SWE	DZA BLZ BIH CHL DMA ECU SLV EST GHA GRC GTM HND JAM KEN MYS MLT MUS NAM PAN PRT SGP	AZE HRV CYP CZE DEU IRL JPN LVA LTU LUX NLD POL ROU SVK SVN CHE	ALB AUT JOR MNG SRB	ARG AUT BLZ CHL CRI NAM PAN SWE	ALB AZE HRV CYP CZE DEU IRL JPN JOR LVA LTU LUX MNG NLD POL ROU SRB SVK SVN CHE	DZA BIH DMA EST GHA GRC KEN MYS MLT MUS PRT SGP	BEL FRA	DNK SWZ NOR	ECU SLV GTM	HND JAM

CONCLUSION

State management to reduce crimes against persons is a complex and multifaceted process. It requires effective interaction of all interested parties, including state authorities, law enforcement agencies, public organizations, and citizens. It should include measures aimed at the prevention, detection, termination, disclosure, and investigation of crimes and at punishing persons who committed them. The key to effective state management to reduce crimes against persons is to increase the effectiveness of law enforcement activities by improving the equipment of law enforcement agencies, improving their qualifications, and introducing modern technologies and scientific achievements in investigating crimes. Strengthening the inevitability of punishment is ensured through improving legislation and strengthening control over the execution of punishments.

This study analyzed the position of Azerbaijan in cluster distributions of three types (clustering by the entire set of crimes and their determinants, clustering by specific types of crime and all types of their determinants, and clustering by all types of crime and a specific socio-economic determinant). It should be noted that the following countries were Azerbaijan's most frequent neighbors in terms of clusters: Albania, Jordan, Mongolia, Romania, Serbia, Argentina, Lithuania, Croatia, and Poland. Azerbaijan should use these countries' best practices and benchmarks when choosing a state policy for regulating crimes against a person.

Thus, for example, in Albania, a national campaign was launched to raise awareness of crimes against the person, and a new law on criminal responsibility was adopted, which toughened the punishment for crimes against the person. The National Center for Domestic Violence was established, which deals with the prevention, detection, and response to domestic violence.

In Jordan, the state fights crimes against the person with the help of the "Break Silence" campaign, the National hotline for victims of violence, and the "Recovery after a Crime against the Person" program.

Table 5 (cont.). Results of clustering by all types of crime and a specific socio-economic determinant (by K-Means and DBSCAN methods)

Clustering by variables: "Type of socio-economic determinants – the level of financial literacy (K9) – all types of crime (K1, K2, K3, K4)"										
Composition of clusters by K-Means method				Composition of clusters by DBSCAN method						
1	2	3	4	0 (outliners)	1	2	3	4	5	6
BEL DNK SWZ FRA NOR SWE	ARG BLZ CRI ECU SLV GTM HND JAM NAM PAN	ALB DZA AZE BIH CYP DMA GHA JPN JOR KEN LTU MYS MUS MNG POL PRT ROU SRB	AUT CHL HRV CZE EST DEU GRC IRL LVA LUX MLT NLD SGP SVK SVN CHE	ARG NAM	ALB DZA AUT AZE BIH CHL CRI HRV CYP CZE DMA ECU SLV EST DEU GHA GRC GTM IRL JPN JOR KEN LVA LTU LUX MYS MLT MUS MNG NLD PAN POL PRT ROU SRB SGP SVK SVN CHE	BEL FRA	BLZ HND JAM	DNK SWZ NOR SWE		

Mongolia has several social programs to help victims of crimes against the person, including housing, education, and health care programs.

In Romania, the maximum penalty for murder was increased from 25 to 30 years in prison, a new law was introduced to punish sexual harassment in the workplace, and the domestic violence law was amended to make it easier for victims to obtain protection.

In Serbia, the government has established several specialized law enforcement units to investigate crimes against the person, introduced programs to increase awareness of crimes against the person, and implemented a program to support victims of crimes against the person.

Argentina has passed a law that provides for up to 20 years in prison for domestic rape and a law that provides for up to 15 years in prison for gender-based murder. In addition, this country has launched a national system of assistance to domestic violence victims.

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Lithuania has adopted a new law on sexual harassment that expands the definition of sexual harassment and increases the maximum penalty for this offense. In addition, this country has implemented a national campaign to raise awareness of domestic violence.

Croatia implements the following measures to combat crimes against the person: strengthening criminal legislation, campaigns to increase awareness of crimes against the person, and assisting victims of crimes against the person.

In Poland, the government created many victim support centers, introduced several programs to prevent domestic violence, and took some measures to prevent human trafficking.

Thus, Azerbaijan, forming its state policy to combat crimes against the person, should systematically combine several of the abovementioned mechanisms, focusing primarily on those that have already proven their effectiveness in the countries mentioned above for years. This will make it possible to create a favorable and safe environment for life in Azerbaijan, make the population more socially protected, and make the country more economically attractive to investors.

AUTHOR CONTRIBUTIONS

Conceptualization: Zamina Aliyeva.
Data curation: Zamina Aliyeva.
Formal analysis: Zamina Aliyeva.
Investigation: Zamina Aliyeva.
Methodology: Zamina Aliyeva.
Project administration: Zamina Aliyeva.
Supervision: Zamina Aliyeva.
Verification: Zamina Aliyeva.
Visualization: Zamina Aliyeva.
Writing – original draft: Zamina Aliyeva.
Writing – review & editing: Zamina Aliyeva.

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