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Research Article

Determining The Significance of Financial Crimes Eploying NMV-Based APLOCO Method and Comparing Crime Levels of United Nations Member Countries

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Abstract: Financial crimes possess an international nature, manifesting in various forms and types, and can spread globally with a single click in the digital age. Controlling these crimes is extremely important for the economic structures of countries. The aim of this study is to determine the significance level of crimes, particularly financial crimes, within the global organized crime index. To achieve this determination, the Normalized Maximum Values (NMV) method, a multi-criteria decision-making approach, was utilized. Subsequently, the Approach on Logarithmic Concept (APLOCO) method was employed to compare the crime levels of countries based on the established weights. According to the findings obtained from the NMV analysis, the significance levels of victim and witness support, prevention, smuggling of affordable goods, and heroin trafficking were identified as the highest. Financial crimes, which are one of the main objectives of the study, were found to have a medium level of significance compared to other crimes. Based on the weights determined by NMV, the results of the APLOCO method indicated that Colombia, Mexico, Myanmar, and Liechtenstein have high crime levels, while countries such as Sao Tome and Principe, Kiribati, Comoros, Eswatini, and Nauru exhibit low crime levels.

Keywords: Financial crimes, NMV and APLOCO methods
Jel Codes: G14, G15, G18

NMV Temelli APLOCO Yöntemiyle Finansal Suçların Öneminin Belirlenmesi ve Birleşmiş Milletler Üyesi Ülkelerin Suç Düzeylerinin Karşılaştırılması

Öz: Finansal suçlar, çok farklı biçimde ve türde kendini gösterebilen hatta dijital çağda tek tuşla dünyanın her yerine yayılabilen uluslararası niteliğe sahiptir. Bu suçları kontrol altına alabilmek, ülkelerin ekonomik yapıları için son derece önemlidir. Yapılan çalışmanın amacı; küresel organize suç endeksi içerisindeki suçların özellikle de finansal suçların önem düzeyini tespit etmektir. Bu tespiti gerçekleştirebilmek için çok kriterli karar verme yöntemlerinden NMV yöntemi kullanılmıştır. Ardından belirlenen ağırlıklara ülkelerin suç düzeyini kıyaslamak için APLOCO yönteminden yararlanılmıştır. Elde edilen NMV bulguları doğrultusunda; mağdur ve tanık desteği, önleme, ödenebilir mallarda kaçakçılık ve eroin ticareti suçlarının önem düzeylerinin en yüksek olduğu saptanmıştır. Çalışmanın ana amaçlarından olan finansal suçlar ise diğer suçlara göre orta düzeyde önemlidir. NMV ile belirlenen ağırlıklar doğrultusunda kullanılan APLOCO yöntemi sonucunda; Kolombiya, Meksika, Myanmar ve Liechtenstein ülkelerinin suç düzeylerinin yüksek olduğu; fakat Sao Tome ve Principe, Kiribati, Comoros, Eswatini ve Nauru gibi ülkelerde ise suç düzeyinin düşük olduğu ortaya konmuştur.

Anahtar Kelimeler: Finansal suçlar, NMV ve APLOCO yöntemleri
Jel Kodları: G14, G15, G18

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1. Introduction

With the increasing information and communication technologies today, the concept of crime has become more organized compared to the past, and thus the types of crimes and the profiles of those committing them can vary significantly. Although many different definitions of crime exist, it can be summarized as the penal sanctions encountered when actions or deeds prohibited by the legal order occur. The underlying reality of the emergence or occurrence of crime is the selfishness or self-interest of individuals (Şentürk & Kasap, 2013, p. 144-145).

To observe the formation, numbers, and regional distribution of crimes in the world and to take preventive measures, the Global Organized Crime Index was developed by ENACT in 2019. ENACT is a project funded by the European Union, conducted by the Institute for Security Studies, INTERPOL, and the Global Initiative consortium, aimed at enhancing Africa's capacity to combat international crimes (Global Initiative, 2020). The developed index assesses the resilience against measurements such as the content and scope of crime and the fight against crime, and it involves the participation of 193 United Nations member countries. By creating the index, the goal is to identify organized crimes and their potential impacts, facilitate strategic actions that can be applied against illegal economies, and observe the effectiveness of these actions. The concept of organized crime as defined by the index is expressed as engaging in illegal activities such as violence and corruption, either directly or indirectly, for the purpose of obtaining material gain at both national and international levels. The index includes averages of criminality, crime markets, human trafficking, smuggling of persons, arms trafficking, flora crimes, fauna crimes, non-renewable resource crimes, heroin trafficking, cocaine trafficking, marijuana trafficking, synthetic drug trafficking, cyber crimes, financial crimes, counterfeit goods trafficking, smuggling, extortion, averages of criminal actors, mafia-type groups, crime networks, state actors, foreign actors, private sector actors, resilience averages, political leadership and governance, government transparency and accountability, international cooperation, national policies and laws, judicial systems and detention, legal sanctions, regional integrity, anti-money laundering, economic regulatory capacity, witness support, prevention, and non-state actors (Global Organized Crime Index, 2023). The Global Organized Crime Index contains both positive and negative preventive measures based on penal sanctions. Therefore, this index consists of indicators that identify crimes, determine their types, propose solutions, and attempt to prevent them.

