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Mapping Criminal Activities Using Biclustering Methods based on Nationality Information of Offenders

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Highlights

- This study applies biclustering techniques to reveal hidden relationships between offenders and crime types.
- The Bimax algorithm is utilized to simultaneously cluster offender nationalities and criminal behaviors.
- Crime routes are identified based on nationality patterns, revealing cross-border criminal trends.
- The proposed approach supports more targeted and data-driven crime prevention strategies.

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Abstract

Crimes such as terrorism, organized crime, cybercrime, smuggling, money laundering, and trafficking represent critical challenges to global security, often involving complex transnational networks. Traditional clustering techniques used to analyze offender data typically focus on either individuals or crime types in isolation. In this study, we propose a biclustering-based approach to simultaneously group offenders and crime categories, enabling the identification of hidden patterns and associations. Using the Bimax algorithm implemented in R, we analyzed a dataset consisting of offenders involved in similar criminal activities. The method facilitates the creation of crime maps that reveal clusters sharing common attributes. Results demonstrate that offenders often cluster according to nationality, leading to the discovery of distinct crime routes linked to specific national groups. These findings highlight the value of biclustering in uncovering latent structures in complex criminal networks and offer a novel methodological perspective for crime analysis. The approach provides actionable insights for law enforcement agencies by supporting targeted interventions based on shared behavioral patterns and demographic indicators. This work not only showcases the effectiveness of biclustering in criminological data analysis but also lays a foundation for future research integrating larger and more diverse datasets or exploring alternative algorithms to enhance predictive accuracy in applied security analytics.

1. INTRODUCTION

Crime patterns emerge as a complex phenomenon resulting from the interaction between social, cultural, political, economic, and psychological conditions and the living environments of offenders. Identifying, preventing, and combating crimes require an understanding of the spatial characteristics of crime-prone areas. The method used to define specific personality traits of offenders is referred to as criminal profiling. The primary aim of criminal profiling is to assist in identifying suspects by analyzing their behavioral tendencies and demographic characteristics [1].

Crime analysis is a multidisciplinary field that integrates criminology, criminal justice, statistics, psychology, social psychology, and sociology [2]. It plays a crucial role in expediting police investigations, resolving cases more efficiently, and optimizing the use of human and technical resources. Crime analysis provides law enforcement agencies with strategic insights into the spatial distribution of crime types and their future trends [3].

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Crimes such as terrorism, organized crime, bribery, tax evasion, money laundering, drug and arms trafficking have become increasingly sophisticated and widespread with the advancement of technology. Consequently, technical infrastructure and analytical methods have gained significance in combating these crimes. There is growing evidence of collaboration between organized crime groups and terrorist organizations. Criminal networks are evolving into decentralized, transnational structures, often utilizing digital platforms for document theft, money laundering, fraud, arms procurement, drug production and trade, and various smuggling activities. As crimes become more international in nature, the nationality profiles of offenders become a critical factor, influencing the formation of distinct crime routes.

This study aims to analyze crime routes and examine crime-nationality associations by leveraging offender nationality data. The dataset used in this study comprises crime records from the Turkish Gendarmerie jurisdiction for the year 2019. The selection of pre-pandemic data is particularly significant, as it allows for future comparisons with post-pandemic crime trends. Such an analysis can provide valuable insights into whether crime routes have changed over time due to external factors such as global crises.

Crime datasets are typically large-scale, and clustering-based data mining techniques are widely utilized in their analysis. For instance, Giray (2016) applied a two-step clustering method to prison inmate data, identifying subgroups with similar characteristics [4]. Sea et al. (2016) examined 111 sexual assault cases in South Korea, identifying 16 distinct crime types and using hierarchical clustering to categorize them into six behavioral profiles [5]. Similarly, Reale et al. (2017) investigated sexually motivated homicides in Canada, employing hierarchical clustering to identify different sadistic crime patterns [6].

There are numerous studies in the field of crime analysis, spanning diverse geographies and methodologies. A study conducted in India used data mining techniques such as k-means clustering and KNN classification for crime detection and criminal identification [7]. Similarly, another study analyzing crime density in New York City utilized k-means clustering to identify spatial patterns [8]. In Argentina, machine learning models combining k-means clustering and neural networks were developed for crime prediction [9]. Clustering approaches vary. A study examining crime trends in the US applied finite mixture models to model heterogeneity in the data [10]. Another study covering OECD countries used hierarchical clustering to examine the relationship between income mobility and crime [11]. Quantitative methods are also prominent in studies in Türkiye; For example, a stochastic multi-criteria decision-making method was proposed to determine crime and security indices [12].

Using unpublished data from 166 countries covering the period between 2006 and 2019, this study examines the geographical distribution and temporal trends of three common types of crime—general crime, homicide, and organized crime—across global regions. The data were obtained from the Gallup World Poll. Employing Ordinary Least Squares (OLS) regression models, the analysis reveals that African and Latin American countries generally experience the highest levels of various types of crime, followed by countries in Asia. In contrast, European, North American, and Australian countries tend to have moderate or relatively low levels of most crime types [13].

Piza et al. (2025) investigate the extent to which Gun Detection Technology (GDT) leads to higher levels of arrests and stops (both pedestrian and traffic) compared to service calls for assistance (CFS) in Chicago, Illinois. The study utilizes data covering the period from July 1, 2018, to January 30, 2019, following the full deployment of the GDT system. The spatial and temporal clustering of GDT alerts with arrests and stops was assessed using a two-process Knox test and a marked point process test. The findings suggest that GDT systems may not contribute to racial disparities in arrests and stops [14].

As seen in the examples above, traditional clustering methods have been widely used. However, instead of clustering the data in a single dimension, clustering in two dimensions (rows and columns) provides a more in-depth analysis of criminal activities. None of the previous studies aim to uncover a specific edge case searched on a row and column basis. Traditional clustering techniques typically focus on grouping samples, whereas biclustering methods allow for the simultaneous clustering of both samples and their attributes. This enables the identification of meaningful subgroups based on multiple features.

Biclustering, unlike traditional clustering methods, groups both rows and columns of a data matrix simultaneously. In other words, while conventional clustering operates on a global model, biclustering follows a local model approach [15]. Initially introduced by Hartigan (1972), this method gained widespread attention with the study by Cheng and Church (2000) [16,17]. Over time, various heuristic algorithms have been developed for biclustering. Among these, the CC algorithm, proposed by Cheng and Church (2000), minimizes the Mean Squared Residue (MSR) to identify coherent biclusters. The Plaid algorithm, introduced by Lazzeroni and Owen (2002), is based on a two-way ANOVA model and allows overlapping biclusters [18]. Bergmann et al. (2003) developed the ISA algorithm, which enables iterative bicluster discovery [19]. The Bimax algorithm, proposed by Prelic et al. (2006), utilizes a binary reference model for biclustering [20].

