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A systematic literature review of illicit financial flows and money laundering: Current state of research and estimation methods

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Abstract

Aim/purpose – The goal of the paper is to examine the current state of research on illicit financial flows (IFF) and money laundering (ML) with a specific focus on detection and estimation methods. This study seeks to identify and evaluate the most promising approaches that can effectively counter IFF and ML in the context of economic stability, ensuring they remain adaptive to constantly evolving threats.

Design/methodology/approach – The analysis was conducted on papers from Scopus and Web of Science, both recognized as leading academic databases. The application of screening analysis (1,249 papers) enabled the exclusion of articles not primarily focused on IFF and ML. In comparison, thematic synthesis (1,135 papers) facilitated the presentation of the current state of literature, highlighting main trends and categorizing articles by thematic dimensions. Textual narrative synthesis (234 papers) allows the identification of existing methods and the variables and proxies used in the literature to detect and estimate IFF and ML.

Findings – The analysis reveals that a multidisciplinary approach to IFF and ML, integrating law, social sciences, and computer science, holds promise. The study emphasizes innovative methodologies, like machine learning, alongside gravity-based models. Specifically, 38% of the literature focuses on systematizing knowledge, while advanced techniques like machine learning (26%) and modified gravity-based models (3.33%) are increasingly influential. Legal and economic approaches provide a broad framework for understanding illicit activities and identifying emerging threats and trends among the

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methods used by criminals. Challenges remain in measuring and detecting IFF/ML due to the secretive nature of such flows.
Research implications/limitations – This review summarizes IFF and ML detection/ estimation techniques, including research up to 2024. Limitations include potential source selection bias (WOS/Scopus) and the exclusion of 81 studies due to access restrictions. Future research should refine source selection and improve access to critical literature.
Originality/value/contribution – This study uniquely integrates thematic and textual narrative synthesis with bibliometric visualization to provide a comprehensive overview of research on IFF and ML. By reviewing existing detection and estimation tools in the context of emerging risks, the research offers valuable insights for enhancing the effectiveness of prevention strategies against these phenomena.

Keywords: money laundering, illicit financial flows, literature review, bibliometric analysis, anti-money laundering.
JEL Classification: E26, F38, K42.

1. Introduction

The phenomenon of illicit financial flows (IFF) attracts significant interest from researchers and practitioners (Ferwerda & Unger, 2021). The transfers in question are derived from proceeds generated by extensive criminal activities, such as drug and gun deals, human trafficking and slavery, corrupting public officials, fraud, or organized crime (Nazzari & Riccardi, 2024; Pataccini, 2023; Prabowo, 2024). To develop effective strategies for preventing IFF, it is essential to understand the phenomenon under analysis (Reuter & Riccardi, 2024).

In this paper, the definition of IFF is presented in a manner consistent with OECD (2014), which defines all cross-border financial transfers that conflict with national or international law. They could be generated by illegal activities (like illegal markets, corruption, exploitation-type activities like slavery, and terrorism financing) or by illicit tax and commercial practices that occur on the border of legal constraints and even in the shadow economy (Yarovenko et al., 2024).

Nevertheless, to capitalize on funds acquired through these means, criminals must first convert illegally obtained funds into seemingly legitimate assets (Koelbing et al., 2024). This operation is widely known as money laundering (ML). As with IFF, there is no universal definition of ML (Olivier & Nortje, 2024), and perception can vary significantly depending on legal, economic, and social perspectives. For example, the legal view of ML focuses on the definition and criminal regulation, treating it as a criminal offense (Korejo et al., 2021; Milon & Zafarullah, 2024). The economic perspective of ML concentrates on its impact on financial stability and economic mechanisms, including an analysis of the effects on financial markets and economic efficiency (Hendriyetty & Grewal, 2017; Tran, 2024). The social perspective of ML concentrates on social norms, values, and reactions to ML practices and their impact on the functioning of society and public institutions (Cretu-Adatte et al., 2024; Kalokoh, 2024). The term "Money laundering" began to be more widely used in the 1970s and 1980s, mainly in the context of linking such activity to drug trafficking. At the same time, the definition evolved several times before achieving its contemporary form (Walker & Unger, 2009).