Financial crimes occupy a significant position among the various types of offenses, particularly those involving the presentation of misleading information in accounting practices or the illegal acquisition of profits through financial transactions. Historical examples of such financial frauds include the Ponzi Scheme, which supports existing investors with the returns from new investors (Özmerdivanlı, 2024), the Enron scandal, which involved significant manipulation of financial statements leading to the company's collapse (Kahramani Koç, 2024), and the WorldCom scandal, where financial data manipulation resulted in inflated stock prices and eventual bankruptcy (Yerdelen Kaygın, 2024). These cases illustrate the severe consequences of financial manipulation and highlight the necessity for stringent regulatory measures to combat such crimes.

The concept of financial crime, initially developed by Becker in 1968, emerged from the broader category of economic crime. Over the years, various models of economic crime have been proposed, with financial crime defined as any illegal activity that leads to financial loss without involving violence (IMF, 2001, p. 20). In today's digital landscape, financial crimes encompass a range of non-violent offenses, including usury, money laundering, and smuggling, as well as violence-related crimes such as terrorism financing (Yüce & Akkaya, 2020, p. 4).

When categorizing financial crimes, they can be broadly classified into several types, including money laundering, terrorism financing, smuggling, fraud, corruption, and tax offenses. Within the realm of terrorism financing, crimes such as human trafficking, drug trafficking, and arms financing are included. Smuggling offenses cover customs evasion, trafficking of cultural artifacts, human smuggling, and fuel or tobacco smuggling. Tax offenses encompass tax evasion, tax loss, and other related crimes, while corruption includes bribery and embezzlement (Akkaya & Yüce, 2023, p. 8-9).

In this study, the significance levels of crimes were determined with the help of the Global Organized Crime Index developed in 2019. To achieve this determination, the NMV method, a multi-criteria decision-making technique, was employed. The NMV method was used to identify which crimes are more significant at the international level, and evaluations were made regarding solutions and measures to address this. However, the main aim of the study is to ascertain the significance level of financial crimes among the various types of crimes and to draw inferences based on this finding. After identifying the significance levels, findings were obtained using the newly developed Aploco method in the literature to compare the crime levels of the country samples used in the study. In other words, a secondary aim of the study is to compare crime levels between countries to determine which country has a higher intensity of organized crime.

2. Literature Review

The literature on financial crimes has been examined chronologically from recent to earlier studies.

In a study conducted by Abdullah et al. (2024), the perceptions of financial crime among students from six countries—India, Iran, Malaysia, Norway, Romania, and the United States—were analyzed. The international diversity of the research enhanced its originality. The findings revealed that factors such as lack of oversight, issues with resource access, and the "heroic criminal syndrome" were prevalent among participants. Additionally, it was found that the ease and allure of committing crimes reached a concerning level. To combat these issues, it was suggested that a conciliatory approach should have beeen adopted and the lack of consensus minimized.

Maulidiyah (2024) explored the role of culture in preventing financial crimes by systematically analyzing 47 publications indexed in Scopus. The study highlighted that countries, not exempt from financial crimes, must have decided how to control these issues in conjunction with their national cultures. The bibliometric analysis identified studies related to tax evasion, money laundering, and corruption, concluding that national culture should have been shaped with an anti-fraud perspective.

Jofre, Bosisio, and Riccardi (2024) developed a risk assessment system analyzing the relationship between corporate secrecy and financial crime, utilizing approximately 2.6 million corporate ownership data from eight European countries. Machine learning techniques were employed to create the risk assessment system, which indicated that owners of complex and intricate businesses had a higher likelihood of committing financial crimes.

Halteh and Tiwari (2023) investigated the potential for combating financial crimes through the prediction of financial failures. Their literature review focused on the relationship between financial crimes and issues such as money laundering, fraud, and terrorism financing. The findings suggested that financial problems arising during crises, such as the COVID-19 pandemic and wars, could lead to an increase in financial crimes, indicating that resolving financial issues at their onset could prevent crime formation.

Kurum (2023) measured the impact of regulatory technologies in preventing money laundering within financial institutions. Two Delphi questionnaire surveys were sent to eight hired personnel and regulatory technology experts. The results indicated that artificial intelligence is highly effective in combating financial crimes and can develop solutions more rapidly than regulatory technologies.

Wronka (2023) aimed to control compliance and challenges in financial crime formation within decentralized structures such as virtual or crypto investments and mobile banking systems. It was suggested that a decentralized financial system should be applied to the banking sector to enhance security within the system.

Trozze et al. (2022) provided insights into the types, scope, and status of existing cryptocurrency frauds. Their review, conducted through high-level experts in the private sector, public sector, and academia, identified 47 different types of cryptocurrency fraud, with Ponzi schemes being the most prominent. They emphasized the need for inter-sectoral collaboration and consensus on cryptocurrency fraud.

Wronka (2022) conducted a comprehensive investigation into the impact of COVID-19 on financial institutions through the lens of financial crime models. The study revealed that the COVID-19 pandemic significantly affected the financial sector, leading to an increase in financial crimes as a direct consequence of this impact. Furthermore, it was noted that new and previously unheard-of financial crime models emerged as a result of the pandemic, adversely affecting financial institutions.