Wang et al. (2016) introduced the BCBimax algorithm, which considers consumer preferences in the mobile phone market [21]. Raponi et al. (2016) proposed model-based biclustering approaches, while Veroneze et al. (2017) developed the In-Close2 Concept Analysis algorithm, which enhances heuristic-based biclustering methods [22,23].

In this study, the Bimax algorithm, a biclustering method, was chosen to cluster both crime types and offender nationalities, contributing to the novelty of the research. The advantage of the proposed model is unlike traditional clustering techniques that analyze crime data in a single dimension, allows for a simultaneous grouping of crimes and offender nationalities. This approach enables the identification of crime clusters associated with specific nationality clusters, providing a more detailed understanding of crime patterns and their underlying structures.

This study explores the application of biclustering methods in crime analysis. In the second section, the methodology used in the research is explained in detail. The third section presents the findings and analysis results, elaborating on the relationship between crime and the nationality of offenders. Finally, the fourth section provides a comprehensive discussion of the study, highlighting the contributions of biclustering to crime analysis and presenting conclusions and recommendations.

2. METHODOLOGY

The data set for this study is from 2019 and consists of crime data collected from the Incident Information System regarding Public Order Crimes, Misdemeanors/Crimes Requiring Investigation, Smuggling and Organized Crime Incidents, Cybercrimes, and Terrorist Incidents. The data was obtained with permission from the General Command of the Gendarmerie.

In this study, biclustering was employed to analyze the relationship between crimes and offenders. While traditional clustering methods offer one-dimensional groupings, biclustering enables simultaneous clustering of both rows and columns, allowing for a more in-depth analysis of complex data structures [15].

Biclustering is particularly effective in high-dimensional datasets, where subgroups share common patterns within a specific subset. Traditional clustering techniques separate data based on rows or columns, whereas biclustering has the capability to simultaneously identify relationships between variables and observations. For this reason, it is widely used in bioinformatics, social network analysis, and crime analysis, where multidimensional data interpretation is essential [17].

This study aims to analyze the relationship between crimes and offenders by identifying how crime types cluster within specific offender groups. Traditional clustering methods in crime analysis either classify individuals into distinct groups or examine crime types independently. However, in order to better model the crime-offender relationship, a biclustering approach was deemed a more suitable method, as it enables the simultaneous detection of patterns across both dimensions.

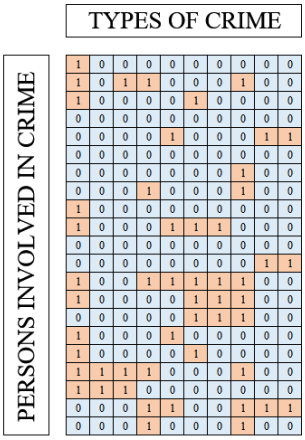

Figure 1. *Sample crime data matrix*

Figure 1 presents a sample crime data matrix, which represents the binary relationships between offenders and crime types. The rows of the matrix correspond to offenders, while the columns represent different types of crimes. The values within the matrix indicate the involvement of individuals in specific crimes, where "1" denotes an individual's involvement in a given crime, and "0" indicates no involvement. This matrix structure offers a deeper analytical perspective by identifying shared patterns between crime types and offenders, facilitating the analysis of complex relationships [24].

In this context, the Bimax algorithm was selected and implemented as the biclustering method. Bimax processes data in a presence/absence (1/0) format, providing a straightforward yet meaningful approach to analyzing crime-offender relationships. Compared to other biclustering algorithms, Bimax stands out due to its deterministic nature, ensuring consistent and reproducible results for a given input dataset. Furthermore, it is resistant to common issues in crime analysis, such as missing or erroneous data, and minimally affected by noise by identifying only the most meaningful subclusters. Previous studies have demonstrated that Bimax has been successfully applied across various disciplines, including bioinformatics, social sciences, and crime analysis, proving to be effective in analyzing complex social relationships, biological datasets, and crime patterns [1,20]. Given these advantages, Bimax is considered a powerful and suitable method for modeling crime-offender relationships.

The Bimax algorithm, developed by Prelic et al. (2006) [20], is a biclustering technique. The algorithm focuses on simultaneously clustering both rows and columns of a data matrix, identifying common patterns within the dataset. Bimax is specifically designed for binary data structures, making it suitable for analyzing datasets consisting solely of "0" and "1" values. It is widely used in fields such as genetic data analysis, social sciences, and crime analysis, where categorical and presence/absence (binary) data types are prevalent. The primary goal of the Bimax algorithm is to identify submatrices that cluster the "1" values within the data matrix, effectively detecting underlying patterns. The algorithm operates using a recursive partitioning technique to analyze the dataset [20].

A data matrix can be transformed into a binary format using a binarization function. More specifically, as presented in Figure 2, the fundamental principle of the Bimax algorithm is to divide a binary matrix into structured subparts.

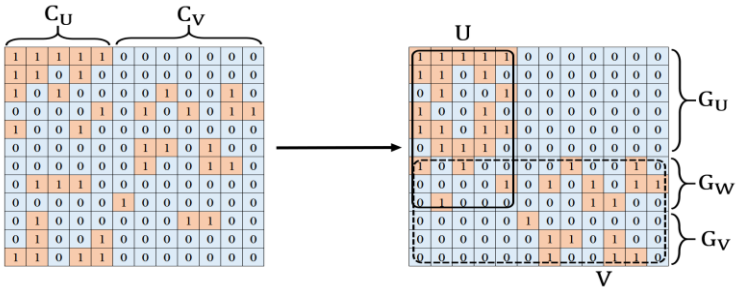

Figure 2. *Representation of the Bimax algorithm on a data matrix*

Initially, the matrix is partitioned into three submatrices composed entirely of 0 values. Since one of these submatrices consists entirely of zeros, it is excluded from the analysis. The remaining two submatrices, U and V, are recursively reprocessed by the algorithm. If the matrix being analyzed contains a bicluster consisting solely of 1 values, the recursive process is terminated.

If the U and V matrices do not share any rows or columns within the binary matrix (i.e., GW is an empty set), these two matrices can be processed independently. However, as illustrated in Figure 2, when U and V contain shared rows (GW), a careful process is required to ensure that biclusters in V share at least one common column with CV. To prevent overlaps, each new bicluster is generated by excluding the rows of previously identified biclusters, ensuring that the algorithm applies the clustering process only to the remaining data [20].

