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Toward tailored AML/CFT strategies: Clustering countries by FATF compliance and effectiveness

Aleksandra Kuzior
Department of Applied Social Science,
Silesian University of Technology, Gliwice,
Poland
Aleksandra.Kuzior@polsl.pl
ORCID 0000-0001-9764-5320

Tetiana Vasylieva
Department of Financial Technologies and Entrepreneurship,
Sumy State University, Sumy,
Ukraine
tavasilyeva@ukr.net
ORCID 0000-0003-0635-7978

Lubos Smutka
Faculty of Economics, Department of Management,
South Bohemian University in Ceske Budejovice,
Czech Republic
lsmutka@ef.jcu.cz,
ORCID 0000-0001-5385-1333

Oumaima Haj Ammar
Faculty of Economics, Széchenyi Istvàn University,
Gyor, Hungary
haj.ammar.oumaima@sze.hu
ORCID 0009-0004-8174-821X

Abstract. Addressing global disparities in Anti-Money Laundering and Counter-Terrorist Financing (AML/CFT) compliance and effectiveness is increasingly critical due to escalating financial crime risks. This study aims to identify natural clusters of countries based on their performance in FATF technical compliance and effectiveness assessments, thereby facilitating tailored AML/CFT support strategies. The study utilised hierarchical clustering, Principal Component Analysis (PCA), and ANOVA tests, employing FATF assessment ratings data for Immediate Outcomes (IO1-IO11) and Recommendations (R.1-R.40). Four

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distinct clusters were identified, highlighting significant variations in AML/CFT compliance and effectiveness. Advanced economies demonstrated high compliance and effectiveness, emphasising the strategic use of technology, cybersecurity, and effective regulatory oversight. Developing and transitional countries exhibited mixed or low performance, reflecting institutional, socio-economic, and governance-related challenges, including weaker institutional frameworks, higher corruption rates, and socio-economic pressures driving financial crime. The research also underscores persistent global challenges in adapting to new technologies and adequately supervising non-financial sectors. These clusters underline the necessity of differentiated, context-specific AML/CFT strategies, emphasising targeted interventions, technology integration, ethical frameworks, and regional cooperation to enhance global financial integrity. Additionally, these findings differ from the FATF's traditional grouping approach, which typically classifies countries primarily based on risk assessments and geopolitical factors rather than performance-based data analysis.

Keywords: AML/CFT, FATF compliance, regulatory effectiveness, technical compliance clustering analysis, policy strategy.

JEL Classification: H56, F36, K42, O17, G28

1. INTRODUCTION

In an era of intensifying global financial interconnectedness, the risks associated with money laundering, terrorist financing, and proliferation financing remain pressing concerns for national governments and international institutions. According to the United Nations Office on Drugs and Crime, the estimated amount of money laundered globally in one year is 2–5% of global GDP, or roughly $800 billion to USD 2 trillion (UNODC, n.d.). These vast sums often move through transnational networks and financial institutions, illustrating how money laundering and related crimes are deeply embedded in global finance, exploiting national and international oversight gaps. The Financial Action Task Force (FATF) is central in evaluating countries' anti-money laundering and counter-terrorist financing (AML/CFT) frameworks. However, translating these assessments into meaningful and targeted reforms remains a challenge. The FATF regularly updates its lists of jurisdictions under increased monitoring and high-risk countries. As of recent evaluations, more than 20 countries remain on these lists, indicating ongoing structural and operational vulnerabilities in global AML/CFT frameworks (FATF, 2025). This persistent monitoring underscores that financial crimes are not confined to isolated regions but are systemic risks that span interconnected financial systems and require coordinated international responses.

The FATF's Fourth Round of Mutual Evaluations consistently highlights a wide disparity in how countries perform across technical compliance and effectiveness ratings (FATF, 2025). For example, while some countries achieve mostly "Compliant" or "Substantially Effective" ratings, others struggle with numerous "Partially Compliant" or "Low Effectiveness" outcomes. These disparities reflect not just differences in legislative frameworks but also institutional capacity, legal culture, and political commitment – factors that demand tailored technical assistance and reform strategies rather than blanket prescriptions. The International Monetary Fund emphasises that AML/CFT frameworks should be tailored to each country's context. In its policy guidance and technical support, the IMF highlights that measures must align with a country's unique risk profile, institutional capacity, and available resources, warning against the application of standardised approaches across diverse jurisdictions (IMF, n.d.).

This research is particularly timely as it bridges the gap between evaluation and policy action by clustering countries based on FATF performance. Such an approach aligns with current global calls for more adaptive and resource-efficient capacity-building strategies, making the topic relevant and urgent for international cooperation, policy design, and regulatory enhancement in financial integrity. Moreover, the findings can inform the development of additional supranational or regional coordination mechanisms and authorities beyond existing structures such as the FATF and the Egmont Group. By identifying groups of countries with similar compliance and effectiveness profiles, the research supports forming new collaborative platforms tailored to regional contexts or shared challenges, thereby strengthening the global AML/CFT architecture.

2. LITERATURE REVIEW

Recent research into AML/CFT underscores the importance of compliance, effectiveness, and tailored strategies. Compliance and effectiveness are intricately linked to governance frameworks, transparency, technological advancements, and socioeconomic conditions.

Studies highlight the relationship between corruption, governance quality, and financial crimes. Bartulovic et al. (2023) established a robust link between corruption and money laundering, emphasising that corruption weakens regulatory compliance and effectiveness. Similar findings were presented by De Souza (2024), indicating that cultural dimensions significantly influence corruption, subsequently affecting national innovation and financial compliance standards. Artyukhov et al. (2024) reinforced this viewpoint by demonstrating through empirical surveys in Ukrainian municipalities that transparency significantly mitigates corruption risks. Vyas-Doorgapersad (2024) critically assessed global shortcomings in anti-corruption initiatives, arguing for comprehensive reforms to enhance AML/CFT effectiveness. Li et al. (2023) also suggested fiscal decentralisation and enhanced financial accounting supervision as vital mechanisms to improve governance and compliance. Kawedar et al. (2025) analysed perceptions of corruption among perpetrators, highlighting underlying factors from attribution theories and the fraud triangle perspective, supporting the need for nuanced strategies.

The existence and dynamics of the shadow economy significantly affect AML/CFT strategies. Bozhenko et al. (2024) highlighted the digitalisation of finance as both a risk and an opportunity, potentially reducing the shadow economy while introducing cybersecurity vulnerabilities. Mazurenko et al. (2023) discussed shadow tax evasion's detrimental impacts on national tax system competitiveness, pointing to the necessity for stringent financial monitoring. Pulungan et al. (2024) illustrated socio-economic challenges driving individuals toward corruption and money laundering, necessitating nuanced country-specific strategies. Vokoun et al. (2024) provided empirical evidence from regional data, emphasising economic activities' relationship with crime types, thus advocating tailored regional AML/CFT policies.

With increasing digitisation, cybersecurity emerges as critical to AML/CFT effectiveness. Yarovenko et al. (2023, 2024b, 2024c) extensively analysed developed countries' socio-economic profiles and illicit practices vulnerable to cybercrimes, advocating tailored strategies according to digital maturity and threat exposure. Dobrovolska et al. (2024) advocated sustainable cyberspace strategies, highlighting cyber threats' implications for national security and financial integrity. Kuzior et al. (2022, 2024) emphasised cybersecurity's critical role in global digital convergence and AML efficiency. Gavenaite-Sirvydiene and Miecinskiene (2023) proposed frameworks for cybersecurity evaluation within the financial sector, reinforcing its strategic importance. Dobrovolska and Rozhkova (2024), Sidii (2024), and Burrell (2024) explored the intersection between digital security, resilience, and sustainability across sectors, broadening cybersecurity's strategic importance.

Technological advancements, especially artificial intelligence (AI), blockchain, and FinTech, are increasingly leveraged to enhance AML/CFT frameworks. Lyeonov et al. (2024a-2024c) and Hariyani et al. (2024) demonstrated the role of cognitive mapping and AI in combating financial fraud, while Utkina (2023) discussed the promise of blockchain technologies in improving financial monitoring effectiveness. Andronie et al. (2023) explored big data algorithms in FinTech, illustrating innovative solutions enhancing financial monitoring. Siddiqui and Rivera (2024) mapped Latvia's FinTech landscape, suggesting tailored regulatory frameworks to boost AML compliance. Balcerzak and Valaskova (2024) further highlighted AI's transformative potential and regulatory compliance challenges. Polishchuk (2023) projected future FinTech trends, aligning with emerging AML/CFT needs. Bucur et al. (2025), Turek et al. (2023), Pouabe et al. (2023), Yarovenko et al. (2024a), Neacsu et al. (2025), and Patel et al. (2023) expanded on the transformative role of advanced technologies and financial typologies in enhancing AML effectiveness.

Country-specific socio-economic factors significantly influence AML/CFT effectiveness. Gharaibeh (2023) found that geopolitical risks significantly affect financial market volatility, indirectly impacting AML/CFT efficacy. Bayar et al. (2023) identified terrorism, corruption, and weak rule of law as threats to economic sectors like tourism, indirectly affecting compliance motivation. Gherghina et al. (2024) provided evidence on the different public debt regimes' impacts on compliance capacity. Wang et al. (2025) analysed employment transformations driven by Industry 4.0, indirectly influencing AML strategies.