The definition of ML applied in this study is consistent with the one used by The United Nations Convention Against Transnational Organized Crime, Article 6 (United Nations Office on Drugs and Crime, 2004). ML currently poses a significant challenge to the global economy with financial and social consequences (Isolauri & Ameer, 2023). Technological progress and globalization have allowed criminals to expand their activities internationally (Tiwari et al., 2024b). Since ML is primarily based on existing financial systems and operations, it is closely related to the activities of institutions offering services in this field (Naheem, 2015; von Haenisch & Egner, 2024). By virtue of the services provided by institutions such as banks, payment institutions, currency exchange offices, and financial intermediaries, the transactions have acquired an international character and ability since national borders no longer bind them (Skinner, 2023). ML typically involves a series of multiple transactions used to conceal illegal sources of financial assets (Gilmore, 2004). ML and related crimes are associated with negative consequences like the growth of the shadow economy, economic imbalances, and a decrease in public safety (Achim et al., 2024; Sigetova et al., 2022). Consequently, the detection and prevention of these illegal practices have become a subject of interest not only for government officials, lawmakers, and enforcement agencies but also attracted the attention of researchers (Ferwerda & Unger, 2021).

The research gap discussed in this paper and identified during the review of previous scientific research stems from an incomplete study of the IFF and ML topic, especially considering the methods of estimating these phenomena. One of the most widely cited estimates regarding the magnitude of ML was presented by the International Monetary Fund in 1998. According to it, the scale of ML ranged from 2% to 5% of the global Gross Domestic Product (GDP) (Camdessus, 1998). Scientists consider estimating the scale of IFF and ML crucial for understanding the problem and its significance (Ferwerda & Unger, 2021). Several researchers (Aljassmi et al., 2024; Amjad et al., 2022; van Duyne & Soudijn, 2009; Ferwerda & Unger, 2021; Perez et al., 2012; Walker & Unger, 2009) have attempted to quantify the volume of IFF and ML; however, due to substantial variations in results and methodologies, a global standard has yet to be established.

The paper aims to verify the current state of knowledge and critically evaluate the analytical methods used by other researchers and the factors they considered, especially for the detection and estimation of IFF and ML. Measuring the extent of IFF is crucial because without knowing the scale of illegal transactions, we cannot evaluate whether policymakers choose the right policies to diminish the size of such activities.

This review will highlight research gaps that need to be developed in-depth, such as advanced machine learning techniques or automated transaction analysis, which point to potential areas for follow-up research.

To provide a comprehensive overview, this study addresses the following questions:

1. What is the current state of knowledge on IFF and ML?
2. What are the methods of detecting and estimating IFF and ML in the literature?
3. What variables/proxies were used to estimate IFF and ML?

A systematic literature review was conducted to verify the current state of research on both IFF and ML and the methods and variables used for detecting and estimating these phenomena. The main contributions of the paper are:

1. It presents the current knowledge about IFF and ML. This review analyzes 1,249 papers from the two most extensive databases (Scopus and Web of Science), providing a broad perspective on the existing literature. This broad overview provides a better understanding of global trends and allows for a more comprehensive assessment of available AML-related methods and tools. Screening analysis (1,249 papers) enabled us to reject articles in which the topics of IFF and ML were side issues. Thematic synthesis (1135 papers) allowed the assignment of selected articles to the appropriate subject areas. It especially allowed us to indicate the papers representing the detection and estimation of IFF and ML.
2. The textual narrative synthesis (234 papers) of the selected articles facilitates the organization and classification of the research methods applied within these studies. It presents examples of variables used in IFF and ML research.
3. The paper provides a “recipe” for conducting a systematic literature review in the areas of IFF and ML. This topic has attracted widespread interest from practitioners and researchers. The instructions presented in Section 2 will enable the replication and simplification of possible future studies.
4. The paper is a critical resource, providing valuable information for both academics and AML practitioners. A review of existing IFF and ML detection methods is an important source of knowledge that enriches the models used by actors like financial institutions or supervisory authorities. Knowledge of best practices allows a more efficient response to the growing threats of ML and IFF.