Steps of the Bimax Algorithm

1. A dataset composed of continuous or categorical variables is transformed into binary values ("0" and "1") based on a predefined threshold. (For example, an offender's involvement in a specific crime can be coded as 1 for participation and 0 for no involvement.)
2. The entire data matrix is divided into submatrices containing only "0" values and those containing at least one "1" value.
3. Submatrices containing "1" values are recursively split to create nested biclusters. This process continues until no further meaningful subclusters can be formed.
4. An overlap analysis is performed among subclusters, and the most significant biclusters are selected to form the final result set.

The Bimax algorithm is a deterministic method that performs exceptionally well on large-scale binary datasets. Its ability to directly process binarized data structures makes it highly effective in analyzing categorical variables, such as crime-offender relationships.

Unlike some traditional biclustering algorithms, which rely on stochastic (random) processes, Bimax employs a deterministic approach, ensuring that it produces identical results when repeated with the same input data. This feature makes it a reliable choice for consistent and reproducible analyses. Additionally, when datasets contain noise or missing values, Bimax minimizes the impact of these inconsistencies by extracting only the most meaningful biclusters, making it a robust and trustworthy method compared to other techniques.

Furthermore, its high scalability enables fast and efficient processing of large datasets, making it particularly useful for wide matrices with thousands of variables, where it continues to deliver accurate and meaningful results.

3. THE RESEARCH FINDINGS AND DISCUSSION

This study primarily aims to construct crime routes and identify crime-related connections based on offender data. To achieve this, the Bimax biclustering algorithm was implemented using the open-source R programming environment to analyze the dataset.

The dataset, classified according to the Turkish Gendarmerie's crime taxonomy, excludes human trafficking and migrant smuggling cases. The data is structured in a matrix format, where rows represent nationalities (119 in total, excluding Turkey) and columns represent crime types (52 in total). Crime types are hierarchically categorized into five main groups: A (Public Order Crimes), B (Misdemeanors/Offenses Requiring Investigation), C (Anti-Smuggling and Organized Crime Cases), D (Cyber Crimes) and E (Terror Incidents). Each of these primary categories is further divided into secondary subcategories. For instance, Category A (Public Order Crimes) has four subcategories, Category B (Misdemeanors/Offenses Requiring Investigation) has two subcategories, Category C (Anti-Smuggling and Organized Crime Cases) has four subcategories, Categories D (Cyber Crimes) and E (Counterterrorism Incidents) each have one subcategory.

At the tertiary level, further subdivisions exist. For example, within Category A, the second-level subcategory AA (Crimes Against Individuals) is further detailed at the third level as AAA (Crimes Against Life and Bodily Integrity). To effectively capture crime diversity and examine the relationship between crime types and nationalities, the third-level classification was selected for analysis. This approach ensures a more detailed and accurate representation of crime typologies. Figure 3 illustrates the hierarchical structure of crime classifications, while a complete list of coded crime categories is provided in the appendix.

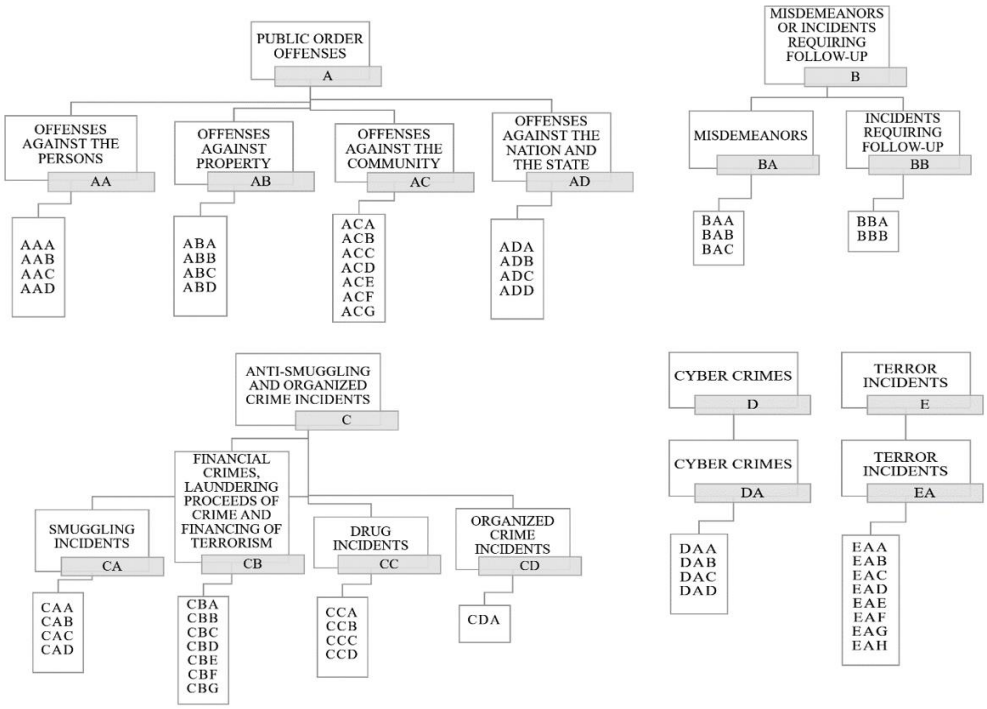

Figure 3. *Hierarchical structure of crime classifications*

The dataset follows a binary encoding scheme to indicate the involvement of foreign nationals in specific crimes. If a crime has been committed by an individual of a particular nationality, the corresponding matrix entry is coded as '1'; otherwise, it is coded as '0'. This binary approach facilitates an efficient analysis of the co-occurrence of crime types and nationalities. Based on the findings, two distinct clustering strategies were developed. In the first approach, the number of crime events was minimized, while the number of nationalities involved was maximized. This method aimed to identify crime routes based on commonly committed specific crimes across a wide range of nationalities. According to the simulation results, the optimal threshold for the number of nationality clusters was determined as 22. The optimal threshold for the number of crime clusters was set at 5. This approach enabled the identification of crime categories that were widely committed across diverse nationalities, shedding light on cross-border crime patterns. In contrast, the second approach adopted a reversed clustering strategy, where the number of nationalities was minimized, while the number of crime events was maximized. According to the simulation results, the optimal threshold for the number of nationality clusters was determined as 5. The optimal threshold for the number of crime clusters was set at 20. This approach allowed for the identification of highly specialized

criminal activities committed by a small number of nationalities, revealing nationality-specific crime patterns. As a result of the study, the biclustering analysis yielded the following:

In the first approach, four distinct clusters were identified, each comprising at least 22 different nationalities involved in a maximum of 5 different crime types (nationalities ≥ 22, crime types ≤ 5).

In the second approach, three distinct clusters were identified, each comprising a maximum of 5 different nationalities involved in at least 20 different crime types (nationalities ≤ 5, crime types ≥ 20).

