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A bimax biclustering analysis of crime types by nationality in Türkiye

Türkiye'de uyruklara göre suç türlerinin bimax ikili kümeleme analizi

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A Bimax Biclustering Analysis of Crime Types by Nationality in Türkiye

Highlights

- *Bimax algorithm was applied to analyze crime–nationality using 2019–2023 data from Türkiye.*
- *Syrian, Afghan, and Iranian nationals accounted for the largest shares of foreign-national crime records.*
- *Five biclusters revealed overlapping crime–nationality patterns.*
- *The method uncovered co-occurrence of crimes such as assault, theft, and drug trafficking.*
- *Findings provide data-driven insights for migration and security policies.*

Graphical Abstract

The study applies the Bimax biclustering algorithm to identify hidden patterns between nationalities and crime types, revealing overlapping clusters that highlight the role of migration-related dynamics in crime trends.

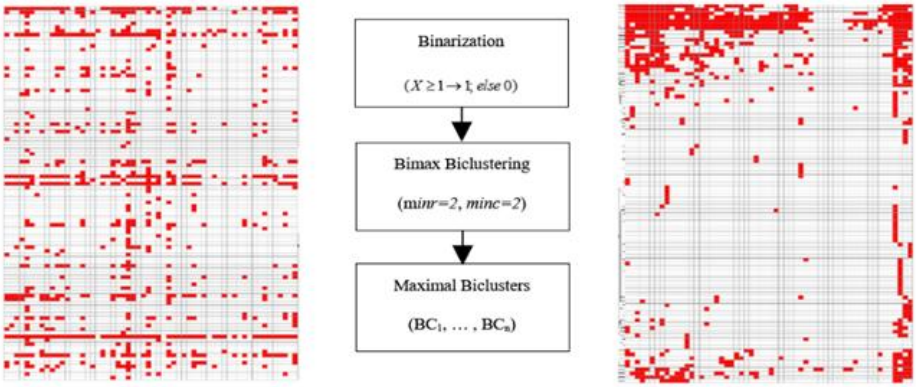

Figure. Analysis workflow for Bimax biclustering of crime types by nationality

Aim

This study aims to examine the relationship between nationalities and crime types in Türkiye using the Bimax biclustering algorithm, focusing on structural patterns rather than individual frequencies.

Design & Methodology

Official judicial data from 2019–2023 were analyzed using the Bimax algorithm in R, with year-specific nationality × crime-type matrices constructed for each period. Following logarithmic transformation and binarization, bicluster visualization techniques were applied to identify stable co-occurrence patterns across varying data dimensions.

Originality

Unlike previous studies focusing on provinces, this research uniquely analyzes crime patterns by nationality across the 2019–2023 period. It demonstrates the capacity of biclustering to reveal cross-national overlaps and provides insights into the intersection of migration and crime.

Findings

Crime records are consistently concentrated in a small number of nationalities during 2019–2023, with Syrian nationals predominating, followed by Afghan and Iranian groups. Bimax biclustering reveals five stable co-occurrence structures linking violent, property, and drug-related crimes across nationalities, indicating persistent, migration-related risk patterns rather than year-specific effects.

Conclusion

The Bimax biclustering approach reveals hidden structural patterns in crime–nationality relations. The findings emphasize that migration dynamics, socio-economic vulnerabilities, and integration challenges are central to understanding crime involvement among foreign nationals.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

A Bimax Biclustering Analysis of Crime Types by Nationality in Türkiye

Araştırma Makalesi / Research Article

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ABSTRACT

This study examines structural relations between nationalities and crime types in Türkiye using the Bimax biclustering algorithm. Official judicial records from 2019–2023 (with varying nationality and crime type structures by year) were converted to binary format and analyzed in the R environment. Bimax identified compact biclusters that uncover recurring co-occurrence patterns across nationalities over the years—for example, the joint appearance of assault, qualified theft, and drug-related offenses—and highlight overlaps between groups rather than single-variable frequencies. The workflow comprises data binarization, biclustering with minimum row/column constraints, and heat-map visualization to interpret membership. Methodologically, the paper demonstrates the utility of Bimax for sparse, high-dimensional administrative data, offering an interpretable alternative to province-level analyses. Substantively, the findings provide policy-relevant signals for targeted prevention and integration strategies, indicating that crime profiles among foreign nationals are shaped by migration-related and socio-economic factors. Because the approach can produce consistent results under different threshold values and algorithm settings, it can be easily adapted to similar administrative datasets and different contextual analyses.

Keywords: Bimax, Biclustering, Crime analysis, Nationality, Migration.

Türkiye'de Uyruklara Göre Suç Türlerinin Bimax İkili Kümeleme Analizi

ÖZ

Bu çalışma, Türkiye'de uyruklar ile suç türleri arasındaki yapısal ilişkileri Bimax ikili kümeleme algoritmasıyla incelemektedir. Resmî 2019–2023 adli kayıtları (yıllara göre değişen uyruk ve suç türü yapıları) ikili forma dönüştürülerek R ortamında analiz edilmiştir. Bimax, uyruklar arasında yıllar boyunca yinelenen birlikte-görülme örüntülerini açığa çıkaran kompakt ikili kümeler belirlemiş; örneğin kasten yaralama, nitelikli hırsızlık ve uyuşturucu bağlantılı suçların birlikte ortaya çıkması gibi yapıları görünür kılmıştır. İş akışı; ikili dönüşüm, satır/sütun alt sınırlarıyla kümeleme ve üyeliklerin ısı haritalarıyla yorumlanması adımlarından oluşur. Yöntemsel olarak çalışma, seyrek ve yüksek boyutlu idari veriler için Bimax'ın açıklanabilir gücünü göstermekte; il düzeyli analizlere alternatif bir çerçeve sunmaktadır. Bulgular, yabancı uyrukluların suç profillerinin göçle ilişkili ve sosyo-ekonomik etmenlerce şekillendiğine işaret ederek, hedefe yönelik önleme ve uyum politikaları için veri temelli ipuçları sağlar. Yaklaşım, farklı eşik değerleri ve algoritma ayarları altında tutarlı sonuçlar üretebilmesi nedeniyle, benzer idari veri setlerine ve farklı bağlamsal analizlere kolaylıkla uyarlanabilir.