Updating the knowledge of available methods and tools positively contributes to the evolving international standards in financial regulation.

The paper is structured as follows: The next section presents a comprehensive literature analysis with the data collection process. The third section discusses the screening methods, thematic synthesis, and textual narrative synthesis and their results. The fourth section examines the relevance of the analysis results and their implications for research and practice. The primary conclusions and recommendations for future research are presented in the final section.

2. Methods and research stages

The literature review in this article was based on papers from two renowned databases: Scopus (1,231 papers) and Web of Science (360 papers). It focused on the analysis of articles on IFF and ML. Nevertheless, the search terms also included conditions relating to terrorist financing (as a flow of funds connected to illegal activity) and obliged institutions, i.e., institutions with an obligation (imposed by legislators) to implement anti-money laundering/countering the financing of terrorism (AML/CFT) rules. The articles used in the analysis cover the period 1992-2024 (the search of the databases by keywords selected by the author took place in February 2025). Duplicates were removed (where there was a duplicate, the paper from the Scopus database was usually retained). The final number of articles identified using the following methods were 1,249 papers for screening analysis, 1,135 papers for thematic synthesis, and 234 papers for textual narrative synthesis (with the latter's results visualized in VOSviewer). The steps taken to obtain the article base for each method are presented in Table 1.

Applying the keywords described above and subsequently selecting articles according to Steps 2-5 provides a replicable database for researching the IFF and ML literature. This study focuses on validating available methods and variables used by other researchers to detect and estimate IFF and ML; therefore, the actions described in Steps 7-8 were undertaken.

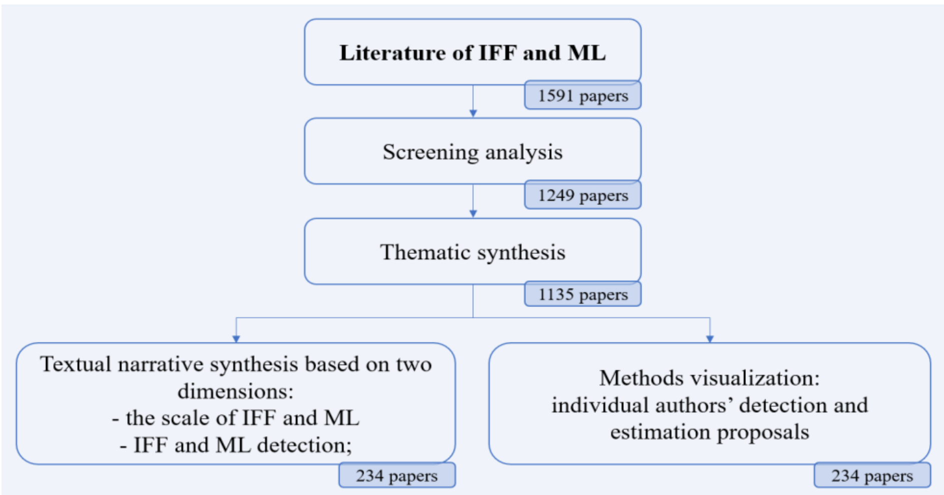
The systematic literature review was conducted in an extensive and multi-stage manner. Figure 1 below provides a visualization to enhance understanding of the methods employed.