Effectiveness in AML/CFT measures depends significantly on ethical frameworks and regulatory rigour. Ishwardat et al. (2024) examined strategies to enhance compliance and ethical behaviour, stressing combined regulatory-ethical training. Steenbergen et al. (2023) revealed the detrimental effects of unethical executive boards on compliance. Udoh and Popesko (2024) illustrated fraud risks within public budgeting systems, emphasising robust internal auditing. Shonhadji and Irwandi (2023), Chowdhury et al. (2024), Nyoman Ayu Suryandari et al. (2023) contributed insights into fraud detection, loyalty determinants, and macroeconomic security related to regulatory compliance. Asare and Samusevych (2023) and Chowdhury et al. (2024) further explored financial fraud, tax tools, and economic security.

In conclusion, existing literature underscores the multifaceted nature of AML/CFT compliance and effectiveness, emphasising that tailored, country-specific strategies must account for governance quality, shadow economy characteristics, cybersecurity readiness, technological innovation, socio-economic risk factors, and ethical-regulatory environments.

The aim of this research is to explore patterns and groupings among countries based on their levels of technical compliance with the Financial Action Task Force Recommendations and the effectiveness of their anti-money laundering and counter-terrorist financing systems. The study seeks to identify natural clusters of countries with similar AML/CFT profiles by applying hierarchical clustering techniques and complementary statistical analyses. This, in turn, provides a data-driven basis for understanding global variations in compliance and effectiveness, and supports the development of differentiated, evidence-based policy and capacity-building strategies tailored to specific country groups.

3. METHODOLOGY

This study applies a quantitative, data-driven approach to examine global Anti-Money Laundering and Countering the Financing of Terrorism (AML/CFT) performance, based on FATF-assessed Immediate Outcomes (IO1-IO11) and Recommendations (R.1-R.40) (Appendix A, Table A1). These indicators, collected from the FATF Consolidated Assessment Ratings database (FATF, 2025), were coded on a standardised scale from 0 to 3. This scale reflects effectiveness for immediate outcomes while measuring technical compliance with recommendations. An additional “not applicable” category was retained for specific criteria where legal or structural exemptions apply.

The methodology followed a multi-stage process combining descriptive analysis, correlation evaluation, dimensionality reduction, and unsupervised learning techniques:

1. *Data preparation and exploration.*

The analysis includes data from 196 countries and jurisdictions, as detailed and numbered in Appendix A. These countries have been selected based on the availability of FATF compliance and effectiveness metrics and are consistently referenced across all clustering visualisations and comparative figures in the appendix. Initial data processing involved filtering countries with complete FATF evaluation data and standardising scores across all variables. Summary statistics were calculated to understand each indicator's central tendency and dispersion. This step provided a foundation for clustering by highlighting patterns and outliers across countries.

2. *Assessment of clustering suitability*

Before applying clustering techniques, evaluating the data's inherent structure is essential to determine whether meaningful groupings are likely to exist. This step is critical to ensure that subsequent clustering algorithms are applied to data with genuine partitioning tendencies, rather than randomly distributed observations.

Both statistical and visual methods were employed to assess the clustering tendency of the dataset. Statistically, the Hopkins statistic was utilised to measure spatial randomness formally. This statistic compares the distribution of distances between real observations and randomly generated points in the same multidimensional space. A value significantly lower than 0.5 indicates the presence of non-randomness and suggests that clustering structures are likely to be present in the dataset.

Complementing this, visual inspection techniques were also employed to provide an intuitive understanding of the data's structure. Principal Component Analysis (PCA) was used to reduce the dimensionality of the dataset while preserving the maximum possible variance. The resulting two-dimensional plot enables an exploratory view of potential clusters or patterns of separation among observations.

A dissimilarity matrix heatmap was also constructed to visualise pairwise distances between observations. This method highlights local patterns of similarity and dissimilarity, allowing for the detection of potential subgroups or anomalies. Combining these methods provides a robust foundation for justifying the use of clustering and guiding the choice of appropriate clustering algorithms.

3. *Hierarchical clustering analysis*

Hierarchical clustering was employed as the primary method for unsupervised classification due to its ability to reveal nested structures and relationships within multivariate data without requiring a priori specification of the number of clusters. Specifically, agglomerative hierarchical clustering was utilised, wherein each observation begins as a single-element cluster and pairs of clusters are progressively merged based on a defined similarity criterion until all observations are grouped into a single cluster.

The clustering process was based on a dissimilarity matrix computed using Euclidean distance, which is appropriate for continuous, scaled variables and preserves the geometric relationships among observations. Ward's minimum variance method was selected to determine the linkage between clusters. This approach minimises the total within-cluster variance at each algorithm step, thereby promoting compact, homogeneous clusters and reducing the risk of chaining effects that can distort cluster shapes.

The output of the hierarchical clustering procedure is typically visualised through a dendrogram. This tree-like diagram illustrates the sequence of cluster agglomerations and the relative distances at which they occur. The dendrogram enables the researcher to assess the hierarchical relationships among observations and to make informed decisions about the appropriate number of clusters to retain by identifying natural breakpoints or using flexible cut-point methods.

This methodology is particularly well-suited for the present study, which involves complex, multidimensional data derived from international compliance and effectiveness assessments. Hierarchical clustering facilitates the exploration of latent groupings within this data, supporting subsequent interpretation and comparative analysis of cluster-specific characteristics.

4. *Cluster validation and interpretation*

Countries were assigned to clusters, and their membership was visualised using colour-coded dendrograms and PCA plots. A world map was also generated to display the geographical distribution of clusters. Cluster-specific mean and median scores for all 51 FATF criteria were calculated and presented to reveal performance profiles.

5. *Statistical testing*

One-way Analysis of Variance (ANOVA) tests were performed for each variable (IO1–IO11 and R.1-R.40) to assess whether statistically significant differences exist between the four clusters. Most variables yielded p-values below 0.001, confirming that the clusters represent distinct AML/CFT performance levels. The ANOVA findings demonstrate the variables with the most excellent discriminative power.

All computations and visualisations were conducted in R Studio using packages such as dplyr, ggplot2, factoextra, cluster, rnaturalearth, and sf.

4. EMPIRICAL RESULTS

Building on the statistical summary of the dataset, it is essential to understand the scales used to evaluate each variable. The Immediate Outcomes (IO1-IO11) are assessed based on levels of effectiveness in combating money laundering and terrorist financing. These are scored on a scale from 0 to 3, where a score of 3 reflects a high level of effectiveness, indicating the outcome is achieved to a considerable extent with only minor improvements needed. A 2 signifies substantial effectiveness, while a 1 indicates only moderate achievement with significant enhancements required. A score of 0 represents a low level of effectiveness, where the outcome is not or barely achieved, and fundamental reforms are necessary.

Similarly, the Recommendations (R.1-R.40) assess technical compliance with FATF standards (FATF, 2013-2023). These are also rated on a scale from 0 to 3, with 3 representing full compliance and 0 indicating non-compliance due to significant shortcomings. The scale distinguishes between largely compliant (2) and partially compliant (1) countries based on the severity of identified gaps. Additionally, a "not applicable" category is used for countries where specific requirements do not apply due to structural or legal reasons. These rating frameworks provide essential context for interpreting the numerical distributions in the summary statistics and serve as the foundation for subsequent clustering analysis.

The dataset comprises 11 Immediate Outcomes (IO1-IO11) representing the effectiveness of AML/CFT systems, and 40 Recommendations (R.1-R.40) reflecting technical compliance with FATF standards (Table B1, Appendix B). A review of the summary statistics reveals that most variables are scored on a scale from 0 to 3, where higher values indicate better compliance or effectiveness. Among the effectiveness measures, IO1, IO2, and IO6 show higher mean scores (above 1), indicating moderate performance across countries in understanding ML/TF risks, ensuring international cooperation, and using financial intelligence. IO11, which addresses the prevention of WMD proliferation financing, shows the lowest mean (0.653), with a median of 0, highlighting significant weaknesses in this area globally.

On the technical compliance side, the Recommendations generally show higher scores. Many variables, such as R.3 (Money Laundering Offence), R.4 (Confiscation), and R.21 (Tipping-off and confidentiality), have median values of 2 or 3 and means above 2.2, indicating widespread adoption of these standards. In particular, R.9 (Financial institution secrecy laws) and R.30 (Responsibilities of law enforcement) have some of the highest average scores (2.684 and 2.612, respectively), suggesting strong compliance in these critical areas. Nevertheless, some variables, such as R.15 (New technologies), R.24 (Transparency of legal persons), and R.28 (DNFBP supervision), reflect lower mean values, indicating persistent global challenges in addressing evolving AML/CFT risks and extending oversight to non-financial sectors.

These descriptive statistics provide an essential foundation for subsequent cluster analysis, allowing researchers to group countries with similar FATF performance profiles and better understand systemic AML/CFT implementation patterns.

Based on the updated correlation heatmap (Figure 1), the analysis of relationships among variables reveals meaningful patterns that suggest internal coherence within the dataset. The plot illustrates that several groups of variables, particularly among the FATF Recommendations (R.1–R.40), are moderately to highly correlated. This indicates that countries exhibit similar levels of technical compliance across related domains, reinforcing that strong performance in one area often aligns with strength in others.