Anahtar Kelimeler: Bimax, İkili kümeleme, Suç analizi, Uyruk, Göç.

1. INTRODUCTION

Crime is a multifaceted social phenomenon that encompasses behaviors violating legal norms, ethical codes, and collectively endorsed values. Its occurrence is shaped by the interplay of demographic structures, socio-economic conditions, psychological characteristics, institutional contexts, and policy environments. Consequently, effective crime analysis requires approaches that move beyond single-factor explanations and accommodate structural, temporal, and contextual complexity [1]. In recent years, the growth, diversification, and administrative integration of crime data—often collected at national scale and at high frequency—have further intensified interest in analytical methods capable of discovering patterns at scale for public safety, resource allocation, patrol optimization, and strategic security planning [1–3]. Conventional statistics remain invaluable for estimation and inference, yet they can be insufficient when analysts face high-dimensional, sparse, and heterogeneous data matrices that embed multiple interacting mechanisms [2–4].

Data-mining and machine-learning techniques have therefore become central to contemporary crime analytics. Among these, clustering traditionally groups similar observations to reveal latent structure; however, classic clustering operates along one mode at a time (e.g., grouping cities by offense rates), which can obscure local relationships that are specific to subsets of both observations and variables. Biclustering addresses this limitation by simultaneously modeling dependencies

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across rows and columns, thereby uncovering co-occurrence structures (submatrices) in which specific groups of observations share specific groups of variables [2–5]. Originally developed for gene-expression analysis, biclustering has been adapted to a wide range of domains and is well suited to administrative crime data in which presence/absence or thresholded events form interpretable binary matrices [3–5].

The appeal of biclustering in crime analytics is twofold. Substantively, it can reveal local criminal opportunity structures where, for example, particular offense types tend to co-appear within particular social or spatial groups. Methodologically, many biclustering algorithms—including Bimax—are designed to handle sparse matrices in which "ones" are informative events and "zeros" denote absence, allowing analysts to focus on compact, interpretable submatrices [4]. Early crime-mining systems already illustrated how pattern discovery supports regional prioritization and investigative workflows [6–8]. More recently, biclustering has been used to delineate crime regions and to compare algorithms on urban datasets [9], and to connect offense profiles with seized materials in smuggling cases, highlighting its capacity to capture interpretable co-occurrences in enforcement data [10]. These developments situate biclustering as a natural bridge between descriptive mapping and predictive risk modeling in public safety [1,11].

Within the Turkish context, prior empirical work has predominantly examined province-by-crime structures, leveraging spatial heterogeneity to group cities and offense types jointly. While such studies illuminate geographic concentration, they leave comparatively underexplored the nationality dimension, which is crucial for understanding migration-related vulnerabilities, exposure to risky environments, and integration challenges. From a policy perspective, the nationality–crime interface matters for the design of targeted prevention, social support, and integration strategies, provided that analyses remain descriptive and structural rather than attributive. In other words, the analytic aim is to detect patterns of co-occurrence between nationalities and offense types—patterns that may reflect socio-economic stressors, settlement dynamics, or opportunity structures—not to essentialize criminality to nationality categories.

To address this gap, the present study applies the Bimax biclustering algorithm to judicial records in Türkiye covering the 2019–2023 period, structured as nationality × crime-type matrices for each year. Because the number of observed nationalities and crime categories varies across years, the analysis focuses on identifying stable co-occurrence structures rather than year-specific frequencies. Raw case counts are log-transformed and binarized to indicate the presence or absence of a given crime type for each nationality, resulting in sparse binary matrices. Bimax then searches for maximal submatrices densely populated with ones, thereby identifying compact biclusters that can overlap across nationalities and crime types—a property that mirrors the empirical reality that individuals, groups, and contexts may be simultaneously involved in multiple offense configurations [4,5]. We complement the algorithmic output with heat-map visualizations and a workflow figure to support interpretation.

This paper makes three contributions. First, to our knowledge, it offers the first nationwide Bimax-based analysis of crime–nationality co-occurrence structures in Türkiye using official judicial data spanning the 2019–2023 period [12]. Second, it demonstrates that Bimax provides an interpretable and scalable approach for sparse administrative matrices, serving as a methodologically transparent alternative to province-level clustering when the analytic focus is on social grouping rather than geography [3–5,9,10]. Third, it delivers a reproducible analysis workflow—from binarization to biclustering and visualization—and a policy-relevant reading of the uncovered stable, cross-year co-occurrence structures, discussing how migration dynamics, socio-economic vulnerabilities, and integration constraints may shape observed co-occurrences without presuming causal or individual-level attribution [1,12]. The remainder of the paper proceeds as follows. Section 2 details the data and methodology, including binarization rules, Bimax parameterization, and robustness checks across thresholds. Section 3 presents the biclustering results and interprets prominent biclusters. Section 4 discusses policy and research implications, limitations, and avenues for temporal extensions and sub-group analyses.

2. DATA and METHODOLOGY

2.1. Data Source and Matrix Construction

We analyze official judicial statistics for Türkiye covering the 2019–2023 period, obtained from the Directorate General of Criminal Records and Statistics. The raw data comprise adjudicated criminal records aggregated at the cross-classification of nationality and crime type for each year. Depending on the annual coverage, the resulting nationality × crime-type matrices vary in size, ranging from 56 to 96 nationalities and 48 to 52 crime categories across years. Rows index nationalities and columns index penal categories coded following the Turkish Penal Code and related statutes [12]. Each matrix entry represents the count of incidents associated with nationality i and crime type j. The construction follows standard administrative aggregation protocols used in prior crime-analytics work in Türkiye (e.g., province-by-crime settings) while shifting the analytical focus from geography to nationality-based social grouping [9,12].