In a study by Teichmann and Falker (2021), the use of cryptocurrencies as a tool for facilitating financial crimes was analyzed, and a proposal for more effective international regulation of blockchain in Liechtenstein was presented. This proposal was developed through qualitative research. The findings indicated that cryptocurrencies are utilized as instruments for committing financial crimes such as money laundering, terrorism financing, and corruption. To counter these issues, the study emphasized the need for a more effective blockchain system and international regulation for cryptocurrencies. It was highlighted that this regulation, when established in Liechtenstein, could serve as a foundational model that may gain international relevance in the future.

Nicholls, Kuppa, and Le-Khac (2021) examined the validity of deep learning techniques in combating emerging cybercrimes in the financial sector. Addressing financial cybercrime is notably complex and challenging, prompting the exploration of various methods to tackle this issue. Despite these attempts, a comprehensive solution has yet to be achieved. The study categorized financial cybercrimes into four groups, including different fraud techniques, systems and algorithms used in fraud prevention, individuals involved in these crimes, and gaps in the field of financial cybercrime. It was concluded that solutions must have been applicable to each of these categories.

Yeoh (2019) identified the positive and negative roles of artificial intelligence in addressing financial crimes. While AI could serve as an antidote in cases of cybercrime, it could also trigger financial crimes. The study concluded that AI was not sufficiently secure and that gaps in the system must have been addressed through government sanctions, advocating for AI to be reinforced as a miraculous solution for preventing financial crimes.

Abdullah and Said (2019) empirically investigated the relationship between audit committees and corporate financial crimes, finding that establishing a risk committee independent of the audit committee assumed an effective role in preventing financial crimes.

Reurink (2016) researched white-collar crimes from a sociological perspective, proposing solutions for financial crimes. The literature review on white-collar crimes provided promising answers and recommendations for future research to minimize these issues.

Eiya and Otalor (2013) assessed the necessity of forensic accounting in combating financial crimes in Nigeria. They found that financial crimes in Nigeria often went unproven due to insufficient evidence. The study suggested that forensic accounting could create evidence and enhanced audit effectiveness, directly impacting the documentation of corruption.

Tomasic (2011) examined whether financial crises promoted financial crimes, concluding that changes in financial institutions during crises are essential. The study noted that insider trading, corruption, tax evasion, money laundering, and fraud tended to increase during crisis periods, accelerating the collapse of financial markets.

Gottschalk (2010) aimed to understand the causes, motivations, and mechanisms of financial crimes to develop solution theories. A thorough examination of the literature on financial crimes was conducted, leading to the formulation of financial crime theories that require validation through future case studies

Hansen (2009) identified financial crimes within firms and proposed solutions to rectify these offenses. The study aimed to diagnose the elements that lead to criminal activities and to address these factors. The findings indicated that businesses should critically examine their corporate structures and implement changes in areas such as communication networks and salary determination. As a solution, the necessity of enhancing corporate social responsibility through these changes was emphasized.

Most of the studies reviewed in the literature provided theoretical insights into financial crimes and proposed solutions. However, the number of empirical studies remains limited, with existing research primarily focusing on qualitative interviews or statistical solutions based on surveys. In contrast, this study aims to identify which types of organized crime are more dominant using multi-criteria decision-making techniques and to determine the significance level of financial crimes. Another unique aspect of this research is to identify which countries have higher or lower crime rates based on the determined significance levels of the crimes.

3. Methodology

In this section, the sample of the research and the methods used in the study are explained.

3.1. The Sample of the Study

Indicators were determined using the Global Organized Crime Index developed by ENACT in 2019. This index was published in 2021 and 2023, thus the analysis encompasses two years. In the 2023 analysis, there are 36 indicators related to crime, while the 2021 analysis includes 30 indicators. For both years, there are 193 member countries of the United Nations. Therefore, the sample consists of 36 criteria and 193 alternatives. Data related to the sample were accessed from the reports published by the Global Organized Crime Index.

3.2. The Method of the Study

The study utilized multi-criteria decision-making techniques. Initially, the Normalized Maximum Values (NMV) method was employed to determine the weights of the criteria. Subsequently, the Aploco method was chosen to rank the performance of the alternatives.

3.2.1. Normalized Maximum Values Method (NMV)

The Normalized Maximum Values method is a technique developed by Bulut (2017) that is easy to implement and can be used to determine weights without distinguishing between negative or positive criteria. This method consists of four steps. In the first step, a decision matrix is established from the created dataset. The second step involves the conversion of data into ratios. The third step entails the creation of a normalization matrix. In the final step, the criterion weights are calculated, and the levels of importance are determined (Bulut, 2022).

3.2.2. Approach on Logarithmic Concept (APLOCO) Method

The APLOCO method, developed by Bulut (2018) using the R programming language, is a technique that can be used for both determining criterion weights and ranking performance. The name of the method, "Approach on Logarithmic Concept," translates to "Logaritmik Kavram Üzerine Yaklaşım" (Bulut, 2018, p. 15). The APLOCO method consists of five steps (Bulut, 2024, p. 261).