Table 1. Steps taken in preparing the literature review

<table>
<tr><th>Journal included</th><th colspan="3">Search terms</th></tr>
<tr><td>Search conducted in:
– Web of Science,
– Scopus.
Period up to 2024</td><td colspan="3">● Web of Science (Topic Search (TS) = searches title, abstract, author keywords, and keywords plus)
TS=(money launder* OR AML OR money-launder* OR anti-money launder* OR anti-money launder* OR terror* financing OR counter-terror* financing) AND TS=(illicit finan* OR illicit flows OR financial flows OR obligated institut*)
● Scopus (TITLE-ABS-KEY = title, abstract, keywords)
TITLE-ABS-KEY (('money launder*) OR ('AML') OR ('money-launder*) OR ('anti-money launder*) OR ('anti-money launder*) OR ('terror* AND 'financing') OR ('counter' AND 'terror* AND 'financing')) AND (('illicit finan*) OR ('illicit flows') OR ('illicit financial flows') OR ('obligated institut*))</td></tr>
<tr><th>Description</th><th>Scopus</th><th>Web of Science</th><th>Number of articles left after removing</th></tr>
<tr><td>Step 1. Searching for articles by keywords.</td><td>1,231</td><td>360</td><td>1,591</td></tr>
<tr><td>Step 2. Removing articles related to medicine.</td><td>–80</td><td>–8</td><td>1,503</td></tr>
<tr><td>Step 3. Merge both bases and remove duplicates.</td><td></td><td>–253</td><td>1,250</td></tr>
<tr><td>Step 4. Removing non-English articles.</td><td></td><td>–1</td><td>1,249</td></tr>
<tr><td>Step 5. Screening analysis.</td><td></td><td>–114</td><td>1,135</td></tr>
<tr><td>Step 6. Thematic synthesis for a breakdown of articles into six dimensions (Tiwari et al., 2020).</td><td></td><td>x</td><td>1,135</td></tr>
<tr><td>Step 7. Selection of articles from two dimensions:
– IFF and ML detection,
– the scale of IFF and ML.</td><td></td><td>–820</td><td>315</td></tr>
<tr><td>Step 8. Removing not-available full-text articles – final sample.</td><td></td><td>–81</td><td>234</td></tr>
</table>

Source: Author's own elaboration.

Figure 1. Methods used to present a systematic literature review



Source: Author's own elaboration.

This study employs various methods, which allow for a comprehensive analysis of current literature, namely screening analysis, thematic synthesis, and textual narrative synthesis, accompanied by bibliometric visualization of the results obtained during the screening and textual narrative synthesis stages. Screening (Polanin et al., 2019) was conducted to initially verify articles based on titles and abstracts to ensure the included studies' relevance and thematic alignment. Thematic synthesis (Lucas et al., 2007) allowed for identifying the primary themes within the analyzed literature, offering an analysis of prevailing research trends and identifying gaps in knowledge. Textual narrative synthesis (Lucas et al., 2007) of selected articles aimed to verify the methods used for detecting and estimating IFF and ML, as well as examples of variables used by other researchers, thereby directly fulfilling the research objective of evaluating current methodological frameworks.

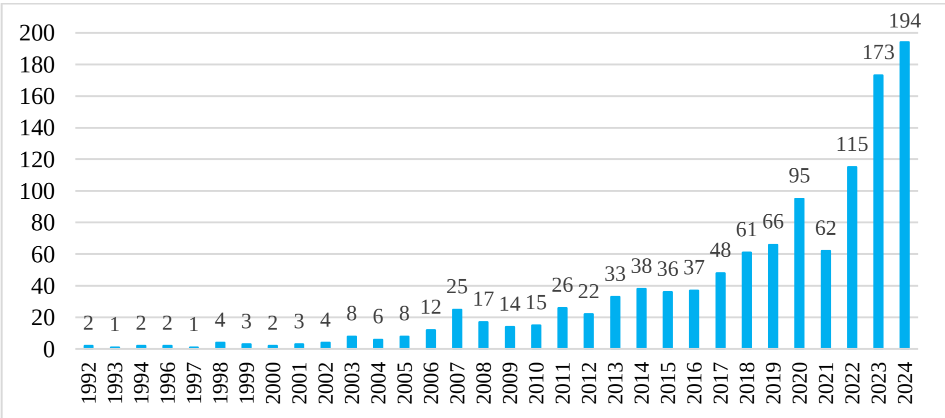
3. Qualitative analysis

3.1. Screening analysis

The screening analysis was based on 1,249 academic publications (mainly articles, but also reports and conference papers). This analysis enabled the dismissal of articles without abstracts or that were out of scope (studies where IFF and ML were side topics) and the classification of the reviewed papers. Through screening, the foundations for thematic synthesis (by cleaning the article database) were established.

The screening analysis resulted in 1,135 academic publications (Table 1). Figure 2 documents a rising number of publications on IFF/ML. This trend highlights these issues' growing importance and relevance within the academic community.