2.2. Binarization Rules and Data Quality Control

Because the Bimax algorithm operates on binary matrices—interpreting ones as presence and zeros as absence—counts are transformed into indicators via a thresholding rule informed by prior biclustering practice on administrative data [3-5]. We set

$$X_{ij}^{(bin)} = 1\{X_{ij} \geq t\}, \quad (1)$$

with threshold t=1 in the main analysis (and t=2 in robustness checks; Section 2.4). Missing entries, which arise rarely after aggregation, are set to zero:

$$X_{ij}^{(bin)} = 0 \ \ if \ X_{ij} \ is \ NA. \quad (2)$$

The resulting matrix attains a ones-density of approximately 12%, which is empirically suitable for Bimax: too few ones hinder the discovery of sizable biclusters, whereas too many ones blur structural contrasts [4,5]. We validate the transformation with summary diagnostics (marginal totals, sparsity, and distribution of ones by row/column) before modeling.

2.3. Notation and Problem Definition

Let $X \in \{0,1\}^{n \times p}$ denote the binarized matrix with n=100 nationalities and p=58 crime types. A bicluster is a submatrix defined by a row index set $I \subseteq \{1,\mathrm{K},n\}$ and a column index set $J \subseteq \{1,\mathrm{K},p\}$, written $B = (I, J)$. In Bimax, biclusters target all-ones submatrices:

$$X_{ij} = 1 \quad \forall i \in I,\ j \in J. \quad (3)$$

A bicluster B is inclusion-maximal if no row or column can be added without violating (Eq. 3): for any $i' \notin I$, there exists $j \in J$ with $X_{i'j} = 0$ for any $j' \notin J$, there exists $i \in I$ with $X_{ij'} = 0$. We further require size constraints

$$|I| \geq \min r, \quad |J| \geq \min c, \quad (4)$$

and allow overlap among biclusters across both modes, reflecting the empirical reality that multiple co-occurrence structures may involve the same nationalities or crime types [4,5].

2.4. The Bimax Algorithm (Concept and Search Strategy)

Bimax (Binary Maximal) searches the lattice of row/column subsets to enumerate maximal all-ones biclusters under (Eq. 4). Practically, implementations leverage recursive partitioning (or specialized itemset-like generation) with pruning rules: whenever a candidate row/column set introduces a zero, that branch is discarded [11]. Relative to mean-squared residue algorithms like CC - which assume additive noise and operate on real-valued matrices [2]-Bimax directly targets presence/absence structures and is therefore well-suited to sparse administrative indicators [13,14]. In our context, the advantages are (i) interpretability (all-ones co-occurrence), (ii) tolerance for overlap, and (iii) computational tractability under reasonable size constraints (*minr*, *minc*) and an upper bound on the number of biclusters returned.

2.4.1. Parameterization and model selection

We parameterize Bimax with size thresholds *minr* =2 and *minc* = 2 to exclude singleton artifacts while permitting compact, interpretable structures. To prioritize readability and downstream policy interpretation, we request up to five biclusters in the main analysis, consistent with prior comparative evaluations emphasizing parsimonious solutions [4]. Two selection diagnostics support this choice: Coverage vectors. For each row i, $r(i)$ counts the number of biclusters containing i; analogously for each column j, $c(j)$. Sorting rows/columns by $r(i)$/$c(j)$ yields an ordered heatmap in which overlapping structures become visually salient. Area ranking and redundancy. We rank biclusters by area and monitor inter-bicluster *Jaccard similarity* on rows and columns; high redundancy suggests tightening minr/minc or lowering the target number to avoid near-duplicates [15,16].

2.4.2. Implementation and visualization workflow

All analyses are conducted in R, using the biclust implementation of Bimax for model fitting and heatmap-based visualization for interpretation [17]. Figure 1 presents the analysis workflow: (i) input binary nationality × crime matrix (hierarchically ordered for context); (ii) a central Bimax step; and (iii) an output Bimax-ordered heatmap sorted by coverage scores $r(i)$,$c(j)$, which clarifies overlapping biclusters (BC1–BC5). This workflow yields a compact graphical abstract and ensures reproducibility by standardizing preprocessing and visualization.

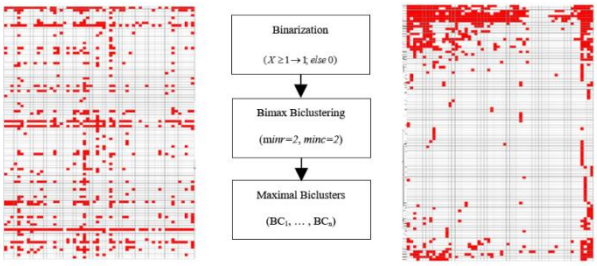

Figure 1. Analysis workflow for Bimax biclustering of crime types by nationality

We assess robustness along three axes:

1.Binarization threshold. We compare t=1 (main) vs. t=2 (conservative). With t=2, ones-density decreases and biclusters typically shrink but the core co-occurrences persist (rows/columns with high coverage remain central).

2.Size constraints. We probe monitoring area, redundancy, and interpretability. Increasing minr or minc filters out fragile biclusters but risks discarding meaningful small patterns—an expected trade-off in sparse settings [4].

3.Target number of biclusters. We vary the cap from 3 to 7 and examine whether additional biclusters add non-redundant structure or merely split existing ones. Our main choice (five) balances completeness and clarity for policy discussion.

Bimax detects structure, not causality. Accordingly, we adopt two safeguards. First, interpretation emphasizes co-occurrence (what appears together) rather than

attribution (who causes what). Second, we triangulate biclusters against marginal distributions to avoid reading artifacts of size alone (e.g., a high-count nationality appearing in multiple biclusters simply due to prevalence). This mirrors best practice in crime analytics where structural signals are contextualized with demographic and policy considerations [12].

3. RESULTS

The study draws on officially sanctioned crime records compiled by the General Directorate of Criminal Records and Statistics (Ministry of Justice, Türkiye). The dataset consists of finalized cases recorded by public prosecutor's offices and covers crimes defined under the Turkish Penal Code (TCK–5237). The 2023 Judicial Statistics Yearbook and the Ministry's publication archive are the authoritative sources for aggregate definitions, scope and totals [18–20]. In addition to the 2023 snapshot used for detailed descriptive summaries, the same case-record framework is leveraged to contextualize year-wise (2019–2023) patterns that are examined comparatively in Section 3.1.