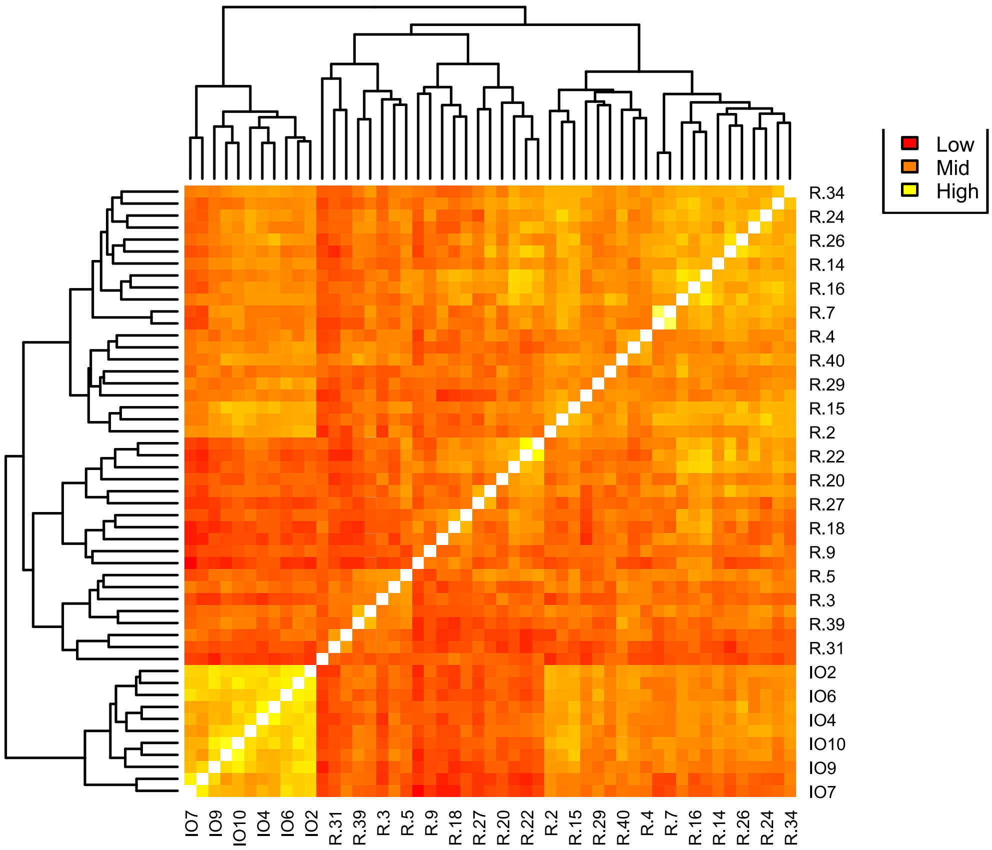

Figure 1. The correlation analysis of the criteria for assessing the effectiveness of AML/CFT systems and technical compliance with the FATF recommendations

Source: authors' calculation in R Studio

Notably, clustered regions in the heatmap highlight consistent associations within thematic areas, such as customer due diligence, reporting, and supervision recommendations. These visually distinct blocks reflect how improvements in one regulatory or enforcement function may be systematically linked to others. For example, countries with strong compliance in customer due diligence (R.10) also tend to score well in record-keeping (R.11) and politically exposed persons (R.12), suggesting cohesive implementation of preventive measures.

At the same time, the heatmap also identifies areas with weaker or negligible correlations, particularly between some Immediate Outcomes and specific Recommendations. This highlights the complex, multi-dimensional nature of AML/CFT implementation, where effective outcomes do not always align perfectly with technical compliance. These findings support using techniques like PCA and clustering by identifying which variables move together and may influence the formation of distinct country groups.

The PCA plot (Figure 2) provides a visual tool for assessing the underlying structure of the dataset by reducing its dimensionality to two principal components that capture the maximum variance. Each point represents a country in the PCA output, projected onto the first two principal components. While some mild grouping can be observed, particularly in denser areas of the plot, the overall distribution suggests that countries are spread relatively evenly, without clear or compact clusters.

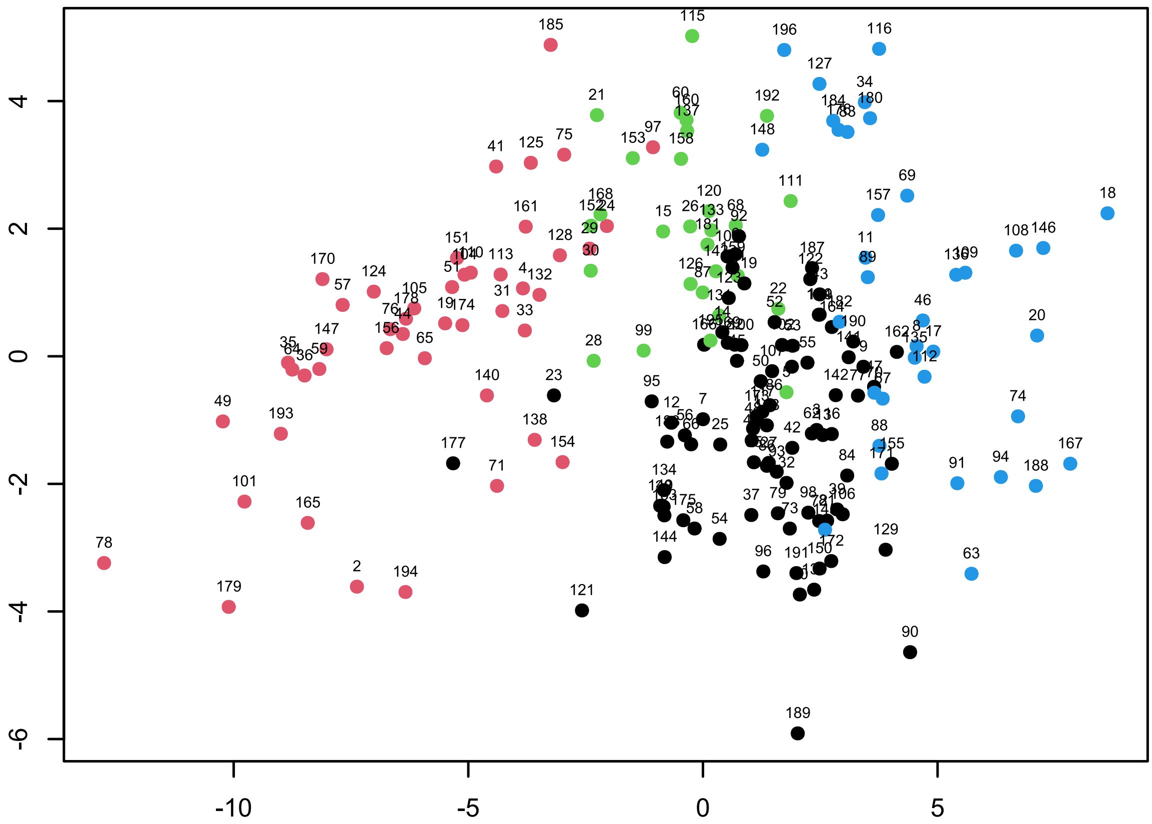

Figure 2. PCA plot is used to assess the underlying structure of the dataset by reducing its dimensionality to two principal components that capture the maximum variance

Source: authors' calculation in R Studio

As such, the PCA plot reinforces that the dataset may contain soft or gradient-based groupings, rather than rigid cluster boundaries. This finding supports hierarchical or fuzzy clustering methods, which can accommodate overlapping membership and better reflect the nuanced relationships in FATF compliance and effectiveness data.

The dissimilarity matrix heatmap visually represents how similar or dissimilar countries are regarding their FATF technical compliance and effectiveness performance (Figure C1, Appendix C). In the heatmap, lighter colours (closer to white/yellow) represent greater dissimilarity between countries, while darker shades (closer to blue) indicate more similarity. From the structure of the heatmap, we observe some localised clusters of similar countries, especially in the lower-left quadrant, where blocks of blue suggest tighter groupings.

However, the overall spread of colour gradients, without distinct large-scale blocks, supports the Hopkins statistic (0.394) result, suggesting that while some countries share close similarities, the dataset does not exhibit strong, well-defined global clusters. The scattered high-dissimilarity areas (in red) further confirm heterogeneity across the dataset.

In combination, this heatmap implies that clustering is possible but subtle. The dataset likely contains fuzzy or overlapping group structures, rather than sharply separated clusters. This further justifies using techniques such as hierarchical clustering with careful tuning or soft clustering approaches to better capture nuanced relationships between countries.

Hierarchical clustering with careful selection of cut height is the most suitable method, possibly supplemented by fuzzy clustering if you want to explore overlapping group structures. This approach aligns well with the characteristics of your dataset, as shown by the exploratory analyses.

Figure 3 presents a colour-coded hierarchical clustering dendrogram that visually separates countries into four main clusters based on their FATF technical compliance and effectiveness profiles. The colour branches illustrate the result of applying a flexible cut point to the dendrogram, which groups countries according to their relative similarity across all assessed variables.