The four clusters obtained in the first approach are detailed in Tables 1, 2, 3, and 4. These results provide a systematic framework for understanding the association between nationalities and crime types, offering critical insights for law enforcement, border security, and transnational crime prevention strategies.

Table 1. *First bicluster of common nationalities by crime types*

Bicluster 1		CCC	AAA	AAC	ABC	ABD
USA Afghanistan Germany Austria Azerbaijan Belgium Algeria Morocco Georgia Netherlands England Iraq Iran	Kazakhstan Kyrgyzstan Turkish Republic of Northern Cyprus Moldova Uzbekistan Pakistan Russia Syria Tunisia Turkmenistan Ukraine	Anti-Smuggling and Organized Crime Incidents	Public Order Crimes	Public Order Crimes	Public Order Crimes	Public Order Crimes
		Drug-related Incidents	Crimes Against Individuals	Crimes Against Individuals	Property Crimes	Property Crimes
		Purchase/ Receipt/ Possession for Personal Use	Crimes Against Life and Bodily Integrity	Crimes Against Liberty and Honor	Damage to Property	Other Property Crimes

Table 2. *Second bicluster of common nationalities by crime types*

Bicluster 2		CCC	AAA	AAC	ABD	DAB
USA Afghanistan Germany Austria Azerbaijan Algeria Morocco Georgia England Iraq Iran Kazakhstan	Kyrgyzstan Libya Egypt Uzbekistan Pakistan Russia Syria Saudi Arabia Tunisia Turkmenistan Ukraine Jordan	Anti-Smuggling and Organized Crime Incidents	Public Order Crimes	Public Order Crimes	Public Order Crimes	Cyber Crimes
		Drug-related Incidents	Crimes Against Individuals	Crimes Against Individuals	Property Crimes	Cyber Crimes
		Purchase/ Receipt/ Possession for Personal Use	Crimes Against Life and Bodily Integrity	Crimes Against Liberty and Honor	Other Property Crimes	Property Crimes

Table 3. *Third bicluster of common nationalities by crime types*

Bicluster 3		CCC	AAA	AAC	BAA	DAB
USA Afghanistan Germany Azerbaijan Bulgaria Algeria Morocco Palestine Georgia England Iraq Iran	Kazakhstan Kyrgyzstan Egypt Uzbekistan Pakistan Russia Syria Tunisia Turkmenistan Ukraine Jordan	Anti-Smuggling and Organized Crime Incidents	Public Order Crimes	Public Order Crimes	Misdemeanors/ Incidents Requiring Follow-up	Cyber Crimes
		Drug-related Incidents	Crimes Against Individuals	Crimes Against Individuals	Misdemeanors	Cyber Crimes
		Purchase/ Receipt/ Possession for Personal Use	Crimes Against Life and Bodily Integrity	Crimes Against Liberty and Honor	Misdemeanors Directly Subject to Administrative Sanctions	Property Crimes

Table 4. *Fourth bicluster of common nationalities by crime types*

Bicluster 4		AAA	AAC	ABD	BAA	DAB
USA Afghanistan Germany Azerbaijan Algeria Morocco Georgia England Iraq Iran Kazakhstan	Kyrgyzstan Egypt Nigeria Uzbekistan Pakistan Russia Syria Tunisia Turkmenistan Ukraine Jordan	Public Order Crimes	Public Order Crimes	Public Order Crimes	Misdemeanors/Incidents Requiring Follow-up	Cyber Crimes
		Crimes Against Individuals	Crimes Against Individuals	Property Crimes	Misdemeanors	Cyber Crimes
		Crimes Against Life and Bodily Integrity	Crimes Against Liberty and Honor	Other Property Crimes	Misdemeanors Directly Subject to Administrative Sanctions	Property Crimes

Upon analyzing the four biclusters presented above, it is observed that Drug-Related Crimes stand out within Anti-Smuggling and Organized Crime Cases, while Crimes Against Individuals and Property emerge as significant under Public Order Crimes, and Crimes Against Property are prominent within Cyber Crimes.

When these crime categories are examined in terms of their subtypes, Drug-Related Crimes include a total of 20 subcategories, primarily involving cannabis, heroin, and stimulant pills. The United Nations Office on Drugs and Crime (UNODC) reports, specifically the "World Drug Reports", indicate the use of various regional and subregional classifications. These classifications are not officially recognized, yet the report explicitly states that the countries relevant to our study are categorized as follows [25].

Within the framework of the regional and subregional classifications provided by the UNODC, the countries relevant to our study are categorized as follows:

- North Africa: Algeria, Egypt, Libya, Morocco, Sudan, and Tunisia.
- North America: Canada, Mexico, the United States, Bermuda, Greenland, Saint Pierre, and Miquelon.
- Central Asia and Transcaucasia: Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.
- Southwest Asia: Afghanistan, Iran (Islamic Republic of), and Pakistan.
- Near and Middle East: Bahrain, Iraq, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, Saudi Arabia, the State of Palestine, the Syrian Arab Republic, the United Arab Emirates, and Yemen.
- Eastern Europe: Belarus, the Republic of Moldova, the Russian Federation, and Ukraine.
- Southeastern Europe: Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Montenegro, North Macedonia, Romania, Serbia, Turkey, and Kosovo.
- Western and Central Europe: Andorra, Austria, Belgium, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Monaco, the Netherlands, Norway, Poland, Portugal, San Marino, Slovakia, Slovenia, Spain, Sweden, Switzerland, the United Kingdom of Great Britain and Northern Ireland, the Faroe Islands, Gibraltar, and the Holy See.

Using the R programming environment, a mapping process was conducted to visualize the relationship between crime types and the nationalities of offenders by country. The resulting geographical distribution map is presented in Figure 4.

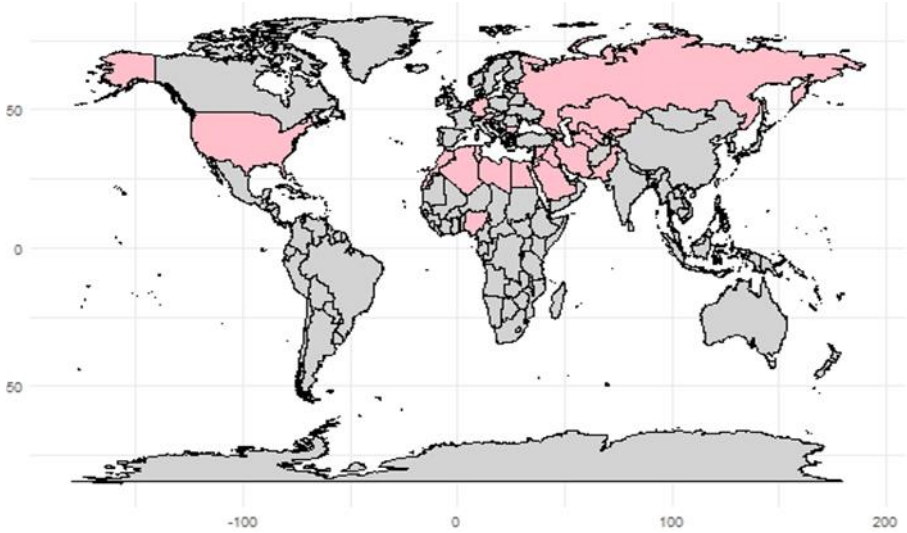

Figure 4. *Geographical distribution of the relationship between crime types and offenders' nationalities by country*