Aggregating case counts by nationality reveals a highly skewed distribution that remains remarkably stable across the 2019–2023 period. Throughout these five years, Syrians consistently constitute the largest share of foreign-national crime records, accounting for approximately half or more of all cases each year. Afghan and Iranian nationals form a second tier, with relatively stable proportions over time, while Iraqi nationals follow closely with modest year-to-year fluctuations. This persistent concentration suggests structural continuity rather than short-term volatility in nationality-based crime representation.

As summarized in Table 1, a small group of nationalities accounts for the majority of finalized case records across all years, whereas several other groups—such as Azerbaijanis, Turkmen, Germans, Algerians, and Georgians—appear consistently at lower but stable levels. Minor shifts are observed at the margins, including a gradual increase among Turkmen nationals and a decline among stateless persons. Importantly, these figures reflect shares of finalized case records rather than per-capita rates and should therefore be interpreted in light of population size, geographic concentration, and differential exposure and enforcement patterns [21,22].

Nationality-level composition alone does not capture the structure of foreign-national crime; equally important is the distribution of offence types over time. To provide a concise overview of offence dynamics prior to the biclustering analysis, Figure 2 summarizes the five most frequent crime types recorded among foreign nationals between 2019 and 2023. These offences—qualified theft, manufacture/trafficking of narcotics, intentional injury (assault), migrant smuggling, and property damage—account for the majority of finalized case records in every year and display stable rank ordering over time. Crime labels and codes follow the Turkish Penal Code (TCK–5237) (see Table 2 for details) [16–18].

Table 1. Percentage distribution of crime records involving foreign nationals (2019–2023)

Nationality	2019 (%)	2020 (%)	2021 (%)	2022 (%)	2023 (%)
Syria	51	48	50	54	54
Afghanistan	10	11	9	10	9
Iran	5	9	9	6	6
Iraq	4	4	6	5	4
Azerbaijan	4	3	2	3	3
Germany	3	3	2	2	2
Turkmenistan	3	2	3	3	5
Georgia	3	2	2	2	1
Stateless	2	2	1	1	0.4
Algeria	2	2	2	2	2
Morocco	2	2	1	2	1
Uzbekistan	1	1	1	1	2
Palestine	2	1	1	1	2

Two recurrent motifs-an interpersonal/conflict motif (assault with threat/insult) and a property/market motif (qualified theft with drug-market crimes/qualified robbery)-prefigure the overlapping structures that Bimax subsequently recovers (Section 3.1). For methodological transparency, our biclustering implementation relies on the biclust R package (Bimax routine), with robustness checks described in Section 2 [23].

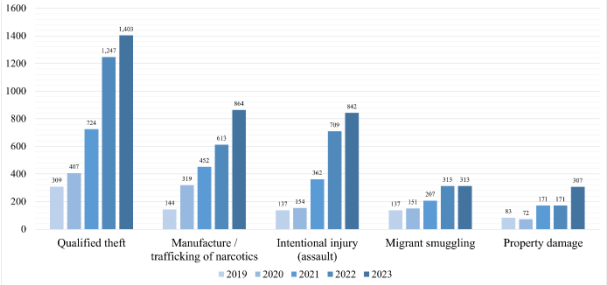

Figure 2. Five most frequent crime types among foreign nationals in Türkiye (2019–2023).

Figure 2 indicates a pronounced and monotonic increase in foreign-national crime counts across all five offence categories over the study period. Qualified theft remains the dominant offence in every year, followed by drug manufacture/trafficking and intentional injury, suggesting a dual structure combining property-related and interpersonal crimes. Migrant smuggling and property damage form a secondary but persistent layer, reflecting border dynamics and urban social exposure. Importantly, while absolute counts increase over time, the relative ordering of offence types remains remarkably stable, pointing to structurally recurring crime combinations rather than year-specific anomalies.

Table 2. Crime codebook

A1_1a	Migrant smuggling and human trafficking	A3_1a	Endangering traffic safety
A2_1a	Aggravated murder (qualified forms of intentional killing)	*A3_1b*	Other crimes creating general danger
A2_1b	Intentional homicide	*A3_2a*	Causing zoning/urban-planning pollution (unpermitted construction)
A2_1c	Negligent homicide	*A3_2b*	Other environmental crimes
A2_2a	Intentional injury (assault)	*A3_3a*	Manufacture and trafficking of narcotics
A2_2b	Negligent injury	*A3_3b*	Possession/acquisition/use of narcotics for personal use
A2_2c	Other crimes against bodily integrity	*A3_3c*	Other crimes against public health
A2_3a	Sexual assault	*A3_4a*	Breaking the official seal
A2_3b	Sexual harassment	*A3_4b*	Forgery of official documents
A2_3c	Other crimes against sexual inviolability	*A3_4c*	Counterfeiting currency
A2_4a	Violation of domicile (unlawful entry)	*A3_4d*	Other crimes against public trust
A2_4b	Threat	*A3_5a*	Prostitution
A2_4c	Deprivation of liberty (unlawful restraint)	*A3_5b*	Providing place/opportunity for gambling
A2_4d	Disturbing the peace and tranquility of persons	*A3_5c*	Other crimes against public morals
A2_4e	Other crimes against liberty	*A3_6a*	Crimes against the family order
A2_5a	Insult	*A3_6b*	Cybercrimes
A2_6a	Fraud	*A3_6c*	Crimes relating to the economy, industry and commerce
A2_6b	Breach of trust (abuse of trust)	*A3_6d*	Crimes against public peace
A2_6c	Trespass to real property (unlawful occupation)	*A3_6e*	Crimes against transportation vehicles or fixed platforms
A2_6d	Theft	*A4_1a*	Resisting an official to prevent performance of duty
A2_6e	Obtaining services without payment (unlawful benefit)	*A4_1b*	Other crimes against reliability/functioning of public administration
A2_6f	Property damage	*A4_2a*	Armed organization
A2_6g	Aggravated property damage	*A4_2b*	Other crimes against the constitutional order and its functioning
A2_6h	Aggravated fraud	*A4_3a*	Escape of convict or detainee
A2_6i	Qualified (aggravated) theft	*A4_3b*	Bringing prohibited items into a penal institution
A2_6j	Qualified robbery	*A4_3c*	Other crimes against the judiciary
A2_6k	Other crimes against property	*A4_4a*	Other crimes against society
A2_7a	Other crimes against persons		