Figure 2. Number of scientific publications on IFF/ML by year based on 1,135 papers



Source: Author's own calculations.

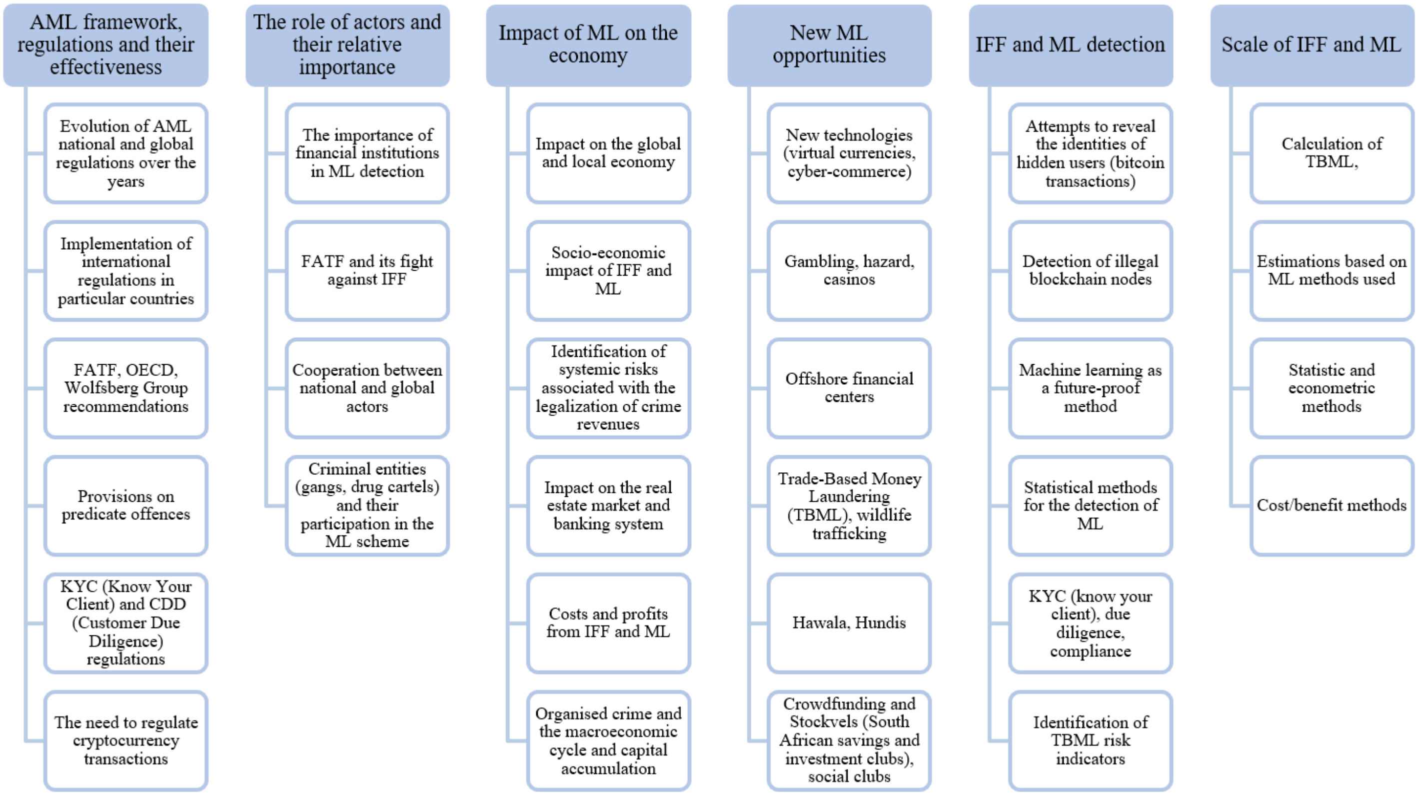
The reason for the increased number of publications since 2017 may be associated with the entrance into force of the European Union's Fourth and Fifth Anti-Money Laundering Directives, aimed at preventing the use of the financial system for ML and terrorist financing, as well as the regulation on information accompanying transfers of funds (Premti et al., 2021). Researchers also point to increased interest in AML, triggered by the growing number of leaks to the public concerning large-scale movement of illicit funds, such as Panama Papers, Swiss leaks, Paradise Papers, and Bahama Leaks, revealing the way criminals use the globalized financial system to hide their illegal assets (Ferwerda & Unger, 2021; Vail, 2018). The increase in publications between 2022 and 2024 is linked to rapidly advancing technological change, the development of artificial intelligence, and the many legal developments that follow them (Pocher et al., 2023). Another reason may also be related to the needs of practitioners in the field: supervisory authorities and obligated institutions (FATF, 2021). They are looking for the most efficient methods of combating and detecting illegal activities that align with the latest technological developments.