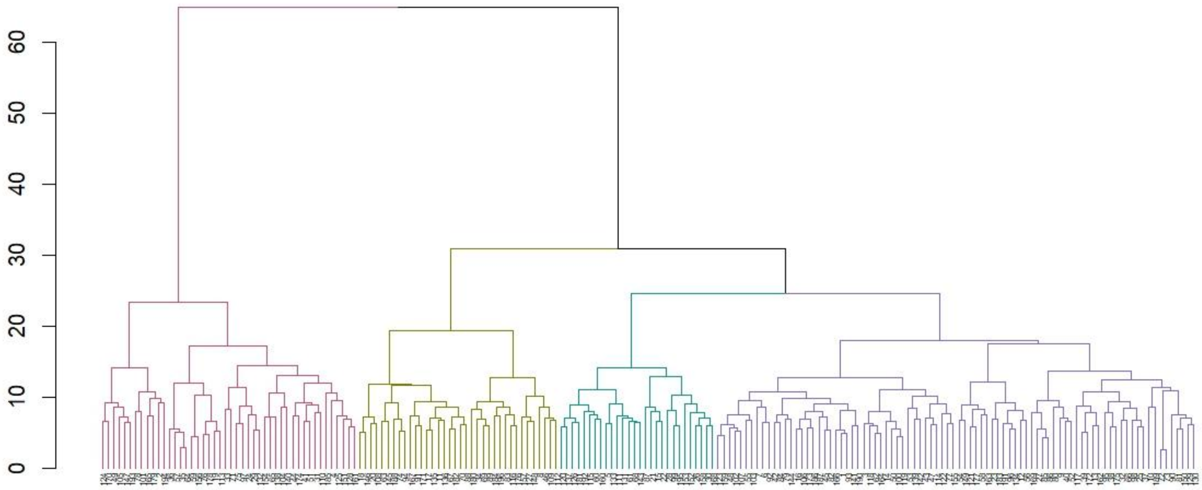

Figure 3. Hierarchical clustering dendrogram, illustrating the grouping of countries based on their similarities in FATF technical compliance and effectiveness metrics

Source: authors' calculation in R Studio

The dendrogram structure suggests that while many countries exhibit shared patterns of compliance and effectiveness, there remains considerable variation between groups. Each coloured branch represents a cluster where internal distances between countries are relatively small, indicating more consistent performance within the group. The vertical height at which branches merge reflects the dissimilarity between clusters; higher merges indicate greater differences.

Although the cluster boundaries are not perfectly distinct, the colour separation highlights regions of the dataset with stronger internal cohesion. This provides a clearer visual summary than an uncoloured dendrogram and supports the identification of meaningful groupings for further analysis. The visual evidence reinforces earlier findings that moderate and interpretable subgroupings exist, while the dataset does not contain sharply defined global clusters, justifying hierarchical clustering with flexible thresholds.

Although no sharply distinct clusters dominate the figure, the dendrogram does display several branches that remain separate until relatively high dissimilarity levels. This suggests the existence of moderate subgroupings within the dataset, though they are not entirely compact or isolated. This is consistent with the Hopkins statistic (0.394) and PCA analysis, which indicated subtle and overlapping structure rather than clearly defined, well-separated clusters.

The structure shown in Figure 3 supports hierarchical clustering with flexible cut points. Depending on the analytical goal, the dendrogram can be cut at various heights to define an appropriate number of clusters, typically between 3 and 5, for further interpretation or policy comparison among countries.

Table D1 (Appendix D) presents the list of countries grouped into four clusters based on hierarchical clustering analysis performed in R Studio. These clusters reflect similarities in countries' FATF technical compliance and effectiveness measures.

Cluster 1 includes a diverse mix of upper-middle and high-income countries and some developing economies, indicating relatively balanced AML/CFT performance across technical and effectiveness indicators. This group comprises jurisdictions from across the globe, such as the United States, Australia, China, Brazil, and several European and Asian countries. The broad representation suggests this cluster contains countries with moderately consistent regulatory frameworks and enforcement practices.

Cluster 2 primarily comprises countries from Sub-Saharan Africa and parts of Southeast Asia and the Pacific. These countries typically exhibit lower levels of compliance and effectiveness, likely due to capacity constraints, weaker institutional infrastructure, or developmental challenges. The presence of nations such as Angola, Haiti, and Mozambique highlights the need for targeted international support and technical assistance in these regions.

Cluster 3 brings together a set of countries that may be characterised by uneven performance – some showing strong technical frameworks but limited implementation, or vice versa. It includes countries like Nigeria, Bolivia, Cambodia, and Sri Lanka. This cluster may represent transitional states with partial alignment to FATF standards but room for improvement in consistency or enforcement.

Cluster 4 comprises advanced economies and financial centres, such as the United Kingdom, France, Germany, Switzerland, and Singapore, often associated with robust AML/CFT systems. These countries likely exhibit higher levels of technical compliance and institutional effectiveness, placing them among the stronger performers in the dataset.

Figure 4 presents a Principal Component Analysis (PCA) plot of countries, visually grouped and colour-coded according to their cluster memberships derived from hierarchical clustering. The PCA reduces the original FATF technical compliance and effectiveness indicators dataset into two principal dimensions (Dim1 and Dim2), which explain a portion of the total variance. Each point represents a country, and the colour indicates its assigned cluster, while the surrounding ellipses represent the concentration and spread of countries within each group.

The plot reveals a reasonable level of separation between clusters, particularly between Clusters 2 and 4, which occupy distinct regions of the PCA space. Clusters 1 and 3 overlap more centrally, suggesting a degree of similarity or shared characteristics among some countries in these groups. The clear differentiation in position and spread reflects underlying patterns in how countries comply with and implement FATF standards.

This visualisation supports the clustering analysis results, offering intuitive confirmation that the identified groups reflect meaningful structure in the data. The PCA plot is also valuable for detecting potential outliers or borderline cases that may not fully align with their assigned clusters.

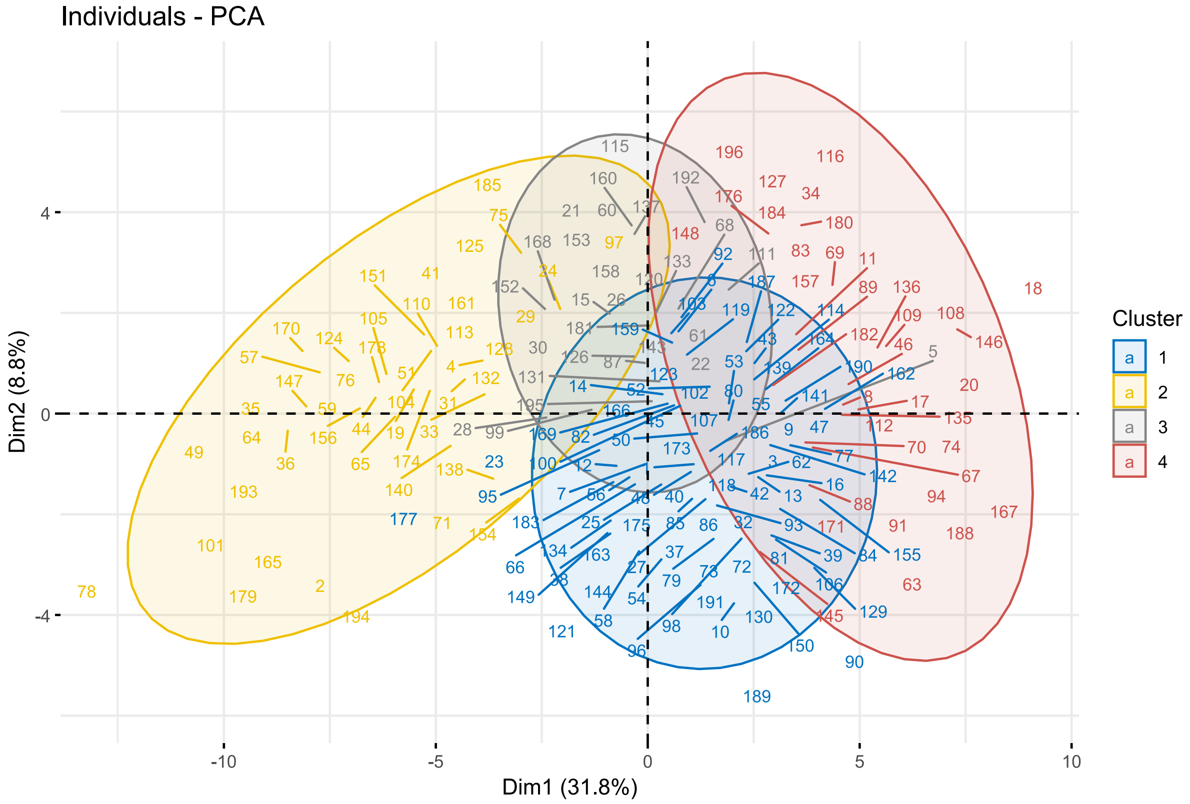

Figure 4. Principal component analysis of countries coloured by cluster

Source: authors' calculation in R Studio

Table D2 (Appendix D) presents the summary statistics, mean, and median of all technical compliance Recommendations (R.1–R.40) and Immediate Outcomes (IO1–IO11) for each cluster identified in the hierarchical clustering analysis. These values provide a quantitative profile of each cluster, highlighting key similarities and differences across groups in their FATF evaluation performance.

Cluster 1 generally exhibits moderately high scores across effectiveness and technical compliance dimensions. Most IOs in this cluster have means between 1 and 1.5 and medians at or above 1, indicating countries in this group are demonstrating reasonable levels of implementation with room for improvement. Recommendation scores typically centre around 2, suggesting a largely compliant technical framework.