The crime mix among foreign nationals is dominated by a small set of patterns that are consistent with our biclustering results. Among Syrians, qualified theft and intentional injury are most prominent, with drug-related crimes band migrant smuggling also present. Afghans show a combination of drug trafficking and assault, alongside a measurable incidence of child sexual abuse (~4.8%) and elevated migrant smuggling. For Iranians, drug crimes lead, with document forgery and traffic-safety violations as secondary categories. Turkmen citizens are mainly represented in theft and property damage; Iraqis exhibit violence and organization-linked crimes; Azerbaijanis tilt toward violence and theft, with prostitution and insult also recorded; Algerian nationals concentrate in qualified theft; German nationals more often appear in violence and land/urban-planning/environmental crimes; Palestinians in theft and drug-related categories (with a few serious crimes such as escape of detainee); and Uzbeks in violence/threat, plus prostitution and fraud. These heterogeneities align with recent engineering-analytics uses of clustering/biclustering to uncover co-occurrence structures in applied domains [24,25].

Demographic characteristics provide important context for interpreting these counts. Finalized case records predominantly involve males, with age concentrated in the 18–34 range. Most individuals are single, and educational attainment is skewed toward primary level or below. These distributions reflect the broader demographic composition of foreign-national populations in Türkiye and underscore that the reported figures represent case counts rather than per-capita risks, being shaped by group size, spatial concentration, and enforcement exposure.

To complement the nationality × crime-type analysis, we examined the geographic distribution of foreign-national crime across Türkiye using province-level data for the 2019–2023 period. Because raw case counts are strongly shaped by population size and regional settlement patterns of foreign nationals, we constructed standardized incidence ratios by dividing yearly case counts by the corresponding foreign-national population of each province [26]. This approach provides a per-capita indicator of crime involvement that is more comparable across provinces and more analytically informative than absolute case numbers.

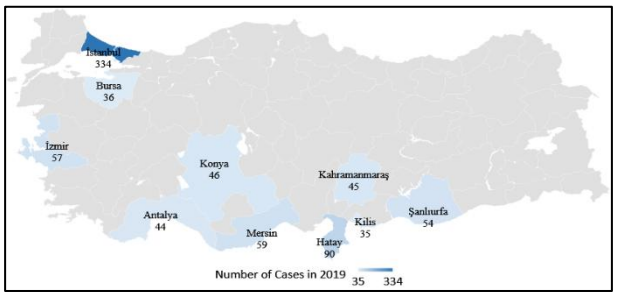

Figure 3a. Spatial distribution of foreign-national crime cases across the top-10 provinces in Türkiye (2019). *Darker shades indicate provinces with higher absolute case counts. Labels show province names and total finalized case numbers.*

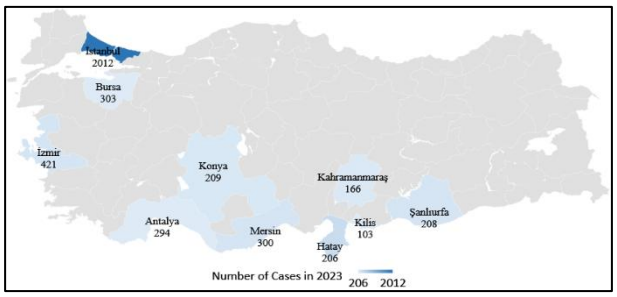

Figure 3b. Spatial distribution of foreign-national crime cases across the top-10 provinces in Türkiye (2023)

Figures 3a–3b present the spatial distribution of the top-10 provinces for 2019 and 2023, highlighting the provinces with the highest concentration of foreign-national crime cases. The 2019 map shows a moderately dispersed pattern centered around İstanbul, İzmir, Antalya, Mersin, Hatay, Şanlıurfa, Gaziantep and Kahramanmaraş. By 2023, this pattern intensifies substantially: İstanbul emerges as an extreme outlier (2,012 cases), and a southern belt of high-incidence provinces becomes more pronounced (Hatay, Mersin, Antalya, Şanlıurfa, Gaziantep). These maps visually demonstrate the persistent spatial clustering of foreign-national crime in metropolitan and migration-corridor provinces.

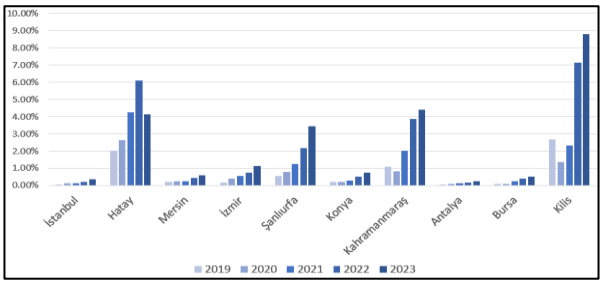

Figure 4. Five-year incidence rates of foreign-national crime cases per foreign-national population (2019–2023).

Figure 4 plots the five-year evolution of province-level incidence rates normalized by foreign-national population. The standardized trends reveal important shifts that are obscured when relying solely on raw case counts. While İstanbul consistently dominates in absolute terms, its per-capita rate remains relatively low due to its very large foreign-national population (0.06% in 2019 rising to 0.34% in 2023). By contrast, several smaller provinces exhibit disproportionately high incidence levels when population-adjusted. For example, Kilis displays the highest relative risk profile, increasing from 2.68% in 2019 to 8.80% in 2023. Hatay (2.01%→4.15%), Kahramanmaraş (1.09%→4.42%), Şanlıurfa (0.56%→3.44%), and Gaziantep (0.20%→2.55%) similarly show sharp population-adjusted increases. İzmir, Antalya and Mersin exhibit moderate but steadily rising trajectories.

These patterns indicate that the spatial concentration of foreign-national crime is not solely a function of metropolitan density but is influenced by heterogeneous settlement patterns, cross-border migration dynamics, and regional exposure conditions. Population-normalized estimates, therefore, offer a more interpretable indicator of regional risk differentials.