3.2. Thematic synthesis

The thematic synthesis consisted of reading the title, keywords, and abstract of the 1135 reviewed articles. Dividing articles into relevant categories along the lines of Tiwari's et al. approach (2020) helps create a clear knowledge structure, making it easier for other researchers to navigate this vast field. This will, in turn, facilitate a comparison of AML approaches across different countries, identifying best practices and formulating globally applicable solutions. As a result of this analysis, the literature was divided into the following six dimensions: AML framework, regulations and their effectiveness, new ML opportunities, the role of actors and their relative importance, the impact of ML on the economy, IFF and ML detection and the scale of IFF and ML. The current paper details the criteria for categorizing into specific dimensions and provides examples of methods and variables utilized by other researchers. Figure 3 outlines factors leading to categorizing an article in a specific dimension and presents the structure of existing knowledge on the studied topics identified during the thematic synthesis.

Thanks to this analysis, two issues – IFF and ML detectionand the scale of IFF and ML – were selected for textual narrative synthesis. The supplementary material is available in a public repository (Popik-Mazur, 2025), and Appendix 1 presents the literature categorized by dimensions.

Figure 3. Results of thematic synthesis based on 1,135 papers



Source: Author's own elaboration.

This study provides a benchmark for papers examining the effectiveness of preventive systems such as the AML system. *The AML framework, regulations, and their effectiveness* dimension contain articles in which the title and abstract mainly indicate a link to the analysis of law, the effects of its implementation, and its impact on the phenomenon of IFF and ML. Despite numerous studies on country-specific legal frameworks, such as those in the United Kingdom (Pontes et al., 2022), Hong Kong (Yim & Lee, 2018), the Netherlands (Barro & Rausch, 2024; Soudijn, 2019), and Tanzania (Mniwasa, 2021) still a lack of comparative studies with a broader geographical scope remains. This is particularly the case for regions such as Sub-Saharan Africa, Southeast Asia, and Latin America. Another area requiring further research in this dimension is the integration of the AML legal frameworks with the continuous development of technology. The creation of new solutions, such as blockchain or artificial intelligence (AI), progresses much faster than legislators' response to the possible risks that arise from them (Al-Tawil, 2023). Furthermore, it is essential to investigate how legislation can address and regulate the use of AI and big data, for example, in the context of privacy protection, transparency of algorithms, and accountability for decisions made by AI (Lyeonov et al., 2024). It would also be worthwhile to carry out a comparative analysis of the legislative approach in different regions concerning the possibility of incorporating the results of analytical tools such as Chainalysis (Amiram et al., 2022; Chainalysis, 2024) or Crystal (2024) into the use of materials for evidentiary purposes in judicial proceedings.

The role of the actors and their relative importance dimension refers to articles examining the subject of criminals trying to transfer and convert their illegally obtained funds (Pellegrini, 2024) and institutions involved in detecting (Lupton, 2023), preventing and disrupting illegal activities. While the available literature has analyzed the role of individual actors in the ML system (Hofmann & Lustenberger, 2023; Tsingou, 2018), it is worth extending this analysis to include a comprehensive mapping of the roles of individual actors and their interactions. A further step should also involve the effectiveness of cooperation between positive actors such as financial institutions, regulators, and law enforcement agencies.