Cluster 2 stands out for its consistently low scores across nearly all variables. Most IO means fall below 0.5, and medians frequently register at 0, reflecting limited effectiveness. Similarly, technical compliance scores hover near one or lower, identifying this group as the weakest overall in AML/CFT alignment.

Cluster 3 shows intermediate performance: higher than Cluster 2, but generally not as strong as Clusters 1 or 4. Median values for many Recommendations are at 2, with IO scores mostly around 0.5 to 1. This suggests uneven implementation – these countries may have adequate frameworks but weaker enforcement or effectiveness.

Cluster 4 emerges as the best-performing group. IO means are mostly above 1, with several medians reaching 2. Recommendation scores are consistently high, exceeding 2.5 in both mean and median. This profile indicates strong technical compliance and well-functioning AML/CFT systems, consistent with developed jurisdictions and financial centres.

This table reinforces earlier cluster interpretations and offers valuable insight for policymakers, allowing them to identify strengths, prioritise reforms, and tailor technical assistance based on cluster-specific needs.

The ANOVA output provides statistical evidence that there are significant differences in the mean scores of the variable under analysis across the four clusters identified in the dataset. Specifically, the F-value of 53.12 and the p-value of less than 0.0001 indicate that the variance in the variable's mean between clusters is significantly greater than within clusters. This highly statistically significant result suggests that the clusters are not arbitrary but reflect meaningful distinctions in country performance.

In practical terms, this means that the clustering approach effectively captured structural patterns in the data – countries grouped in the same cluster tend to have similar performance levels in the tested variable (such as an Immediate Outcome or FATF Recommendation). In contrast, countries in different clusters perform differently. These findings validate the clustering as a reliable segmentation of countries and support further analysis of inter-cluster differences and targeted policy recommendations.

Table 1 summarises the results of one-way ANOVA tests applied to each FATF evaluation criterion (Immediate Outcomes and Recommendations), assessing whether the average values of these variables differ significantly across the four identified country clusters. Most criteria show highly significant p-values ($p < 0.001$), indicating that the clusters are not randomly formed but capture real and meaningful differences in AML/CFT performance.

The most statistically significant differences across clusters are observed in several Immediate Outcomes, particularly IO2 (international cooperation), IO4 (preventive measures), and IO1 (risk understanding and coordination), with F-statistics exceeding 50 and p-values approaching zero (e.g., 1.12e-32 for IO2). These results strongly suggest that countries in different clusters exhibit substantially different levels of effectiveness in these key areas.

Additionally, many Recommendations show strong discriminative power across clusters, such as R.19 (higher-risk countries), R.15 (new technologies), and R.16 (wire transfers). Even among Recommendations with relatively lower F-values (e.g., R.30, R.9, R.31), the p-values remain below conventional significance thresholds, further supporting the validity of the clustering structure.

Table 1 confirms that the clusters derived from hierarchical analysis reflect substantial differences in technical compliance and effectiveness outcomes, justifying their use for comparative policy assessments and targeted improvement strategies.

Figure 5 provides a spatial visualisation of the four clusters derived from the hierarchical clustering analysis of countries based on their FATF technical compliance and effectiveness indicators. Each country is coloured according to its assigned cluster, illustrating geographic patterns and regional similarities in AML/CFT system performance. Cluster 1 (green) includes a wide range of countries across continents, reflecting a globally distributed group with relatively moderate to firm performance. Cluster 2 (orange) broadly covers Sub-Saharan Africa and Southeast Asia, indicating generally weaker compliance and effectiveness scores. Cluster 3 (blue) appears scattered, including several small or developing nations with intermediate profiles. Cluster 4 (purple) encompasses a group of higher-performing countries concentrated in Europe and the Middle East.

Grey-shaded areas represent countries for which clustering data was not available or applicable, such as russia, or regions of Ukraine occupied by russia, or regions excluded from the analysis (Iran, Somalia, Afghanistan etc.). The map underscores the global diversity of AML/CFT performance and highlights regional clustering tendencies that may inform policy benchmarking and capacity-building initiatives.

The clustering results reveal distinct groupings of countries based on their levels of technical compliance with FATF Recommendations and the effectiveness of their AML/CFT systems. These groupings suggest that a uniform approach to capacity building and policy support may not be optimal.

Instead, differentiated strategies tailored to each cluster's specific needs and characteristics would likely yield more effective outcomes.

Table 1

ANOVA results: significance of differences across clusters (IO1–IO11 and R.1–R.40)

Variable	df	statistic	p-value	Variable	df	statistic	p-value
IO2	3	76,78039	<0.0001	R.23	3	26,86085	<0.0001
IO4	3	64,38196	<0.0001	R.35	3	24,41546	<0.0001
IO1	3	53,12091	<0.0001	R.40	3	24,11314	<0.0001
R.19	3	52,49943	<0.0001	IO7	3	21,40625	<0.0001
IO6	3	51,97633	<0.0001	IO8	3	21,18447	<0.0001
IO5	3	51,79249	<0.0001	R.33	3	17,05541	<0.0001
R.15	3	49,72405	<0.0001	R.5	3	16,97085	<0.0001
IO3	3	49,2752	<0.0001	R.37	3	16,83263	<0.0001
IO10	3	48,59589	<0.0001	R.29	3	16,38585	<0.0001
R.28	3	48,18512	<0.0001	R.20	3	15,59981	<0.0001
R.16	3	45,92558	<0.0001	R.39	3	15,27837	<0.0001
IO11	3	45,05802	<0.0001	R.4	3	14,71785	<0.0001
R.26	3	44,78716	<0.0001	R.38	3	14,46103	<0.0001
R.10	3	44,08846	<0.0001	R.32	3	14,4388	<0.0001
IO9	3	43,59072	<0.0001	R.11	3	13,70672	<0.0001
R.25	3	41,88752	<0.0001	R.17	3	11,85575	<0.0001
R.8	3	41,1304	<0.0001	R.27	3	11,59235	<0.0001
R.1	3	39,59952	<0.0001	R.36	3	7,185734	0,000135
R.34	3	38,21835	<0.0001	R.3	3	6,600159	0,000288
R.22	3	38,13729	<0.0001	R.18	3	6,593999	0,00029
R.24	3	38,1019	<0.0001	R.30	3	6,318817	0,000415
R.7	3	36,7905	<0.0001	R.9	3	5,614218	0,001039
R.14	3	36,45666	<0.0001	R.21	3	5,024052	0,002247
R.2	3	30,08489	<0.0001	R.13	3	4,521927	0,00434
R.12	3	30,01969	<0.0001	R.31	3	3,084244	0,028503
R.6	3	28,02135	<0.0001				

Source: authors' calculation in R Studio.

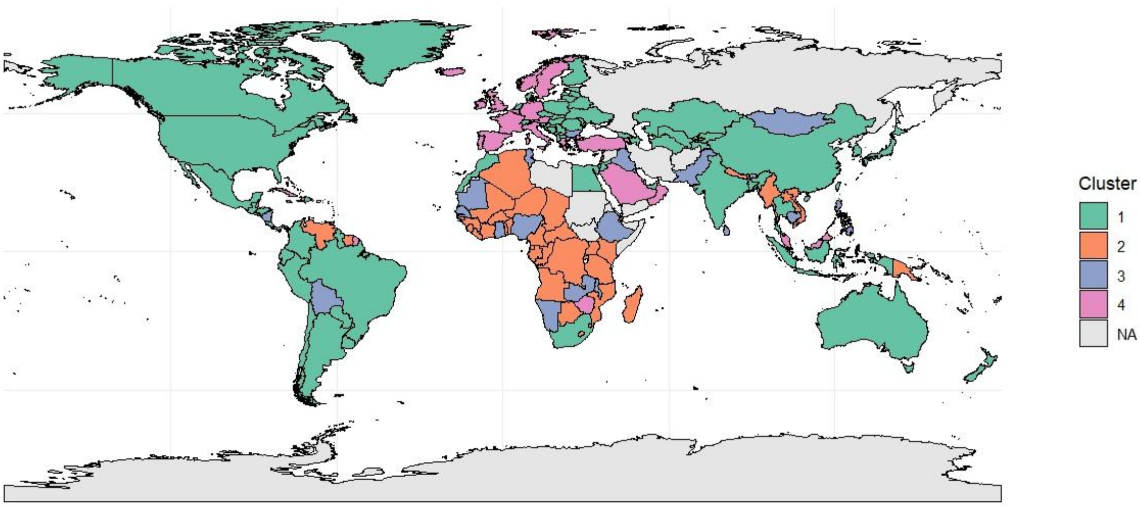

Figure 5. World map of countries coloured by cluster

Source: authors' calculation in R Studio

For example, countries in high-performing clusters may benefit from targeted technical enhancements and cross-border cooperation initiatives. In contrast, countries in lower-performing clusters may require more foundational support, including legislative reforms, institutional strengthening, and sustained capacity development. Regional similarities within some clusters suggest the potential for collaborative regional programs and peer learning mechanisms. By aligning policy interventions with the observed performance patterns, international bodies and national authorities can allocate resources more efficiently and support countries in progressing toward full AML/CFT compliance and effectiveness.

5. DISCUSSION

The discussion section of this research contextualises the clustering results within broader literature insights, emphasising the nuanced approach required for AML/CFT strategies based on distinct compliance and effectiveness clusters identified among countries.