In this article, we focus on the nationality × crime-type perspective and apply biclustering to a series of binary matrices constructed from finalized criminal case records covering the 2019–2023 period. For each year, the original nationality-by-crime frequency tables were first log-transformed to reduce the influence of extreme values and then binarized by assigning a value of 1 to entries equal to or greater than one case and 0 otherwise. This procedure allows the analysis to emphasize the presence or absence of offence co-occurrence patterns rather than absolute frequency differences driven by population size. The resulting yearly matrices vary in dimension, reflecting changes in the observed scope of nationalities and crime categories over time: 56 × 48 in 2019, 54 × 51 in 2020, 68 × 51 in 2021, 82 × 52 in 2022, and 96 × 51 in 2023. Using the Bimax algorithm, we searched for up to five maximal biclusters per year, each containing at least two nationalities and two crime types, in order to capture stable co-occurrence structures shared across subsets of groups. Sensitivity analyses with alternative thresholds (≥2 and ≥3 cases) yielded qualitatively similar configurations, indicating that the identified biclusters are robust to threshold choice rather than artifacts of year-specific fluctuations [4]. For reference, Table 2 presents the crime codebook used consistently across all years.

3.1. Bimax Biclustering Outcomes

To examine whether nationality × crime co-occurrence patterns are temporally stable, the Bimax biclustering procedure was applied separately to each year between 2019 and 2023 using a consistent methodological specification. Leveraging year-specific binary nationality × crime matrices, we applied the Bimax algorithm with minimum bicluster sizes rows ≥ 2 and columns ≥ 2, capping the solution at five biclusters (BC1–BC5). Bimax searches for maximal all-ones submatrices—submatrices that cannot be enlarged along rows or columns without introducing zeros—an especially suitable property for sparse 0/1 crime matrices [4,23].

Table 3. Membership of biclusters

Year	Bicluster (rows x columns)	Nationalities (Crime codes)
2019	BC1 (8x2)	Afghanistan, Germany, Azerbaijan, Georgia, Stateless, Iraq, Syria, Turkmenistan (A2_2a, A2_6f)
	BC2 (6x2)	Afghanistan, Germany, Stateless, Iraq, Iran, Syria (A2_2a, A3_1a)
	BC3 (5x3)	Afghanistan, Germany, Stateless, Iraq, Syria (A2_2a, A2_6f, A3_1a)
	BC4 (4x3)	Afghanistan, Germany, Azerbaijan, Syria (A2_2a, A2_4b, A2_6i)
	BC5 (3x4)	Afghanistan, Germany, Syria (A2_2a, A2_4b, A2_6f, A3_1a)
2020	BC1 (8x2)	Afghanistan, Germany, Azerbaijan, Iraq, Iran, Uzbekistan, Russia, Syria (A2_2a, A2_6i)
	BC2 (4x2)	Afghanistan, Germany, Austria, Iran (A2_2a, A2_5a)
	BC3 (4x3)	Afghanistan, Germany, Iraq, Syria (A2_2a, A2_3b, A2_6i)
	BC4 (3x3)	Afghanistan, Germany, Iran (A2_2a, A2_5a, A2_6i)
	BC5 (2x4)	Afghanistan, Germany (A2_2a, A2_3b, A2_5a, A2_6i)
2021	BC1 (8x2)	Afghanistan, Germany, Morocco, Iraq, Iran, Uzbekistan, Pakistan, Syria (A2_4c, A3_3a)
	BC2 (8x2)	Afghanistan, Germany, Azerbaijan, Iraq, Iran, Uzbekistan, Russia, Syria (A2_2a, A2_6f)
	BC3 (7x2)	Afghanistan, Germany, Iraq, Iran, Moldova, Uzbekistan, Syria (A2_4c, A2_6f)
	BC4 (10x2)	Afghanistan, Germany, Azerbaijan, Netherlands, Iraq, Iran, Uzbekistan, Serbia, Syria, Greece (A2_2a, A3_3a)
	BC5 (9x2)	Afghanistan, Germany, Azerbaijan, Bulgaria, Iraq, Iran, Uzbekistan, Syria, Turkmenistan (A2_6f, A3_3a)
2022	BC1 (19x2)	Afghanistan, Germany, Azerbaijan, Algeria, Morocco, Palestine, Georgia, Stateless, Iraq, Iran, Kazakhstan, Kyrgyzstan, Nigeria, Uzbekistan, Russia, Syria, Tunisia, Turkmenistan, Ukraine (A2_2a, A2_6i)
	BC2 (12x2)	Afghanistan, Germany, Azerbaijan, Morocco, Iraq, Iran, Kyrgyzstan, Libya, Russia, Syria, Turkmenistan, Ukraine (A2_6i, A3_1a)
	BC3 (11x3)	Afghanistan, Germany, Azerbaijan, Morocco, Iraq, Iran, Kyrgyzstan, Russia, Syria, Turkmenistan, Ukraine (A2_2a, A2_6i, A3_1a)
	BC4 (11x2)	Afghanistan, Germany, China, Armenia, Palestine, Iraq, Iran, Egypt, Uzbekistan, Syria, Turkmenistan (A2_4c, A2_6i)
	BC5 (12x2)	Afghanistan, Germany, Austria, Azerbaijan, Georgia, Stateless, Iraq, Iran, Kazakhstan, Uzbekistan, Syria, Turkmenistan (A2_2a, A2_6f)
2023	BC1 (12x2)	Afghanistan, Germany, Austria, Azerbaijan, Georgia, Stateless, Iraq, Iran, Uzbekistan, Pakistan, Syria, Turkmenistan (A2_6f, A2_6i)
	BC2 (22x2)	Afghanistan, Germany, Austria, Azerbaijan, Bulgaria, Algeria, China, Morocco, Palestine, Georgia, Iraq, Iran, Kazakhstan, Libya, Nigeria, Uzbekistan, Russia, Somalia, Syria, Tajikistan, Turkmenistan, Ukraine (A2_2a, A2_6i)
	BC3 (12x3)	Afghanistan, Germany, Azerbaijan, China, Georgia, Iraq, Iran, Kazakhstan, Syria, Tajikistan, Turkmenistan, Ukraine (A2_2a, A2_6i, A3_1a)
	BC4 (12x2)	Afghanistan, Germany, Austria, Azerbaijan, Georgia, Iraq, Iran, Kyrgyzstan, Egypt, Uzbekistan, Syria, Turkmenistan (A2_2a, A2_6f)
	BC5 (11x3)	Afghanistan, Germany, Austria, Azerbaijan, Georgia, Iraq, Iran, Kyrgyzstan, Uzbekistan, Syria, Turkmenistan (A2_2a, A2_4b, A2_6f)