Step 1: The first step involves the creation of a decision matrix. In this matrix, the criteria are represented by the rows, while the alternatives are represented by the columns, as shown in Matrix 1.

$$X_{ij} = \begin{bmatrix} C1 \\ C2 \\ \dots \\ \dots \\ \dots \\ C_c \end{bmatrix} \begin{bmatrix} x_{11} & x_{12} \dots & x_{1r} \\ x_{21} & x_{22} \dots & x_{2r} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ x_{c1} & x_{c2} \dots & x_{cr} \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} \dots & x_{1r} \\ x_{21} & x_{22} \dots & x_{2r} \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ \dots & \dots & \dots \\ x_{c1} & x_{c2} \dots & x_{cr} \end{bmatrix} \quad (1)$$

Step 2: The second step entails calculating the values of the initial criterion, referred to as the Starting Point Criterion (SPC). When calculating the SPC, if the criterion is maximum, the criterion values are derived from the maximum value; if the criterion is minimum, the criterion values are obtained by subtracting from the minimum value. The results of this calculation are illustrated in Equations 2. The new matrix formed as a result of Equation 2 is presented in Matrix 3.

$(X_{ij} – minp_{ij})$ if P_{ij} is minimum, $(maxp_{ij} – Xij)$ if P_{ij} is maximum (2)

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1r} \\ P_{21} & P_{22} & \dots & P_{2r} \\ \dots & \dots & \dots & \dots \\ P_{c1} & P_{c2} & \dots & P_{cr} \end{bmatrix} \quad (3)$$

Step 3: The third step involves the creation of the Logarithmic Transformation (LC) matrix. The equation used to obtain the LC matrix is shown in Equation 4.

$$L_{ij} = 1 / [\ln (p_{ij} + 2)] \quad (4)$$

The new LC matrix resulting from Equation 4 is displayed in Matrix 5.

$$L_{ij} = \begin{bmatrix} l_{11} & l_{12} & \dots & l_{1r} \\ l_{21} & l_{22} & \dots & l_{2r} \\ \dots & \dots & \dots & \dots \\ l_{c1} & l_{c2} & \dots & l_{cr} \end{bmatrix} \quad (5)$$

Step 4: In the fourth step, the Weighted Logarithmic Transformation (WLC) matrix is created by multiplying the previously determined criterion weights with the LC matrix obtained in Step 3. This WLC matrix is illustrated in Matrix 6.

$$T_{ij} = \begin{bmatrix} t_{11} & t_{12} & \dots & t_{1r} \\ t_{21} & t_{22} & \dots & t_{2r} \\ \dots & \dots & \dots & \dots \\ t_{c1} & t_{c2} & \dots & t_{cr} \end{bmatrix} \quad (6)$$

Step 5: The final step involves identifying the optimal alternative. The maximum criterion value from each row is taken to find the optimal solution values (βj), and these values are summed to obtain the βsj scores. The scores for each alternative (θ) are calculated by taking the ratio of the total criterion values of the alternatives (αsi) to the total of the optimal solution values (βsj), as shown in Equation 7. The resulting θ scores range between 0 and 1, and the optimal alternative is determined by ranking these scores in descending order.

$$\theta_i = \frac{a_{si}}{\beta_{sj}} \quad (7)$$

4. Findings

In the study, two different analyses were conducted using multi-criteria decision-making methods. First, the weights of the criteria were determined for the years 2023 and 2021 using the NMV method. The results for the year 2023 are presented in Table 1.

Table 1. NMV Scores for the Year 2023

Criteria	Scores	Percentage Values
Victim and Witness Support	0.03372447	3.37244716
Prevention	0.03313588	3.31358788
Illegal Trade of Goods Subject to Excise Tax	0.03250443	3.25044336
Heroin Trafficking	0.03178486	3.17848564
Extortion and Protection Racket	0.03139928	3.13992790
Average of Crime Markets	0.03053061	3.05306135
Trafficking of Counterfeit Goods	0.03011472	3.01147218
Cannabis Trafficking	0.02964869	2.96486925
Territorial Integrity	0.02951125	2.95112473
Government Transparency and Accountability	0.02930462	2.93046206
Combating Money Laundering	0.02915502	2.91550232
Economic Regulatory Capacity	0.02884736	2.88473608
Synthetic Drug Trafficking	0.02870331	2.87033091
Judicial System and Detention	0.02864114	2.86411440
Average of Criminality	0.02860929	2.86092902
Average of Resilience	0.02859870	2.85987047
Political Leadership and Governance	0.02852112	2.85211213
Mafia-style Groups	0.02813294	2.81329384
Average of Criminal Actors	0.02806572	2.80657193
Crime Networks	0.02792765	2.79276512
Law Enforcement Agencies	0.02774031	2.77403112
Cocaine Trafficking	0.02700045	2.70004545
Fauna Crimes	0.02687644	2.68764356
Cyber-dependent Crimes	0.02683695	2.68369466
Non-governmental Actors	0.02653264	2.65326441
Flora Crimes	0.02619025	2.61902471
Foreign Actors	0.02616249	2.61624899
Human Trafficking	0.02592380	2.59237967
Financial Crimes	0.02588677	2.58867666
Non-renewable Resource Crimes	0.02556164	2.55616370
National Policies and Laws	0.02535890	2.53589028
Private Sector Actors	0.02476112	2.47611221
Arms Trafficking	0.02376765	2.37676522
Human Smuggling	0.02261104	2.26110399
State-affiliated Established Actors	0.02106973	2.10697329
International Cooperation	0.02085874	2.08587432

According to the NMV scores for the year 2023 presented in Table 1, each index value holds a different level of weight. The most significant weight is attributed to victim and witness support, accounting for approximately 3.37%. Following this, the criteria for prevention and smuggling of consumable goods are prominent, with weights of 3.31% and 3.25%, respectively. The least significant weight is assigned to international cooperation, which stands at 2.08%. Financial crimes, which constitute the primary objective of the study, hold a significance level of 2.58%. The NMV scores for the year 2021 are provided in Table 2.