The impact of ML on the economy dimension focuses on articles presenting the socio-economic effects of this phenomenon, both from the local and global perspectives. This dimension includes papers exploring the influence of ML on various markets: real estate (Barone, 2023), capital (Atems & Mullen, 2016; Toan, 2022), and labor (Dileo & Giorno, 2023). The primary purpose of the aforementioned articles was to emphasize the threat of ML on economic stability and national security (Barone et al., 2022; de Koker et al., 2023). Authors such as Hendritetty and Grewal (2017) provided an extensive macroeconomic analysis. However, it is also worthwhile to conduct quantitative and empirical studies of the impact of ML on different sectors of the economy. Equally, it is interesting to consider a benchmarking analysis of the phenomenon of how ML impacts the economy according to the type of financial crime committed.

The new ML opportunities dimension analyses articles discussing the methods for legitimizing illicit funds, which criminals constantly develop. While there are some "fixed" techniques used in the process, like the creation of shell companies, over the years, criminals have been looking for different methods of ML, from investment in precious metals, art, or real estate to increasingly popular virtual currencies (Prendi et al., 2023; Sartori et al., 2023; Sigetova et al., 2022). While the literature on this topic is well-developed (Badawi & Jourdan, 2020; Farooqi, 2010; Mbarek et al., 2019), specific strategies for effective countermeasures are lacking. There remains a research gap regarding feasible solutions the scientific community offers law enforcement agencies (LEAs) for instant responses to emerging threats.

The IFF and ML detection dimension focuses on research aimed at identifying illicit activities using various methods like tracking irregularities associated with trade flows (Gara et al., 2019) or detecting anomalies in virtual currency transactions (Lorenz et al., 2020; Pocher et al., 2023). The aforementioned studies are based on statistical and machine-learning methods to estimate the risk of IFF and/or ML. Developing systems for detecting suspicious activity and alerting the relevant authorities of the potential risks requires further research. Studies on particular countries' political and social implications (Reganati & Oliva, 2018; Solaiman, 2016) are also worth a deeper analysis. The advent of Web 3, the next phase of Internet technology, has introduced both new opportunities and challenges in combating IFF (Goldbarsht, 2024). Based on blockchain technology, cryptocurrency tokens, and cryptocurrencies, Web3 enables the decentralization of applications. It shifts ownership from centralized entities to creators, introducing increased financial inclusion and anonymity for illicit actors. The development of threats in the form of attacks on Web3 platforms, including scams, Ponzi schemes, and wash trading (Krishnan et al., 2023), requires adaptation to a dynamic ecosystem of digital assets. Especially the use of AI and automated algorithms in IFF/ML detection and their impact on customer profiling in financial services for risk assessment (Kute et al., 2021; Tharani et al., 2024).