The results affirm the importance of tailored AML/CFT strategies, as indicated in prior literature. Clusters revealed substantial disparities in performance reflecting variations in governance quality, institutional capacity, and socio-economic contexts. These observations are consistent with Bartulovic et al. (2023) and De Souza (2024), who highlight corruption's role in undermining AML compliance and effectiveness. Countries in Cluster 2, predominantly in Sub-Saharan Africa and Southeast Asia, likely reflect weaker institutional frameworks and higher corruption, necessitating intensive, foundational capacity-building interventions, aligning with recommendations from Vyas-Doorgapersad (2024).

Secondly, the intermediate performance of Cluster 3, featuring transitional states like Nigeria and Sri Lanka, resonates with the argument by Pulungan et al. (2024) that socio-economic pressures and shadow economic activities significantly influence AML/CFT effectiveness. This cluster, characterised by uneven implementation, calls for strategies that strengthen institutional oversight while addressing socio-economic drivers of financial crime.

Cluster 4, comprising advanced economies and established financial centres, aligns closely with findings by Yarovenko et al. (2023, 2024b, 2024c) and Dobrovolska et al. (2024), highlighting the strategic role of cybersecurity and digital innovation in enhancing AML effectiveness. These countries generally exhibited robust technical compliance and effectiveness, suggesting that advanced technology-driven regulatory frameworks effectively mitigate financial crime risks. However, persistent vulnerabilities, particularly regarding new technologies (R.15), underscore the continuing importance of technological adaptation and innovation highlighted in research by Lyeonov et al. (2024) and Utkina (2023).

Furthermore, the clusters identified align closely with regional groupings, reinforcing the argument of the International Monetary Fund (IMF) that AML/CFT interventions should be context-specific rather than standardised. The clusters offer a data-driven foundation for developing regional collaborative frameworks, consistent with recommendations from the FATF (2025) on regional and supranational coordination mechanisms.

This research further validates the necessity for ethical and regulatory frameworks emphasized by Ishwardat et al. (2024), Steenbergen et al. (2023), and Udoh and Popesko (2024), particularly evident in the effective implementation seen in Cluster 4. Ethical training and robust regulatory oversight remain crucial across all clusters to sustain and enhance AML/CFT effectiveness.

The study's methodological robustness, employing hierarchical clustering and PCA, mirrors approaches advocated by prior studies such as Gavenaite-Sirvydiene & Miecinskiene (2023), reinforcing the utility of data-driven analytical methods for policy development in AML/CFT frameworks. However, the research also acknowledges limitations consistent with broader methodological debates, such as data subjectivity and temporal disparities across FATF evaluations, which future studies could mitigate by incorporating longitudinal analyses or qualitative insights.

While the present study offers valuable insights into clustering countries based on their FATF technical compliance and effectiveness, several limitations should be acknowledged. First, the analysis relies exclusively on publicly available evaluation scores, subject to variations in interpretation, timing, and assessment quality. Differences in the timing of evaluations may mean that countries are being compared despite significant changes in their AML/CFT systems over time. Furthermore, qualitative judgments by assessors can introduce a degree of subjectivity into the scoring process, potentially affecting the consistency of the data across countries. Second, although hierarchical clustering is a robust and widely used technique for exploratory analysis, it is sensitive to initial distance measures and linkage methods. While theoretically justified, Euclidean distance and Ward's method may not capture all aspects of structural dissimilarities, particularly for categorical or ordinal components not fully represented in the dataset. Additionally, the assignment of countries to clusters is inherently influenced by the scaling and transformation of variables. While standardisation was applied, some nuances in national AML/CFT systems may be masked. Finally, while the analysis identifies groupings of countries with similar characteristics, it does not imply causal relationships or account for contextual factors such as geopolitical dynamics, legal traditions, or levels of economic development. The clusters are descriptive and should be interpreted cautiously, especially in policymaking contexts. Future research could benefit from incorporating longitudinal data, additional qualitative variables, or expert validation to refine the clustering outcomes and enhance the interpretability of results.

6. CONCLUSION

This study addresses the growing need for more differentiated and data-informed strategies in global AML/CFT efforts. Specifically, the research aimed to identify natural groupings of countries based on their levels of technical compliance and effectiveness as assessed by the Financial Action Task Force (FATF), to move from a one-size-fits-all policy approach to more targeted, context-sensitive support mechanisms.

The methodology employed a robust quantitative framework combining descriptive statistics, correlation analysis, dimensionality reduction via Principal Component Analysis (PCA), and unsupervised hierarchical clustering. These techniques enabled the classification of countries into four distinct clusters based on their performance across FATF's 40 Recommendations and 11 Immediate Outcomes. The data was sourced from the most recent FATF Consolidated Assessment Ratings and standardised to allow cross-national comparison.

The main findings highlight clear disparity patterns in technical compliance and effectiveness. Cluster 4 included advanced economies with high scores across both dimensions, while Cluster 2 represented countries facing significant structural and institutional challenges. Clusters 1 and 3 fell in between, reflecting transitional or moderately performing jurisdictions. The analysis also revealed regional tendencies, suggesting potential for peer learning and region-specific interventions.

These findings have significant policy implications. Tailoring AML/CFT strategies to the specific needs of each cluster, ranging from foundational institutional support in lower-performing countries to advanced technical coordination in higher-performing ones, can enhance the efficiency and impact of global financial integrity initiatives. Moreover, this clustering framework can support the design of new supranational or regional mechanisms for cooperation beyond the existing FATF and Egmont Group structures, especially in regions with shared risks or resource constraints. Ultimately, this research contributes a practical, evidence-based tool for international organisations, donors, and national policymakers to better align reform efforts with country-specific realities.

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APPENDIX A

List of the jurisdictions and their numbers in the analysis

1. Albania
2. Algeria
3. Andorra
4. Angola
5. Anguilla
6. Antigua and Barbuda
7. Argentina
8. Armenia
9. Aruba
10. Australia
11. Austria
12. Azerbaijan
13. Bahrain
14. Bangladesh
15. Barbados
16. Belarus
17. Belgium
18. Belize
19. Benin
20. Bermuda
21. Bhutan
22. Bolivia
23. Bosnia and Herzegovina
24. Botswana
25. Brazil
26. British Virgin Islands
27. Brunei-Darussalam
28. Bulgaria
29. Burkina Faso
30. Cambodia
31. Cameroon
32. Canada
33. Cape Verde
34. Cayman Islands
35. Central African Republic
36. Chad
37. Chile
38. China
39. China Taipei
40. Colombia
41. Comoros
42. Cook Islands
43. Costa Rica
44. Ivory Coast
45. Croatia
46. Cuba
47. Cyprus
48. Czech Republic
49. Democratic Republic of Congo
50. Denmark
51. Djibouti
52. Dominica
53. Dominican Republic
54. Ecuador
55. Egypt
56. El Salvador
57. Equatorial Guinea
58. Estonia
59. Eswatini
60. Ethiopia
61. Fiji
62. Finland
63. France
64. Gabon
65. TC Gambia
66. Georgia
67. Germany
68. Ghana
69. Gibraltar
70. Greece
71. Grenada
72. Guatemala
73. Guatemala
74. Guernsey
75. Guinea
76. Guinea-Bissau
77. Guya0
78. Haiti
79. Holy See
80. Honduras
81. Hong Kong
82. Hungary
83. Iceland
84. India
85. Indonesia
86. Indonesia
87. Iraq
88. Republic of Ireland
89. Isle of Man
90. Israel
91. Italy
92. Jamaica
93. Japan
94. Jersey
95. Jordan
96. Kazakhstan
97. Kenya
98. South Korea
99. Kuwait
100. Kyrgyzstan
101. Laos
102. Latvia
103. Lebanon
104. Lesotho
105. Liberia
106. Liechtenstein
107. Lithuania
108. Luxembourg
109. Macau
110. Madagascar
111. Malawi
112. Malaysia
113. Mali
114. Malta
115. Mauritania
116. Mauritius
117. Mexico
118. Moldova
119. Monaco
120. Mongolia
121. Montenegro
122. Montserrat
123. Morocco
124. Mozambique
125. Myanmar
126. Namibia
127. Nauru
128. Nepal
129. Netherlands
130. New Zealand
131. Nicaragua
132. Niger
133. Nigeria
134. North Macedonia
135. Norway
136. Oman
137. Pakistan
138. Palau
139. Panama
140. Papua New Guinea
141. Paraguay
142. Peru
143. Philippines

144. Poland
145. Portugal
146. Qatar
147. Republic of the Congo
148. Republic of the Marshall Islands
149. Romania
150. russia
151. Rwanda
152. Saint Kitts and Nevis
153. Saint Lucia
154. Samoa
155. San Marino
156. São Tomé and Príncipe
157. Saudi Arabia
158. Senegal
159. Serbia
160. Seychelles
161. Sierra Leone
162. Singapore
163. Slovakia
164. Slovenia
165. Solomon Islands
166. South Africa
167. Spain
168. Sri Lanka
169. Saint Vincent and the Grenadines
170. Suriname
171. Sweden
172. Switzerland
173. Tajikistan
174. Tanzania
175. Thailand
176. The Bahamas
177. Timor Leste
178. Togo
179. Tonga
180. Trinidad and Tobago
181. Tunisia
182. Turkey
183. Turkmenistan
184. Turks and Caicos Islands
185. Uganda
186. Ukraine
187. United Arab Emirates
188. United Kingdom
189. United States
190. Uruguay
191. Uzbekistan
192. Vanuatu
193. Venezuela
194. Vietnam
195. Zambia