Table 2. NMV Scores for the Year 2021

Criteria	Scores	Percentage Values
Prevention	0.039958	3.995820
Victim and Witness Support	0.038625	3.862531
Heroin Trafficking	0.038476	3.847567
Criminal Markets	0.037763	3.776311
Criminal Actors	0.036737	3.673710
Cannabis Trafficking	0.035929	3.592895
Human Trafficking	0.03546	3.546049
Cocaine Trafficking	0.035414	3.541387
Government Transparency and Accountability	0.034882	3.488173
Judicial System and Detention	0.034516	3.451643
Combating Money Laundering	0.034479	3.447896
Regional Integrity	0.034039	3.403891
Synthetic Drug Trafficking	0.034028	3.402838
Economic Regulatory Capacity	0.033919	3.391896
Political Leadership and Governance	0.033752	3.375230
Mafia-style Groups	0.033671	3.367122
Human Smuggling	0.033462	3.346230
Law Enforcement	0.033168	3.316824
Foreign Actors	0.032951	3.295124
Fauna Crimes	0.032595	3.259496
Resilience	0.032287	3.228692
Arms Trafficking	0.031217	3.121684
Criminality	0.031131	3.113102
National Policies and Laws	0.031097	3.109661
Non-state Actors	0.030976	3.097623
Non-renewable Resource Crimes	0.029458	2.945752
Crime Networks	0.029218	2.921823
Flora Crimes	0.028640	2.864033
International Cooperation	0.026855	2.685548
State-affiliated Established Actors	0.025295	2.529450

In the NMV scores for the year 2021 presented in Table 2, the prevention criterion holds the highest weight at 3.99%, making it the most significant criterion. This is followed by victim and witness support at 3.86% and heroin trafficking at 3.84%. The criterion with the lowest weight is state-affiliated established actors, which stands at 2.52%. This result indicates that the importance level of state-affiliated established actors is the least among the criteria. In 2021, the financial crime criterion does not appear directly in the index; instead, it comprises subcategories such as money laundering, smuggling, usury, and terrorism financing. Therefore, the weight of financial crime cannot be measured directly in 2021.

After determining the weights of the criteria in the index using the NMV method, the APLOCO method, which is gaining recognition in the literature, was employed to compare the performance of the 193 member countries of the United Nations. The APLOCO results for the year 2023 are presented in Table 3.

Table 3. APLOCO Results for the Year 2023

Countries	Theta Scores	Countries	Theta Scores
Myanmar	0.554978445	Andorra	0.446568455
Colombia	0.543363293	Indonesia	0.445495499
Mexico	0.527164814	Vietnam	0.443876555
Finland	0.516121479	Latvia	0.443163545
Liechtenstein	0.511631051	Switzerland	0.441936175
Paraguay	0.498082601	Australia	0.439813324
Nigeria	0.494126512	India	0.439701494
Denmark	0.494111938	Central African Republic	0.439072790
Afghanistan	0.493045164	Japan	0.438544879
China	0.484988329	Thailand	0.438184893
Korea Republic	0.482972984	Ukraine	0.437848846
Democratic Republic of Congo	0.481457735	Philippines	0.436916626
Iran	0.478400794	Austria	0.436763452
United Kingdom	0.477366500	Peru	0.435842884
Brazil	0.474987703	Uruguay	0.433964615
South Africa	0.474523683	Venezuela	0.433927235
Singapore	0.471407868	Yemen	0.433405778
Iceland	0.470511432	Saudi Arabia	0.432744575
Syria	0.470053532	Belgium	0.430136034
United States	0.469721913	Jamaica	0.429885125
Libya	0.468914189	Guatemala	0.425537753
Lebanon	0.466500896	Laos	0.424882004
Italy	0.463187548	Ethiopia	0.423332391
Germany	0.463147932	Nepal	0.422191931
Kenya	0.462623089	Somalia	0.421177199
United Arab Emirates	0.461649081	Israel	0.420527297
Iraq	0.460247978	Tanzania	0.420446216
France	0.460193039	Uganda	0.420412875
Estonia	0.458884834	Senegal	0.419904474
Norway	0.456907017	Luxembourg	0.419828242
Panama	0.456793629	Canada	0.419447591
Netherlands	0.455298432	Lithuania	0.419209248
Russia	0.455291410	Ghana	0.418338934
Spain	0.454671238	Chile	0.415323118
Ecuador	0.453980531	Pakistan	0.414856750
Malaysia	0.453678233	Côte d'Ivoire	0.414823101
New Zealand	0.452294216	Costa Rica	0.413702450
Honduras	0.451617376	Qatar	0.413526308
Ireland	0.451291550	Serbia	0.412332405
Turkey	0.451017130	Sudan	0.412306772
Sweden	0.450273035	Mozambique	0.411504223
Cambodia	0.447588760	Kuwait	0.409615127
Portugal	0.409498300	Solomon Islands	0.382991270
Guyana	0.408966905	Benin	0.382498955
Cabo Verde	0.408157770	Tunisia	0.381115894
Cameroon	0.408066221	Liberia	0.381031118
South Sudan	0.407861823	Eritrea	0.380081422
Argentina	0.406551444	Guinea-Bissau	0.379682994
Democratic People's Republic of Korea	0.406454524	Fiji	0.379550486
Czech Republic	0.405932373	Zimbabwe	0.379466043
Bulgaria	0.402805263	Kyrgyzstan	0.379283941
Montenegro	0.402671722	Hungary	0.378952077
Papua New Guinea	0.402653757	Nicaragua	0.378915447
Bahrain	0.402132931	Malawi	0.378885898
Croatia	0.401672800	Chad	0.378391789
Trinidad and Tobago	0.401006096	Zambia	0.377895675
Morocco	0.400879312	Djibouti	0.377812057
Mali	0.400433694	Sierra Leone	0.377400294
Romania	0.399793793	Tajikistan	0.377095721
Jordan	0.399262942	Rwanda	0.376930021
Niger	0.398085221	Gabon	0.375121926
El Salvador	0.397545114	Bahamas	0.373790475
Poland	0.397477942	Barbados	0.372284701