Under this threshold specification, each annual analysis yielded five coherent and partially overlapping biclusters. The year-wise memberships of these biclusters, including their row–column dimensions, are reported comparatively in Table 3, enabling direct assessment of temporal continuity and structural change across the 2019–2023 period. Because Bimax allows overlaps, specific nationalities and crime codes can contribute to more than one bicluster, reflecting multiple co-occurrence mechanisms rather than a forced partition. Crime labels and codes follow TCK-5237 and the cited special laws [18–20].

Two coherent crime-set profiles emerge consistently across the year-wise biclustering results summarized in Table 3. The first is an interpersonal or expressive pattern in which intentional injury (A2_2a) and threat (A2_4b) recur together across several nationalities, and in a tighter subset also co-occur with insult (A2_5a), mirroring the progression from BC1 to BC2 observed in multiple years. The second is a property- or market-oriented pattern in which qualified theft (A2_6i) aligns with drug manufacture or trafficking (A3_3a), and in a stronger variant also appears with qualified robbery (A2_6j), consistent with the transitions from BC3 to BC4 across

the study period. A further mixed configuration links assault with qualified theft in BC5, indicating environments where conflict dynamics and opportunity-driven crimes intersect. These patterns should be read as structures in counts of finalized case records rather than as per-capita risks. Sound interpretation therefore requires attention to demographic denominators by nationality, spatial concentration in large urban areas, and variability in exposure and enforcement, as documented in the legal and statistical sources cited [12,18–20,21,22].

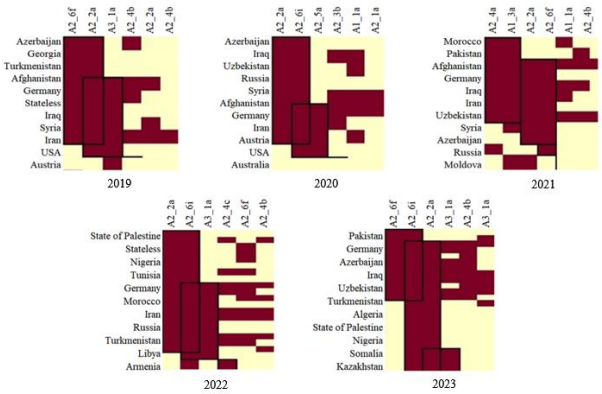

Figure 5. Focused heatmaps of nationality × crime matrices (2019–2023) with projected Bimax biclusters (BC1–BC5)

To visually synthesize these year-wise biclustering outcomes, Figure 5 presents focused heatmaps of the nationality × crime matrices for each year between 2019 and 2023, with projected Bimax biclusters (BC1–BC5) overlaid. In each panel, rows (nationalities) and columns (crime codes) are reordered to emphasize bicluster membership, and bicluster boundaries are explicitly delineated, even where overlaps occur. This visualization highlights both the persistence of core co-occurrence structures and the gradual expansion or reconfiguration of bicluster memberships over time, thereby complementing the tabular summaries reported in Table 2.

3.2. Bicluster Interpretation and Robustness Analysis

BC1 aggregates nationalities for which intentional injury (A2_2a) and threat (A2_4b) co-occur above the threshold, a pairing that recurs consistently across the 2019–2023 analyses. This pairing is consistent with routine-activity and conflict-interaction mechanisms frequently discussed in applied criminology, where verbal intimidation and bodily harm co-manifest in the same incident chains or social contexts. BC2 retains a illustrates Bimax maximality: once a third crime consistently co-occurs for a subset of rows, a new maximal bicluster emerges rather than diluting the original. BC3 pinpoints nationalities with concurrent qualified theft (A2_6i) and drug manufacture/trafficking (A3_3a), a pattern observed repeatedly across multiple years. The combination is characteristic of illicit-market exposure and opportunity structures (e.g., handling of stolen goods, shadow logistics). BC4 broadens BC3 by adding qualified robbery (A2_6j), representing contexts where theft-and-drug patterns intersect with more overt, violent appropriation. BC5 couples an interpersonal crime (A2_2a) with a property crime (A2_6i), suggesting overlapping risk environments in which conflictual encounters and economic motivations appear in tandem a pattern observed repeatedly across multiple years.

These biclusters summarize matrix-level co-occurrence and do not imply individual-level causation. Because entries are counts (not rates), denominator effects (population size by nationality), uneven spatial settlement (e.g., high-density metropolitan areas), and exposure/enforcement patterns shape the observed structures [12,21,22]. Crime codes and legal definitions follow TCK-5237 [18-20]. Our implementation uses the biclust R package (Bimax), as detailed in Section 2 [23].

To assess robustness, the Bimax procedure was re-estimated for each year at alternative thresholds of at least one and at least three cases and the two dominant profiles persisted with only modest shifts in membership. We then perturbed the matrix by resampling rows and columns and tracked the overlap of offence sets across runs using the Jaccard index; the cores remained stable. Finally we varied the row and column priorities used to draw the heatmap and observed that these ordering changes affected only the visual placement of blocks in Figure 5 while the memberships reported in Table 2 were preserved. Taken together these diagnostics indicate that the structures are not artifacts of threshold choice sparsity or ordering and they follow established practice in engineering analytics and the recent literature that extends biclustering to applied domains [25].

The biclusters provide policy relevant analytical insights along two axes by indicating which offences tend to appear together and for which nationalities those combinations recurrently reach the reporting threshold across the 2019–2023 period. This enables more precise prevention and outreach such as mediation and social services where interpersonal tensions dominate, and socioeconomic support where opportunity driven property crimes are concentrated. The analysis is intended to support targeted prevention and service provision rather than stigmatize groups and the results should be read in light of demographic denominators and spatial concentration as noted above.