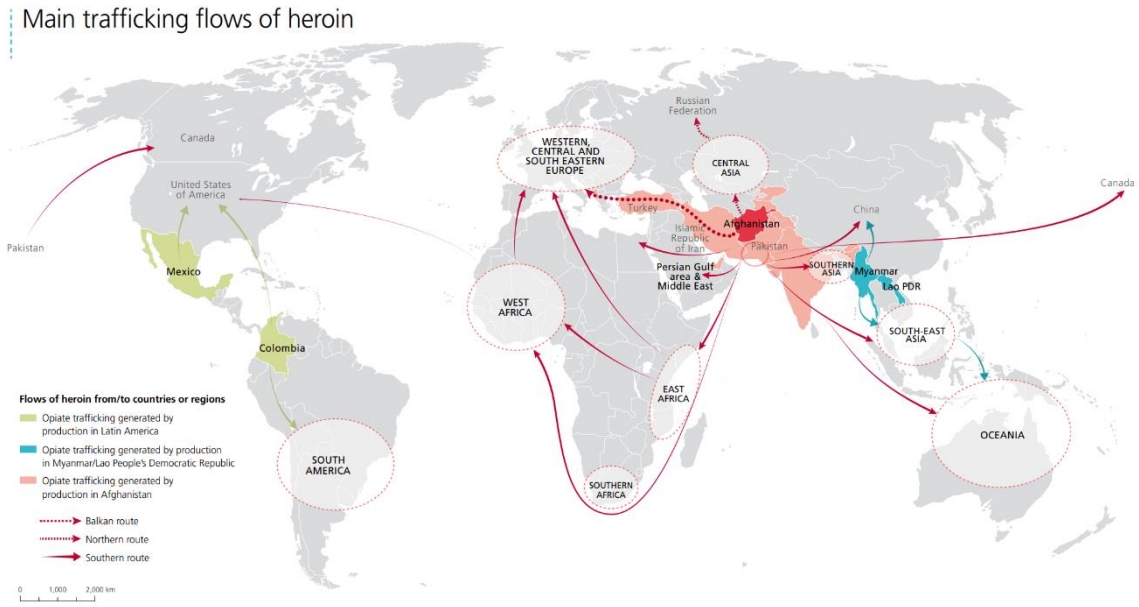

Figure 5. *Global drug trafficking routes [25]*

Source: UNODC, responses to annual report questionnaire and individual drug seizure database.

Reports from the UNODC indicate a high degree of similarity between the regional and subregional classifications and the nationalities of foreign individuals apprehended for drug-related offenses within the jurisdiction of the Turkish Gendarmerie (Figure 4).

The UNODC reports highlight that major drug trafficking routes, particularly the Balkan Route, along with its side and sub-routes, such as the Caucasus Route, Northern Black Sea Route, Eastern Mediterranean Route, and Northern Iraq-Syria Route, are intensively used in drug smuggling operations (Figure 5). Among these main routes, the Balkan Route is the most frequently used pathway for heroin and other opiates smuggled into Europe. It starts in Afghanistan and extends through Iran, Turkey, and the Balkan countries before reaching Central and Western Europe. The Southern Route transports Afghan-origin heroin to Gulf countries and East Africa via Pakistan (and partially Iran), then reaches Europe through Southern or Western Africa. Compared to the Balkan and Northern routes, the Southern Route is the most frequently used for maritime drug trafficking. The Northern Route extends from Afghanistan’s northern borders

through Tajikistan, Kyrgyzstan, and Kazakhstan, ultimately reaching the Russian Federation and Ukraine [26,27].

The 2019 European Drug Report by the European Monitoring Centre for Drugs and Drug Addiction (EMCDDA) states that in 2017, the total amount of heroin seized across 28 EU countries (5.4 tons) was significantly lower than the amount seized by Turkish law enforcement agencies (17.4 tons). This highlights Turkey's crucial role in intercepting Afghan-origin heroin trafficked toward the European illicit market [26,27].

Under public order crimes, the category of crimes against individuals and property includes 19 specific offenses, such as homicide, assault, fraud, threats, and extortion. Law enforcement records indicate that individuals involved in these crimes typically originate from conflict zones affected by violence and persecution, such as Afghanistan, Iran, Iraq, and Syria. Additionally, many offenders come from countries where work permits are often not obtained, including Azerbaijan, Turkmenistan, and Uzbekistan. Others migrate due to war and harsh living conditions in Russia, Ukraine, and Syria, which subsequently leads to their involvement in criminal activities.

Chayes (2015) states that in some countries, governments have effectively turned into organized crime networks, where corruption, threats, extortion, homicide, and assault have become routine activities [28]. It is particularly noted that in Afghanistan, Egypt, Tunisia, Nigeria, and Uzbekistan, these crimes are openly discussed, while in Ukraine and Kyrgyzstan, armed criminal organizations can be established, and law enforcement officials can be assassinated for financial compensation. Additionally, it is argued that the financial systems that have evolved since the 1980s, culminating in the 2008 financial crisis, along with the ideology of the sanctification of money, have significantly contributed to the expansion of these crime networks.

In all identified biclusters, cyber (digital) crimes within property-related offenses are found to include qualified fraud and grand theft. With advancing technology, these crimes are increasingly being committed online, primarily through e-commerce fraud (selling counterfeit or non-existent products online), identity theft and phishing techniques, and the theft of bank and credit card account information. A report published by the American cybersecurity firm CrowdStrike highlights that Russia, North Korea, China, and Iran are the fastest-growing sources of cybercriminals. Additionally, hackers from the United States, Israel, Ukraine, Pakistan, and India are identified as highly advanced in committing cybercrimes worldwide (The World's Fastest Hackers Are Russians[1]).

Analysis of individuals arrested for cybercrime reveals that suspects from the United States, Russia, Ukraine, Iran, and Pakistan frequently appear in the identified pairs.

For the second analysis, three biclusters were identified where the maximum number of nationalities is 5, and the minimum number of crime types is 20 (nationalities ≤ 5, crime types ≥ 20). These three biclusters are presented with Tables 5, 6 and 7.