Angola	0.397115136	St, Lucia	0.372281977
Burkina Faso	0.396637415	Uzbekistan	0.372002735
Belarus	0.396139119	Sri Lanka	0.371813666
Greece	0.396083349	Micronesia	0.371485741
Moldova	0.395438602	Cuba	0.371204685
Haiti	0.394627051	Mongolia	0.371024192
Bolivia	0.392895210	Tonga	0.370487796
Bosnia and Herzegovina	0.392136586	Seychelles	0.369227495
Albania	0.390256455	Kazakhstan	0.368462981
Madagascar	0.390207201	Cyprus	0.368373585
North Macedonia	0.389327000	Congo Republic	0.368325226
Malta	0.388461885	Burundi	0.368120229
Botswana	0.388276138	Namibia	0.366552996
Slovenia	0.387655622	Marshall Islands	0.366339437
Togo	0.387296622	Suriname	0.365834432
Dominican Republic	0.387237461	St, Vincent and the Grenadines	0.365781086
Algeria	0.387008094	Azerbaijan	0.365742210
Mauritius	0.386351966	Georgia	0.365620472
Gambia	0.386265016	Equatorial Guinea	0.365296628
Egypt	0.385016446	Guinea	0.365002307
Slovakia	0.384297875	Bhutan	0.364873784
Bangladesh	0.383821874	Samoa	0.364598690
Oman	0.383447710	St, Kitts and Nevis	0.364412128
Armenia	0.364239790	Eswatini	0.353793182
Belize	0.363060944	Dominica	0.353276217
Tuvalu	0.362147983	Timor-Leste	0.352320030
Maldives	0.361738520	Vanuatu	0.352168142
Mauritania	0.361328015	Lesotho	0.351741546
Monaco	0.361124901	Nauru	0.350842308
San Marino	0.360210959	Brunei	0.348892354
Palau	0.359805886	Antigua and Barbuda	0.346999116
Turkmenistan	0.358392943	Comoros	0.342104949
Grenada	0.355760653	Kiribati	0.341535623
		Sao Tome and Principe	0.338751655

The APLOCO results for the year 2023, as shown in Table 3, indicate that Myanmar, Colombia, and Mexico exhibit high crime performance. Myanmar is located in Southeast Asia, Colombia in South America, and Mexico in North America. Therefore, it can be inferred that these countries contribute to high crime rates in Southeast Asia, South America, and North America, respectively. Conversely, countries with low crime rates include small island nations such as São Tomé and Príncipe, Kiribati, and Comoros. The low crime rates in these countries are likely attributed to factors such as small population sizes and geographical remoteness. The APLOCO results for the year 2021 are presented in Table 4.