Table A1

Criteria for assessing the effectiveness of AML/CFT systems and technical compliance with the FATF recommendations

IO1	Money laundering and terrorist financing risks are understood and, where appropriate, actions are coordinated domestically to combat money laundering and the financing of terrorism and proliferation.
IO2	International cooperation delivers appropriate information, financial intelligence, and evidence, and facilitates action against criminals and their assets.
IO3	Supervisors appropriately supervise, monitor and regulate financial institutions, DNFBPs and VASPs for compliance with AML/CFT requirements commensurate with their risks.
IO4	Financial institutions, DNFBPs and VASPs adequately apply AML/CFT preventive measures commensurate with their risks and report suspicious transactions.
IO5	Legal persons and arrangements are prevented from misuse for money laundering or terrorist financing, and information on their beneficial ownership is available to competent authorities without impediments.
IO6	Competent authorities appropriately use financial intelligence and all other relevant information for money laundering and terrorist financing investigations.
IO7	Money laundering offences and activities are investigated and offenders are prosecuted and subject to effective, proportionate and dissuasive sanctions.
IO8	Proceeds and instrumentalities of crime are confiscated.
IO9	Terrorist financing offences and activities are investigated, and persons who finance terrorism are prosecuted and subject to effective, proportionate and dissuasive sanctions.
IO10	Terrorists, terrorist organisations and terrorist financiers are prevented from raising, moving and using funds, and from abusing the NPO sector.
IO11	Persons and entities involved in the proliferation of weapons of mass destruction are prevented from raising, moving and using funds, consistent with the relevant UNSCRs.
R.1	Assessing risks and applying a risk-based approach
R.2	National co-operation and coordination
R.3	Money laundering offence
R.4	Confiscation and provisional measures
R.5	Terrorist financing offence
R.6	Targeted financial sanctions related to terrorism and terrorist financing
R.7	Targeted financial sanctions related to proliferation
R.8	Non-profit organisations
R.9	Financial institution secrecy laws
R.10	Customer due diligence
R.11	Record keeping
R.12	Politically exposed persons
R.13	Correspondent banking
R.14	Money or value transfer services
R.15	New technologies
R.16	Wire transfers
R.17	Reliance on third parties
R.18	Internal controls and foreign branches and subsidiaries
R.19	Higher risk countries
R.20	Reporting of suspicious transactions
R.21	Tipping-off and confidentiality
R.22	Designated non-financial businesses and professions: customer due diligence
R.23	Designated non-financial businesses and professions: other measures
R.24	Transparency and beneficial ownership of legal persons
R.25	Transparency and beneficial ownership of legal arrangements
R.26	Regulation and supervision of financial institutions
R.27	Powers of supervisors
R.28	Regulation and supervision of designated non-financial businesses and professions
R.29	Financial intelligence units
R.30	Responsibilities of law enforcement and investigative authorities
R.31	Powers of law enforcement and investigative authorities

R.32	Cash couriers
R.33	Statistics
R.34	Guidance and feedback
R.35	Sanctions
R.36	International instruments
R.37	Mutual legal assistance
R.38	Mutual legal assistance: freezing and confiscation
R.39	Extradition
R.40	Other forms of international co-operation

Source: FATF, 2021-2023.

APPENDIX B

Table B1

Summary statistics of the criteria for assessing the effectiveness of AML/CFT systems and technical compliance with the FATF recommendations

Variables	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	SD
IO1	0	0	1	1,066	2	3	0,797875
IO2	0	1	1	1,327	2	3	0,832365
IO3	0	0	1	0,6939	1	2	0,588926
IO4	0	1	1	0,6789	1	2	0,529877
IO5	0	0	1	0,6224	1	2	0,640758
IO6	0	0	1	1,01	2	3	0,771212
IO7	0	0	1	0,5918	1	2	0,629802
IO8	0	0	1	0,8214	1	3	0,793402
IO9	0	0	1	0,9796	2	3	0,865043
IO10	0	0	1	0,7347	1	3	0,731013
IO11	0	0	0	0,6531	1	3	0,785798
R.1	0	2	2	1,832	2	3	0,59676
R.2	0	2	2	2,173	3	3	0,694676
R.3	1	2	2	2,24	3	3	0,597986
R.4	1	2	2	2,25	3	3	0,619139
R.5	0	2	2	2,112	3	3	0,669981
R.6	0	1	2	1,658	2	3	0,810498
R.7	0	1	2	1,49	2	3	0,936386
R.8	0	1	1	1,265	2	3	0,847936
R.9	1	2	3	2,684	3	3	0,508329
R.10	0	2	2	1,974	2	3	0,585607
R.11	1	2	2	2,449	3	3	0,57508
R.12	0	2	2	2,087	3	3	0,763009
R.13	0	2	2	2,27	3	3	0,73264
R.14	0	2	2	2,184	3	3	0,755791
R.15	0	1	1	1,281	2	3	0,875789
R.16	0	2	2	1,98	2	3	0,757589
R.17	0	2	2	1,974	3	3	0,913917
R.18	0	2	2	2,122	3	3	0,636743
R.19	0	2	2	2,046	3	3	0,878772
R.20	0	2	3	2,464	3	3	0,711625
R.21	1	2	3	2,622	3	3	0,554983
R.22	0	1	2	1,694	2	3	0,707588
R.23	0	1	2	1,765	2	3	0,713259
R.24	0	1	1	1,413	2	3	0,662263
R.25	0	1	2	1,515	2	3	0,806875
R.26	0	1	3	1,816	2	3	0,677052
R.27	1	2	2	2,388	3	3	0,61823
R.28	0	1	1	1,439	2	3	0,811031
R.29	1	2	2	2,398	3	3	0,652251
R.30	0	2	3	2,612	3	3	0,592823
R.31	0	2	2	2,306	3	3	0,647015
R.32	0	2	2	1,995	2	3	0,675562
R.33	0	1	2	1,985	3	3	0,850201
R.34	0	2	2	2,082	3	3	0,725696
R.35	0	1	2	1,781	2	3	0,692696
R.36	1	2	2	2,133	3	3	0,618315
R.37	0	2	2	2,071	2	3	0,540655
R.38	0	2	2	1,995	2	3	0,636476
R.39	0	2	2	2,163	3	3	0,585183
R.40	0	2	2	1,918	2	3	0,499712

Source: authors' calculation in R Studio.

APPENDIX C

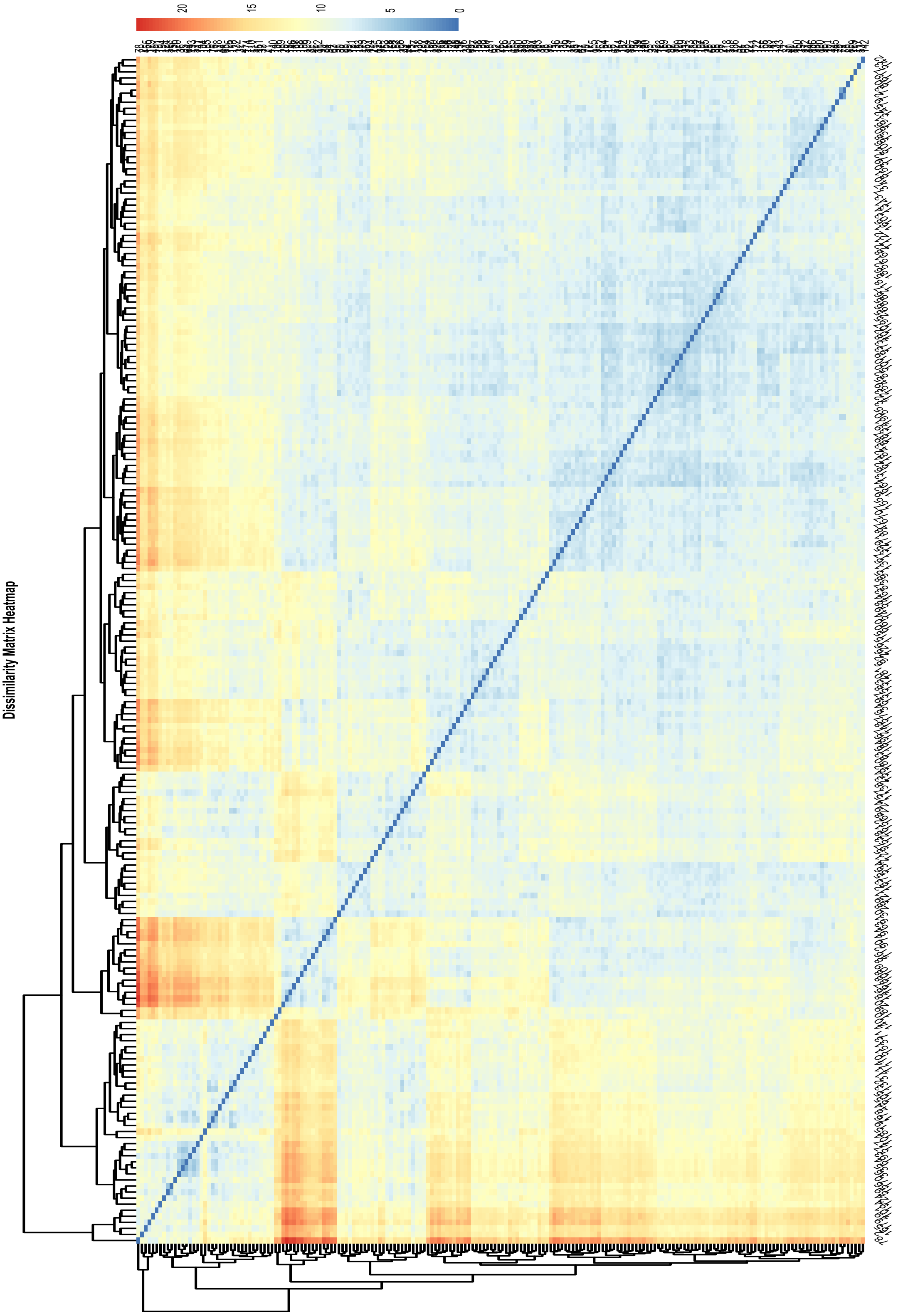

Figure C1. The dissimilarity matrix heatmap of the countries and their FATF technical compliance and effectiveness performance