[1]*News reports on global cybersecurity trends indicate that Russian hackers are among the fastest in the world. Retrieved from https://www.karar.com/dunyanin-en-hizli-hackerlari-ruslar-1124634*

Table 5. *First bicluster of common crimes by nationalities*

	Afghanistan, Azerbaijan, Iran, Uzbekistan, Syria			
Bicluster 1	CAA	Anti-Smuggling and Organized Crime Incidents	Smuggling Incidents	Crimes within Anti-Smuggling Operations
	CBG		Financial Crimes, Money Laundering, and Terrorism Financing	Forgery in Official Documents (within Turkish Penal Code)
	CCA		Drug-related Incidents	Manufacture and Trafficking
	CCC		Drug-related Incidents	Purchase/Receipt/Possession for Personal Use
	CDA		Organized Crime Incidents	Organized Crimes

	AAA	Public Order Crimes	Crimes Against Individuals	Crimes Against Life and Bodily Integrity
	AAB		Crimes Against Individuals	Crimes Against Sexual Integrity
	AAC		Crimes Against Individuals	Crimes Against Liberty and Honor
	ABA		Property Crimes	Theft
	ABC		Property Crimes	Damage to Property
	ABD		Property Crimes	Other Property Crimes
	ACA		Crimes Against Society	Crimes Creating General Danger
	ACC		Crimes Against Society	Crimes Against Family Order
	ADA		Crimes Against Nation and State	Crimes Against Reliability and Functioning of Public Administration
	ADC		Crimes Against Nation and State	Crimes Specified in Other Laws
	EAC	Terror Incidents	Terror Incidents	Apprehension
	BAA	Misdemeanors / Incidents Requiring Follow-up	Misdemeanors	Misdemeanors Directly Subject to Administrative Sanctions
	BAB		Misdemeanors	Misdemeanors Subject to Administrative Sanctions by Civil Authorities
	BBB		Incidents to be Monitored	Other Incidents to be Monitored
	DAB	Cyber Crimes	Cyber Crimes	Property Crimes

Table 6. *Second bicluster of common crimes by nationalities*

	Afghanistan, Azerbaijan, Iraq, Uzbekistan, Syria			
Bicluster 2	CAA	Anti-Smuggling and Organized Crime Incidents	Smuggling Incidents	Crimes within Anti-Smuggling Operations
	CBG		Financial Crimes, Money Laundering, and Terrorism Financing	Forgery in Official Documents (within Turkish Penal Code)
	CCA		Drug-related Incidents	Manufacture and Trafficking
	CCC		Drug-related Incidents	Purchase/Receipt/Possession for Personal Use
	CDA		Organized Crime Incidents	Organized Crimes
	AAA	Public Order Crimes	Crimes Against Individuals	Crimes Against Life and Bodily Integrity
	AAB		Crimes Against Individuals	Crimes Against Sexual Integrity
	AAC		Crimes Against Individuals	Crimes Against Liberty and Honor
	ABA		Property Crimes	Theft
	ABC		Property Crimes	Damage to Property
	ABD		Property Crimes	Other Property Crimes
	ACA		Crimes Against Society	Crimes Creating General Danger
	ACC		Crimes Against Society	Crimes Against Family Order
	ADA		Crimes Against Nation and State	Crimes Against Reliability and Functioning of Public Administration
	EAC	Terror Incidents	Terror Incidents	Apprehension
	BAA	Misdemeanors / Incidents Requiring Follow-up	Misdemeanors	Misdemeanors Directly Subject to Administrative Sanctions
	BAB		Misdemeanors	Misdemeanors Subject to Administrative Sanctions by Civil Authorities
	BAC		Misdemeanors	Misdemeanors Reported to Relevant Institutions
	BBB		Incidents to be Monitored	Other Incidents to be Monitored
	DAB	Cyber Crimes	Cyber Crimes	Property Crimes

Table 7. *Third bicluster of common crimes by nationalities*

	Afghanistan, Azerbaijan, Uzbekistan, Russia, Syria			
Bicluster 3	CAA	Smuggling and Organized Crime Incidents	Smuggling Incidents	Crimes within Anti-Smuggling Operations
	CBG		Financial Crimes, Money Laundering, and Terrorism Financing	Forgery in Official Documents (within Turkish Penal Code)
	CCC		Drug-related Incidents	Purchase/Receipt/Possession for Personal Use
	CDA		Organized Crime Incidents	Organized Crimes

AAA	Public Order Crimes	Crimes Against Individuals	Crimes Against Life and Bodily Integrity
AAB		Crimes Against Individuals	Crimes Against Sexual Integrity
AAC		Crimes Against Individuals	Crimes Against Liberty and Honor
ABA		Property Crimes	Theft
ABC		Property Crimes	Damage to Property
ABD		Property Crimes	Other Property Crimes
ACA		Crimes Against Society	Crimes Creating General Danger
ACC		Crimes Against Society	Crimes Against Family Order
ADA		Crimes Against Nation and State	Crimes Against Reliability and Functioning of Public Administration
ADC		Crimes Against Nation and State	Crimes Specified in Other Laws
BAA	Misdemeanors / Incidents Requiring Follow-up	Misdemeanors	Misdemeanors Directly Subject to Administrative Sanctions
BAB		Misdemeanors	Misdemeanors Subject to Administrative Sanctions by Civil Authorities
BAC		Misdemeanors	Misdemeanors Reported to Relevant Institutions
BBA		Incidents to be Monitored	Accidents (Excluding Traffic Accidents)
BBB		Incidents to be Monitored	Other Incidents to be Monitored
DAB	Cyber Crimes	Cyber Crimes	Property Crimes

An analysis of the three identified biclusters reveals that offenders originate from seven different nationalities (Afghanistan, Azerbaijan, Iran, Iraq, Uzbekistan, Syria, and Russia). The distribution of these offenders and their associated crime types is visualized in the map presented in Figure 6. Findings indicate that individuals of these nationalities are primarily involved in drug-related crimes, organized crime, threats, extortion, assault, terrorism, and cybercrime incidents.