4. DISCUSSION AND CONCLUSIONS

The biclustering results reveal a compact organization of nationality–offence co-occurrence that remains structurally stable across the 2019–2023 period, with the 2023 analysis illustrating its most pronounced form. The first is an interpersonal or expressive profile anchored in intentional injury (A2_2a) and threat (A2_4b), which for a subset extends to insult (A2_5a) and mirrors the BC1→BC2 progression. The second is a property- or market-oriented profile combining qualified theft (A2_6i) with drug manufacture/trafficking (A3_3a) and,

in a stronger variant, qualified robbery (A2_6j), consistent with the BC3→BC4 expansion. A mixed configuration (BC5) links assault with qualified theft, suggesting settings where conflict dynamics and opportunity-driven crimes intersect. Year-by-year descriptive analyses indicate that these offence-set combinations recur throughout the five-year window, while their relative prominence intensifies in parallel with the overall growth in recorded cases. Because entries are counts of finalized case records rather than per-capita rates, these structures should be read alongside nationality-specific denominators and spatial concentration (e.g., megacities), as noted in Section 3 and in the legal/statistical sources. Robustness checks across alternative thresholds, resampling, and ordering choices indicate that the core offence-set motifs persist with only modest shifts in membership, which increases confidence that the observed blocks are not artifacts of sparsity or visualization.

Interpersonal biclusters point to conflict-interaction contexts in which verbal intimidation and bodily harm co-manifest along routine-activity pathways. The persistence of these clusters across years suggests enduring social-interaction mechanisms rather than short-term shocks. In such places, de-escalation, community mediation, and victim-support services are likely to produce measurable benefits when targeted at locales exhibiting the BC1→BC2 pattern. Property/market biclusters align with opportunity structures around stolen-goods handling and drug supply chains; here, situational prevention-meaures guardianship, supply-chain disruption, and compliance checks—becomes salient. The steady expansion of property- and drug-related offences between 2019 and 2023 reinforces the interpretation of these biclusters as structurally embedded market-oriented configurations rather than episodic events. The mixed BC5 profile, coupling assault with qualified theft, signals the need for blended interventions that combine social support with situational measures. Across all profiles, interpretation should avoid essentializing nationalities: biclusters summarize matrix-level co-occurrence rather than individual-level causation.

Operationally, biclusters provide “dual-axis” intelligence by indicating which offences tend to appear together and for which nationalities those combinations cross the reporting threshold over the study period. This perspective supports more precise prevention and outreach (e.g., mediation for interpersonal clusters; socioeconomic assistance and market guardianship where property/market clusters dominate), helps align provincial resources with concentrated mixes. A fairness-aware implementation should include safeguards such as de-identification, aggregation to appropriate spatial units, transparent thresholding, and continuous monitoring for disparate impacts.

Several limitations inform how the results should be used. First, the analysis is based on counts, not rates; nationality-specific population denominators and differences in opportunity/exposure can shift relative prominence. Second, spatial settlement is heterogeneous, and large metropolitan areas exert high leverage on co-occurrence patterns, a leverage that becomes more visible as total case numbers increase over time. Third, reporting and enforcement intensity vary across space and offence types, potentially shaping the matrix. Fourth, overlaps in biclustering capture multi-mechanism environments but do not imply causal linkages between particular groups and offences. In light of these considerations, biclusters are best viewed as decision-support artefacts for prevention and service provision, not as labels for communities.

An additional methodological consideration concerns the binarization of crime-count data. While the 0/1 transformation is intrinsic to the Bimax algorithm and well suited for uncovering structural co-occurrence patterns in sparse, high-dimensional administrative matrices, it necessarily abstracts away information on offence magnitude and frequency. As a result, the identified biclusters capture the presence of stable nationality–offence configurations rather than their relative intensity. Future research could extend the present framework by integrating quantitative or weighted biclustering approaches that preserve crime-count information, enabling simultaneous analysis of co-occurrence structure and offence intensity. Such extensions would allow a more fine-grained assessment of policy relevance, particularly in distinguishing between widespread low-frequency patterns and concentrated high-frequency risk profiles.

In terms of future work, several extensions would deepen inference. Rate-based matrices using nationality-specific denominators would complement the current count-based view; longitudinal coverage would allow structural change to be tracked; offence-severity weights could reflect harm rather than frequency; and geospatial layering would support deployment at provincial scales. Comparative evaluations with alternative biclustering families (e.g., PLAID, spectral, meta-heuristic variants) and explicit uncertainty quantification (bootstrap stability, Jaccard distributions with confidence bands) will further strengthen external validity [23–25]. Substantively, linking these patterns to administrative and social indicators—migration flows, labour-market data, housing stress, and local service availability—can help separate opportunity from propensity and guide coordinated multi-agency interventions.

In summary, applying Bimax to a national-scale 0/1 matrix constructed from multi-year judicial data yields interpretable, partially overlapping offence profiles that are robust to reasonable threshold and ordering choices. The interpersonal and property/market motifs organize much of the observed co-occurrence throughout the 2019–2023 period and translate into actionable levers for targeted prevention and inter-agency coordination. When read with appropriate denominators and spatial context, the results provide a principled bridge from pattern discovery to practice, while underscoring the need for

fairness-aware deployment and continued methodological refinement.

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DECLARATION OF ETHICAL STANDARDS

The authors declare that this study is based exclusively on secondary, aggregated, and anonymized official judicial records obtained with formal authorization from the Ministry of Justice of the Republic of Türkiye. No individual-level or identifiable personal data were used. Therefore, the study did not require additional ethics committee approval.

AUTHORS' CONTRIBUTIONS

Ahmet KOCATÜRK contributed to the conceptualization of the study, data analysis, and interpretation of the results.

Demet ALBASAR contributed to data preparation, analytical procedures, and validation of the findings.

H. Hasan ÖRKCÜ contributed to the methodological design, writing of the manuscript, and critical revision of the final version.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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