Source: authors' calculation in R Studio

APPENDIX D

Table D1

The list of countries per cluster

Cluster	Countries
1	Albania, Andorra, Antigua and Barbuda, Argentina, Aruba, Australia, Azerbaijan, Bahrain, Bangladesh, Belarus, Bosnia and Herzegovina, Brazil, Brunei-Darussalam, Canada, Chile, China, China Taipei, Colombia, Cook Islands, Costa Rica, Croatia, Cyprus, Czech Republic, Denmark, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Finland, Georgia, Guatemala, Guatemala, Guyana, Holy See, Honduras, Hong Kong, Hungary, India, Indonesia, Indonesia, Israel, Jamaica, Japan, Jordan, Kazakhstan, South Korea, Kyrgyzstan, Latvia, Lebanon, Liechtenstein, Lithuania, Malta, Mexico, Moldova, Monaco, Montenegro, Montserrat, Morocco, Netherlands, New Zealand, North Macedonia, Panama, Paraguay, Peru, Poland, Romania, russia, San Marino, Serbia, Singapore, Slovakia, Slovenia, South Africa, Saint Vincent and the Grenadines, Switzerland, Tajikistan, Thailand, Timor Leste, Turkmenistan, Ukraine, United Arab Emirates, United States, Uruguay, Uzbekistan
2	Algeria, Angola, Benin, Botswana, Burkina Faso, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Ivory Coast, Democratic Republic Congo, Djibouti, Equatorial Guinea, Eswatini, Gabon, TC Gambia, Grenada, Guinea, Guinea-Bissau, Haiti, Kenya, Laos, Lesotho, Liberia, Madagascar, Mali, Mozambique, Myanmar, Nepal, Niger, Palau, Papua New Guinea, Republic of the Congo, Rwanda, Samoa, São Tomé and Príncipe, Sierra Leone, Solomon Islands, Suriname, Tanzania, Togo, Tonga, Uganda, Venezuela, Vietnam
3	Anguilla, Barbados, Bhutan, Bolivia, British Virgin Islands, Bulgaria, Cambodia, Ethiopia, Fiji, Ghana, Iraq, Kuwait, Malawi, Mauritania, Mongolia, Namibia, Nicaragua, Nigeria, Pakistan, Philippines, Saint Kitts and Nevis, Saint Lucia, Senegal, Seychelles, Sri Lanka, Tunisia, Vanuatu, Zambia
4	Armenia, Austria, Belgium, Belize, Bermuda, Cayman Islands, Cuba, France, Germany, Gibraltar, Greece, Guernsey, Iceland, Republic of Ireland, Isle of Man, Italy, Jersey, Luxembourg, Macau, Malaysia, Mauritius, Nauru, Norway, Oman, Portugal, Qatar, Republic of the Marshall Islands, Saudi Arabia, Spain, Sweden, The Bahamas, Trinidad and Tobago, Turkey, Turks and Caicos Islands, United Kingdom

Source: authors' calculation in R Studio.

Table D2

Summary statistics of technical compliance and effectiveness by cluster

Cluster	1	2	3	4	Cluster	1	2	3	4
IO1_mean	1,453488	0,26087	0,607143	1,527778	R.16_mean	2,046512	1,195652	2,178571	2,666667
IO1_median	1	0	1	2	R.16_median	2	1	2	3
IO2_mean	1,825581	0,369565	0,892857	1,694444	R.17_mean	1,883721	1,5	2,321429	2,527778
IO2_median	2	0	1	2	R.17_median	2	2	2	3
IO3_mean	0,953488	0,086957	0,428571	1,055556	R.18_mean	2,104651	1,869565	2,142857	2,472222
IO3_median	1	0	0	1	R.18_median	2	2	2	2,5
IO4_mean	0,965116	0,086957	0,428571	0,944444	R.19_mean	2,232558	1,043478	2,214286	2,75
IO4_median	1	0	0	1	R.19_median	2	1	2	3
IO5_mean	0,825581	0,021739	0,25	1,194444	R.20_mean	2,5	1,956522	2,642857	2,888889
IO5_median	1	0	0	1	R.20_median	3	2	3	3
IO6_mean	1,476744	0,282609	0,5	1,222222	R.21_mean	2,581395	2,586957	2,428571	2,916667
IO6_median	1	0	0,5	1	R.21_median	3	3	2,5	3
IO7_mean	0,860465	0,108696	0,357143	0,75	R.22_mean	1,604651	1,108696	2,071429	2,361111
IO7_median	1	0	0	1	R.22_median	2	1	2	2
IO8_mean	1,197674	0,26087	0,464286	0,916667	R.23_mean	1,755814	1,217391	1,857143	2,416667
IO8_median	1	0	0	1	R.23_median	2	1	2	2
IO9_mean	1,383721	0,173913	0,464286	1,444444	R.24_mean	1,593023	0,73913	1,357143	1,888889
IO9_median	1	0	0	2	R.24_median	2	1	1	2
IO10_mean	1,023256	0,065217	0,25	1,277778	R.25_mean	1,627907	0,695652	1,607143	2,222222
IO10_median	1	0	0	1	R.25_median	2	1	2	2
IO11_mean	0,930233	0	0,071429	1,277778	R.26_mean	1,918605	1,152174	1,75	2,472222
IO11_median	1	0	0	1	R.26_median	2	1	2	2
R.1_mean	1,930233	1,195652	2,071429	2,222222	R.27_mean	2,267442	2,152174	2,607143	2,805556
R.1_median	2	1	2	2	R.27_median	2	2	3	3
R.2_mean	2,418605	1,478261	2,214286	2,444444	R.28_mean	1,406977	0,695652	1,607143	2,333333
R.2_median	2	1	2	2	R.28_median	1	1	1,5	2
R.3_mean	2,209302	2,021739	2,25	2,583333	R.29_mean	2,569767	1,869565	2,5	2,583333
R.3_median	2	2	2	3	R.29_median	3	2	2,5	3
R.4_mean	2,348837	1,804348	2,25	2,583333	R.30_mean	2,709302	2,304348	2,607143	2,777778
R.4_median	2	2	2	3	R.30_median	3	3	3	3
R.5_mean	2,081395	1,717391	2,142857	2,666667	R.31_mean	2,313953	2,130435	2,25	2,555556
R.5_median	2	2	2	3	R.31_median	2	2	2	3
R.6_mean	1,825581	0,891304	1,75	2,166667	R.32_mean	2,093023	1,5	2,071429	2,333333
R.6_median	2	1	2	2	R.32_median	2	1	2	2
R.7_mean	1,651163	0,521739	1,75	2,138889	R.33_mean	2,197674	1,282609	2,178571	2,222222
R.7_median	2	0	2	2	R.33_median	2	1	2	2
R.8_mean	1,488372	0,347826	1,357143	1,833333	R.34_mean	2,244186	1,304348	2,285714	2,527778
R.8_median	2	0	1	2	R.34_median	2	1	2	3
R.9_mean	2,662791	2,5	2,714286	2,944444	R.35_mean	1,72093	1,326087	1,857143	2,444444
R.9_median	3	3	3	3	R.35_median	2	1	2	2
R.10_mean	2,011628	1,391304	2,107143	2,527778	R.36_mean	2,22093	1,804348	2,107143	2,361111
R.10_median	2	1	2	3	R.36_median	2	2	2	2
R.11_mean	2,372093	2,173913	2,571429	2,888889	R.37_mean	2,127907	1,673913	2,107143	2,416667
R.11_median	2	2	3	3	R.37_median	2	2	2	2
R.12_mean	2,104651	1,413043	2,357143	2,694444	R.38_mean	2,104651	1,543478	1,964286	2,333333
R.12_median	2	1	2	3	R.38_median	2	1,5	2	2
R.13_mean	2,325581	1,956522	2,535714	2,333333	R.39_mean	2,174419	1,869565	2	2,638889
R.13_median	2	2	3	3	R.39_median	2	2	2	3
R.14_mean	2,290698	1,413043	2,428571	2,722222	R.40_mean	2,023256	1,521739	1,785714	2,277778
R.14_median	2	1	2	3	R.40_median	2	2	2	2
R.15_mean	1,5	0,391304	1,035714	2,083333					
R.15_median	1	0	1	2					

Source: authors' calculation in R Studio.