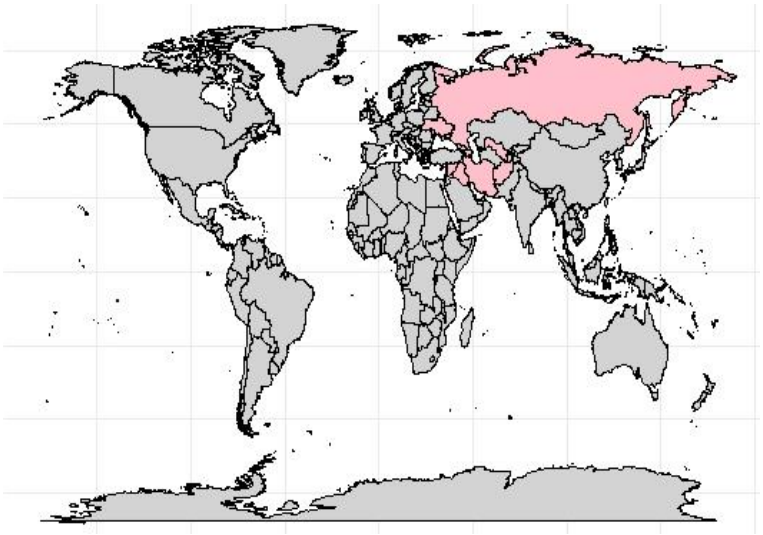

Figure 6. *World map of common crimes by nationalities*

An analysis of the nationalities of offenders in the three biclusters reveals that the common regions identified in these clusters stand out due to the organized nature of crimes, financial incentives, and connections with terrorist organizations.

Terrorist organizations fund their activities through drug trafficking, just like organized crime groups. The 2023 Turkey Drug Report highlights that many global terrorist organizations maintain close ties to the drug trade.

International reports confirm that drug trafficking is one of the main sources of income for terrorist organizations. Key findings include [29]:

- Children aged 8-12 were used to sell drugs in Germany, with the proceeds funneled to the organization.
- Terrorist organizations was orchestrating drug trafficking across Europe.
- Terrorist organizations engaged in heroin production and trafficking to finance terrorism.
- Terrorist organizations was involved in money laundering, illicit drug trafficking, and human smuggling across Europe.
- Organized crime zones along the Balkan Route overlapped with terrorist activity hotspots.
- Terrorist organizations was actively engaged in drug trafficking to fund terrorist operations.
- Persons of interest arrested along the Afghanistan-Turkey drug route had direct ties to terrorist organizations.
- Iraq was becoming a key hub for illegal drug cultivation and heroin production, further fueling criminal and terrorist networks.

Moreover, according to 2017 estimates, the European retail drug market had a minimum value of €30 billion, with 38% of criminal organizations engaged in drug trafficking [30]. Reports also indicate that heroin trafficking and trade within the EU frequently involve individuals holding Turkish, Iraqi, and Iranian citizenships [31].

Afghanistan, Iraq, Iran, and Syria have established strong connections with terrorist organizations. These groups engage in large-scale illegal activities, including drug production and trafficking, smuggling, and counterfeiting, often in coordination with organized crime syndicates within their respective countries. This dynamic illustrates the transnational structure of crime and the interrelation between criminal activities and offender nationalities.

Additionally, information compiled from various news sources indicates that Russian, Serbian, Azerbaijani, and Georgian crime syndicates, collectively referred to as the "Russian-speaking mafia," have used Turkey as a base to connect with their networks in Europe and the Americas. These groups have been involved in drug and arms trafficking, bombings, smuggling, and money laundering, often operating under false identities[2].

4. CONCLUSION AND RECOMMENDATIONS

An analysis of the biclusters formed based on crime types and offender nationalities highlights the importance of clustering related crimes and identifying the nationalities of offenders to uncover patterns in crime routes. In crime prevention efforts, identifying such connections is crucial. To achieve this, the Bimax biclustering method, which simultaneously clusters both crime types and foreign offenders, was applied. This study examined crimes committed within the jurisdiction of Turkey's Gendarmerie, including "Public Order Crimes," "Misdemeanors/Incidents Requiring Legal Action," "Anti-Smuggling and Organized Crime," "Cyber Crimes," and "Counterterrorism", as well as the nationalities of the foreign offenders involved.

The Bimax algorithm was chosen for its ability to provide more detailed and realistic results compared to traditional clustering methods.

The aim of this study was not only to identify specific crimes committed by certain foreign nationals but also to analyze whether these crimes were committed along specific routes, either individually or through organized crime and terrorist networks.

When analyzing the relationship between offenders' nationalities and crime types, it was determined that offenders from Afghanistan, Azerbaijan, Iran, Iraq, Uzbekistan, Syria, and Russia were linked to drug production and trafficking, threats, extortion, assault, forgery, grand fraud, and grand theft. These crimes

were frequently committed in an organized manner and were often linked to terrorist activities. With its geopolitical position between Asia, the Middle East, and Europe, Turkey serves as a bridge for international travel and trade, making it a critical area for understanding crime routes and connections between offenders.

The advancement of technology has also changed the nature of crime, with traditional crimes such as theft and fraud shifting to online platforms, including phishing scams and financial fraud. Our study confirms that crime is a global phenomenon involving offenders from various nationalities. As illicit financial gains remain a major incentive, some criminals engage in crime due to economic hardship, while others seek power, status, or financial stability through criminal networks.

To combat crime effectively: Public awareness must be increased, Rule of law and transparency must be ensured, Criminal and terrorist organizations must be dismantled and their leaders prosecuted, Technological advancements must be closely monitored, international cooperation agreements should be strengthened for coordinated crime prevention efforts. The data used in this study are derived from the jurisdiction of the Gendarmerie General Command. Therefore, the analysis primarily covers rural areas rather than the entire country. If police records become accessible, more comprehensive and detailed findings could be obtained for the national level.

[2]*News reports indicate that Russian-speaking crime syndicates have used Turkey as a base for their operations, engaging in activities such as drug and arms trafficking, bombings, smuggling, and money laundering. These reports highlight connections between these syndicates and networks in Europe and the Americas (News abc, 2020; Short Wave, 2022; Hürriyet, 2020). See: News abc (2020, August 20). Azerbaijani crime syndicate leader killed in Antalya! Retrieved from https://abcgazetesi.com/azeri-suc-orgutu-lideri-antalyada-olduruldu-355519; Short Wave (2022, January 11). Russian-speaking murders. Retrieved from https://kisadalga.net/yazar/rusca-konusan-cinayetler_45558; Hürriyet (2020, February 5). Breaking news… Major operation against Russian mafia in Istanbul: 16 arrested. Retrieved from https://www.hurriyet.com.tr/gundem/son-dakika-haberler-istanbulda-rus-cetesine-buyuk-operasyon-16-gozalti-41434236.*