Table 4. APLOCO Results for the Year 2021

Countries	Theta Scores	Countries	Theta Scores
Colombia	0.555150	Jamaica	0.439391
Liechtenstein	0.541269	Belgium	0.439386
Mexico	0.526665	Paraguay	0.439001
Denmark	0.525738	Central African Republic	0.438479
Finland	0.523448	Honduras	0.437832
Democratic Republic of Congo	0.512088	Panama	0.437715
New Zealand	0.507990	Malaysia	0.435223
United Kingdom	0.497490	Libya	0.434472
Myanmar	0.496391	Ecuador	0.434195
Singapore	0.486810	Venezuela	0.434075
Australia	0.483865	Peru	0.434071
Nigeria	0.482209	Luxembourg	0.433097
Iceland	0.482161	United Arab Emirates	0.432782
Norway	0.479495	Canada	0.430977
Germany	0.475985	Ghana	0.424188
Brazil	0.470402	Guatemala	0.424144
Sweden	0.467507	Saudi Arabia	0.424101
Japan	0.466500	Mozambique	0.423953
Korea Republic	0.464562	Vietnam	0.422828
Afghanistan	0.464154	India	0.421484
France	0.463152	Chile	0.419995
Estonia	0.461844	Tanzania	0.419768
Uruguay	0.461779	Thailand	0.419136
Ireland	0.460166	Indonesia	0.418889
Netherlands	0.459912	Pakistan	0.418262
Iraq	0.459587	Lithuania	0.417929
Syria	0.459018	Kuwait	0.414329
China	0.457694	Sudan	0.414291
Iran	0.454039	Serbia	0.414128
Turkey	0.453942	Cambodia	0.413867
South Africa	0.453885	Côte d'Ivoire	0.413755
Spain	0.453289	Russia	0.413253
Switzerland	0.452653	Qatar	0.412743
Andorra	0.451313	Portugal	0.409863
Kenya	0.451086	El Salvador	0.409639
Lebanon	0.450126	Cabo Verde	0.408249
Italy	0.448970	Jordan	0.408143
Austria	0.446755	Czech Republic	0.407474
United States	0.443065	Argentina	0.407405
Philippines	0.439946	South Sudan	0.406621
Latvia	0.439880	Cameroon	0.405910
Albania	0.405126	Egypt	0.384218
Bahrain	0.404493	Zambia	0.384175
Senegal	0.404281	Togo	0.384175
Israel	0.403346	Hungary	0.383885
Laos	0.403268	Haiti	0.383284
Ukraine	0.402800	Chad	0.383205
Costa Rica	0.402064	Kyrgyzstan	0.381747
Poland	0.401601	Tajikistan	0.381376
Nepal	0.400672	Rwanda	0.381317
Morocco	0.400656	Cuba	0.380879
Uganda	0.400507	Gabon	0.380850
Bulgaria	0.400117	Benin	0.380137
Mauritius	0.399768	St. Kitts and Nevis	0.379838
Montenegro	0.399620	Sierra Leone	0.379622
Croatia	0.398213	St. Vincent - Grenadines	0.379153
Yemen	0.398133	Bangladesh	0.378280
Niger	0.397881	Algeria	0.378090
North Macedonia	0.396937	Fiji	0.377282
Ethiopia	0.396813	Congo Republic	0.376223
Gambia	0.395405	Bahamas	0.376221
Slovenia	0.395054	Namibia	0.375437
Trinidad and Tobago	0.394603	Belarus	0.374339

Romania	0.393966	Mongolia	0.373803
Bosnia and Herzegovina	0.393580	Armenia	0.373397
Somalia	0.393535	Barbados	0.373052
Angola	0.391864	Tonga	0.372094
Guinea-Bissau	0.391223	Azerbaijan	0.371714
Greece	0.390679	Guinea	0.371686
Dominican Republic	0.390438	Uzbekistan	0.371615
Madagascar	0.389549	Georgia	0.371520
Papua New Guinea	0.389119	Kazakhstan	0.370331
Mali	0.388997	Tuvalu	0.369502
St. Lucia	0.388150	Sri Lanka	0.369321
Solomon Islands	0.387533	Tunisia	0.369036
Malta	0.387395	Micronesia	0.368842
Bolivia	0.386996	Suriname	0.368693
Burkina Faso	0.386456	Liberia	0.368278
Guyana	0.386143	Djibouti	0.366609
Slovakia	0.385668	Cyprus	0.365812
Nicaragua	0.385024	Monaco	0.365031
Eritrea	0.384996	Bhutan	0.364847
Oman	0.384883	Samoa	0.364491
Democratic People’s Republic of Korea	0.384741	Malawi	0.363158
Botswana	0.384685	Seychelles	0.363136
Zimbabwe	0.384478	Equatorial Guinea	0.361061
Moldova	0.360039	Marshall Islands	0.355068
Burundi	0.359601	Palau	0.354895
Vanuatu	0.358833	Antigua and Barbuda	0.352889
Turkmenistan	0.358483	Lesotho	0.352183
Belize	0.358232	Brunei	0.351755
Grenada	0.357902	Timor-Leste	0.350100
Dominica	0.357799	Sao Tome and Principe	0.346541
Maldives	0.357139	Kiribati	0.345663
San Marino	0.356961	Nauru	0.345589
Mauritania	0.356692	Eswatini	0.342581
		Comoros	0.341367

The APLOCO scores for the year 2021, presented in Table 4, indicate that Colombia, Liechtenstein, and Mexico have high crime levels. In addition to the findings for 2023, it is noted that Liechtenstein has experienced an increase in its crime level, while the other two countries have consistently exhibited high crime levels in both 2021 and 2023. Liechtenstein is a small state located in Central Europe, situated between Switzerland and Austria. Factors contributing to the high crime rate in this country include its position between larger nations, its status as a border crossing, and its role as an international junction point. Conversely, Comoros, Eswatini, and Nauru are identified as the countries with the lowest crime rates. The low crime rates in these nations can be attributed to factors such as small population sizes, their status as small island nations, and being closed tribal states with limited immigration. All justifications related to the findings are elaborated upon in greater detail in the results and discussion section.

5. Results and Discussion

In a globalized world, emerging economic problems do not remain confined within the borders of individual countries; rather, they profoundly affect multiple nations and, alongside technological advancements, lead to changes and increases in the rates and types of financial crimes due to digitalization. This increase results in the emergence of international crime, giving rise to a criminal economy. Therefore, combating the criminal economy is a challenge that countries cannot tackle alone; it is a problem that necessitates the establishment of international collaborations and organizations.