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

APPENDIX

A Complete List of Coded Crime Categories

CRIMES CODES	TYPES OF CRIMES
AAA	OFFENCES AGAINST LIFE AND BODILY INTEGRITY
AAB	OFFENCES AGAINST SEXUAL INVIOLABILITY
AAC	OFFENCES AGAINST FREEDOM AND HONOUR
AAD	OTHER OFFENCES AGAINST PERSONS
ABA	THEFT
ABB	ROBBERY
ABC	DAMAGE TO PROPERTY
ABD	OTHER OFFENCES AGAINST PROPERTY
ACA	OFFENCES CREATING GENERAL DANGER
ACB	OFFENCES AGAINST PUBLIC MORALITY
ACC	OFFENCES AGAINST FAMILY ORDER
ACD	OFFENCES AGAINST THE ENVIRONMENT
ACE	OTHER OFFENCES AGAINST SOCIETY
ACF	OFFENCES AGAINST PUBLIC TRUST
ACG	OFFENCES AGAINST ANIMALS WITHIN THE SCOPE OF LAW NO 5199
ADA	OFFENCES AGAINST THE RELIABILITY AND FUNCTIONING OF PUBLIC ADMINISTRATION
ADB	OFFENCES AGAINST THE JUDICIARY

ADC	OFFENCES SPECIFIED IN OTHER LAWS
ADD	OTHER OFFENCES AGAINST THE NATION AND THE STATE
BAA	MISDEMEANOURS SUBJECT TO DIRECT ADMINISTRATIVE SANCTIONS
BAB	MISDEMEANOURS SUBJECT TO ADMINISTRATIVE SANCTIONS BY THE LOCAL AUTHORITY
BAC	MISDEMEANOURS NOTIFIED TO THE RELEVANT INSTITUTION/ORGANISATION
BBA	ACCIDENTS (EXCLUDING TRAFFIC ACCIDENTS)
BBB	OTHER EVENTS TO FOLLOW
CAA	OFFENCES WITHIN THE SCOPE OF THE FIGHT AGAINST SMUGGLING
CAB	OFFENCES AGAINST THE LAW NO. 5307 ON THE MARKET OF LIQUEFIED PETROLEUM GASES (LPG)
CAC	OFFENCES AGAINST CULTURAL AND NATURAL ASSETS
CAD	OFFENCES UNDER THE LAW NO. 6136 ON FIREARMS / BLADES / OTHER INSTRUMENTS
CBA	OFFENCES UNDER THE LAW NO. 5549 ON THE PREVENTION OF LAUNDERING PROCEEDS OF CRIME (TPC ART282)
CBB	FALSIFICATION (FORGERY) OF MONEY OFFENCES UNDER THE TURKISH PENAL CODE (TPC)
CBC	FALSIFICATION OF PRIVATE DOCUMENT OFFENCES UNDER THE TURKISH PENAL CODE
CBD	QUALIFIED FRAUD OFFENCES UNDER THE TURKISH PENAL CODE
CBE	OFFENCES UNDER THE TAX PROCEDURE LAW
CBF	FALSIFICATION OF VALUES CONSIDERED EQUIVALENT TO MONEY UNDER THE TURKISH PENAL CODE
CBG	FALSIFICATION OF OFFICIAL DOCUMENTS UNDER TURKISH PENAL CODE
CCA	MANUFACTURE AND TRAFFICKING IN DRUG CASES
CCB	FACILITATING USE IN DRUG CASES
CCC	BUYING/ACCEPTING/POSSESSING FOR USE IN DRUG CASES
CCD	ILLEGAL CULTIVATION IN DRUG CASES
CDA	ORGANISED CRIME
DAA	OPPOSITION TO THE ELECTRONIC SIGNATURE LAW NUMBERED 5070 IN CYBERCRIMES
DAB	OFFENCES AGAINST PROPERTY IN CYBERCRIMES
DAC	OFFENCES IN THE FIELD OF INFORMATION TECHNOLOGY
DAD	CRIMES IN THE FIELD OF INFORMATION IN CYBERCRIMES
EAA	CLASHES IN TERRORIST INCIDENTS
EAB	TERRORIST ACTS UNDER THE GUISE OF SOCIAL EVENTS IN TERRORIST INCIDENTS
EAC	ARREST IN TERROR INCIDENTS
EAD	SEIZURE OF WEAPONS, AMMUNITION AND MATERIALS IN TERRORIST INCIDENTS
EAE	FINDING MINES AND EXPLOSIVES IN TERRORIST INCIDENTS
EAF	SURRENDER IN TERRORIST INCIDENTS
EAG	OTHER EVENTS IN TERRORIST INCIDENTS
EAH	OFFENCES UNDER THE LAW NO. 6415 ON THE PREVENTION OF FINANCING OF TERRORISM IN TERRORIST INCIDENTS

A Complete List of Nationalty

No	Nationality	No	Nationality	No	Nationality	No	Nationality	No	Nationality
1	USA	26	Other Country	51	Ireland	76	Hungary	101	Somalia
2	Afghanistan	27	Indonesia	52	Scotland	77	Macedonia	102	Sudan
3	Germany	28	Eritrea	53	Spain	78	Malawi	103	Syria
4	Angola	29	Armenia	54	Israel	79	Malaysia	104	Saudi Arabia
5	Argentina	30	Estonia	55	Sweden	80	Mali	105	Tajikistan
6	Albania	31	Ethopia	56	Switzerland	81	Egypt	106	Tatarstan
7	European Union (EU)	32	Morocco	57	Italy	82	Mongolia	107	Thailand
8	Australia	33	Ivory Coast	58	Cameroon	83	Moldova	108	Tunisia
9	Austria	34	Philippines	59	Canada	84	Myanmar (Birmanca)	109	Tuvalu

10	Azerbaijan	35	Palestine	60	Qatar	85	Niger	110	Turkmenistan
11	Bahrain	36	Finland	61	Kazakhstan	86	Nigeria	111	Uganda
12	Bangladesh	37	France	62	Kenya	87	Norway	112	Ukraine
13	Belgium	38	Gabon	63	Republic of Northern Cyprus	88	Republic of Central Africa	113	Oman
14	Belerus	39	Gambia	64	Kyrgyzstan	89	Uzbekistan	114	Jordan
15	Uncertain	40	Ghana	65	Colombia	90	Pakistan	115	Vietnam
16	United Arab Emirates	41	Guinea	66	Congo	91	Poland	116	Yemen
17	United Republic of Tanzania	42	Republic of South Africa	67	Kosovo	92	Romania	117	New Zealand
18	Bosnia Herzegovina	43	South Korea	68	Kuwait	93	Russia	118	Greece
19	Brazil	44	Georgia	69	Turkish Republic of Northern Cyprus	94	Seierra Leone	119	Zimbabwe
20	Bulgaria	45	Haiti	70	Cuba	95	Senegal		
21	Algeria	46	India	71	Latvia	96	Chile		
22	Djibouti	47	Holland	72	Liberia	97	Singapore		
23	Czechya	48	England	73	Libya	98	Serbia		
24	China	49	Iraq	74	Lithuania	99	Slovakia		
25	Denmark	50	Iran	75	Lebanon	100	Slovenia		

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