This study aims to determine the significance of various crimes using the Global Organized Crime Index. To achieve this assessment, the NMV and APLOCO methods were employed. The NMV method was utilized to identify which types of crimes are more prevalent, providing justifications and solution proposals based on these findings. Additionally, the study aimed to delineate the position of financial crimes among other offenses and to highlight the risks posed by financial crimes. The APLOCO method was used to compare the crime levels of countries based on the weights of the crimes, thereby illustrating the distribution of crime intensity across nations.

The NMV findings for the years 2023 and 2021 indicate that victim and witness support, prevention, smuggling of consumable goods, and heroin trafficking are prominent. The variable of victim and witness support can be expressed as a security approach aimed at preventing criminal actors in the fight against organized crime. Therefore, eliminating security issues in victim and witness support is crucial for both establishing a strong state structure and reducing crime rates. Another important variable is prevention activities. Prevention is based on the initiatives of the state and the support of citizens for these initiatives. In this way, states will become more resilient, and the allure of illegal activities will diminish, leading to a decrease in organized crime tendencies. States with robust prevention plans are highly resilient against organized crimes. Financial crimes, which are the main focus of this study, pose a medium-level problem for countries. In fact, in 2021, financial crimes were not included in the index. However, with expert opinions gathered in the subsequent process, financial crimes were incorporated into the index in 2023. Financial crimes manifest in various forms, ranging from fraud to embezzlement, and can spread to the economic systems of countries. Moreover, with digitalization, financial crimes can acquire an international nature with a single click. Consequently, the social and economic structures of countries can be significantly weakened. Therefore, financial crimes are among those that must be kept under control to prevent a country from developing a fragile economic structure.

The determination of crime weights has allowed for the comparison of crime levels or crime performance among countries employing the APLOCO method. According to the findings, it has been established that Myanmar, Colombia, Mexico, and Liechtenstein exhibit high crime levels overall for both years analyzed. In Latin American countries such as Mexico and Colombia, located in North and South America, various factors contribute to the high crime rates, including income inequality, high unemployment rates, poor quality of education, insufficient punitive measures for committed crimes, an increase in violent tendencies, the state's inability to maintain control, informality in the economy, distorted urbanization, the rising prevalence of organized crime syndicates, drug trafficking, and the use of weapons and alcohol. In Myanmar, situated in Southeast Asia, a military coup occurred following allegations of fraud in the 2020 general elections, resulting in the seizure of power. In the aftermath of the military coup, insurrections and protests led to numerous fatalities, and many demonstrators were detained. Following the 2021 military coup, crimes such as human trafficking and smuggling have seen an increase, positioning Myanmar among the countries with the highest crime rates due to these and similar reasons. Liechtenstein, located in Central Europe between Switzerland and Austria, is one of the smallest countries in the world. Therefore, the finding regarding its high crime levels may seem surprising; however, the underlying reality is different. Liechtenstein is categorized as a tax haven where international tax evasion occurs. Being a tax haven not only leads to tax evasion but also results in its inclusion among countries where crimes are likely to be committed. This is because the cash flow in these countries is utilized in illegal activities that constitute crimes, such as corruption, embezzlement, drug trafficking, terrorist financing, and money laundering. Furthermore, countries with low crime levels identified through the APLOCO method include Sao Tome and Principe, Kiribati, Comoros, Eswatini, and Nauru. The low crime rates in these countries can be attributed to several factors, including their status as small island nations, low population sizes, and their geographical remoteness from urban centers.

Financial crimes represent a significant problem with substantial impacts on financial systems. Examining these impacts reveals that they create an environment of instability and insecurity within financial systems, lead to a scarcity of economic resources, distort competition, generate financial losses, jeopardize the integrity of the financial system through money laundering, impose restrictions on investments, result in a loss of reputation for financial institutions, and hinder the allocation of resources by these institutions. Consequently, financial crimes threaten financial stability by damaging global economies at both national and international levels.

In order to minimize the negative effects of financial crimes on financial systems, effective measures must be implemented. These measures include the implementation of customer identification systems by financial institutions, the reporting of suspicious transactions, conducting risk analyses, organizing training and awareness programs, utilizing technological solutions, fostering international cooperation, ensuring full compliance with regulations, conducting regular and effective internal and external audits, establishing policies and procedures related to the prevention of financial crimes, providing persuasive training to clients, and collaborating with civil society and public institutions. The effective execution of such measures is crucial for both financial institutions and society. This approach will help protect financial systems, rebuild trust within the community, and enable individuals to lead more prosperous and peaceful lives.

In conclusion, the identification, detection, prevention, and resolution of financial crimes hold international significance. In today's world, it is unlikely that crimes remain confined to local regions. Therefore, significant responsibilities fall on both lawmakers and international organizations. From a literature perspective, it is suggested that studies related to financial crimes should not be limited to theoretical viewpoints but should be based on empirical findings. A noteworthy aspect of this study in relation to the literature is the lack of research on the importance of crime types identified through multi-criteria decision-making techniques and their comparative analysis across countries. It is recommended that this study be expanded utilizing various techniques and that additional analyses incorporating in-depth examinations of multiple techniques be conducted to achieve international validity.

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