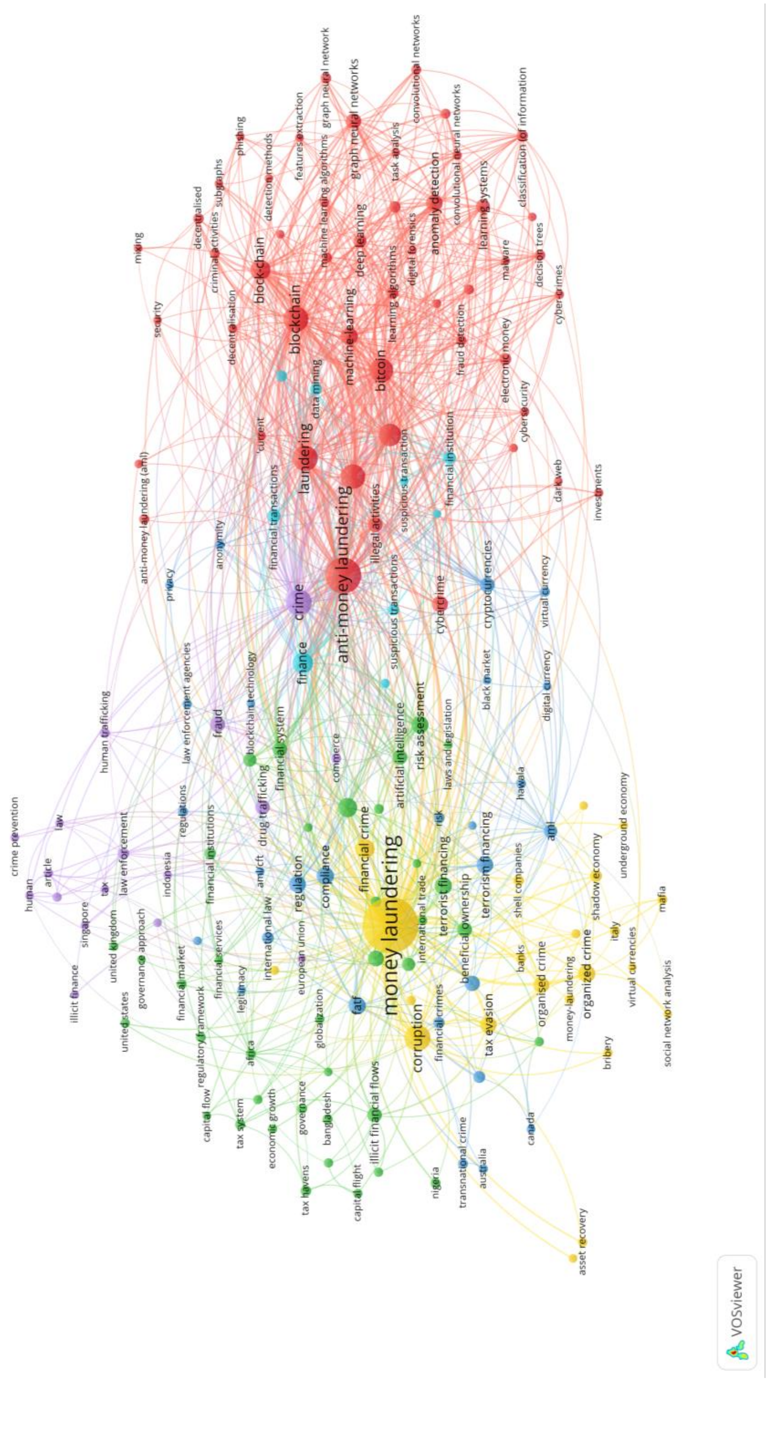
The IFF and ML dimension scale contains articles whose abstract and title suggest that the papers contain quantitative analysis aimed at estimating the volume of these illegal practices (Ajide & Ojeyinka, 2024). A significant problem raised by most researchers in the reviewed literature was the limited access to data from financial institutions or LEA on which the proposed IFF and ML estimation models could be tested (Collin, 2020; Ferwerda & Kleemans, 2019).

A relevant direction for development may be integrating advanced data analysis and machine learning based on statistical and econometric methods. Furthermore, conducting a cross-regional comparative analysis would be valuable to understand the cultural and psycho-social determinants of IFF/ML and to focus on insufficiently researched high-risk areas.

A bibliometric analysis was conducted to find support for the answer to Question 1. Constructing and visualizing the bibliometric network will enable the visualization of the main areas in the literature studied (Lyeonov et al., 2024). The screening analysis results, including 1,135 papers, were imported into VosViewer software (van Eck & Waltman, 2011). This paper analyzes the most popular types of relations between pairs of nodes: keyword co-occurrence relations, countries-citation relations, and authors' citations. A typical bibliometric network contains nodes (e.g., publications, authors, journals, keywords) and edges (which present relations between pairs of nodes). The distance between pairs of nodes presents the strength of the relationship of the nodes in VOSviewer – the shorter the distance, the stronger the dependency on each other. The visualization created in the program assigns the nodes in a network to clusters, i.e., sets of closely related nodes. Each cluster is represented by its own color in the graph (van Eck & Waltman, 2014).

After the screening analysis, the co-occurrence keywords were prepared. Numerous co-occurrence keywords indicate the extensive literature on IFF and ML. After entering the data into VOSviewer, 2,767 keywords were obtained, which have been frequently used in the literature over the years. A minimum number of occurrences of a keyword was applied at the level of five, and 163 distinctive keywords surpassed that threshold. The node's size portrays the significance of the keyword's occurrence (Krauskopf, 2018). VOSviewer categorizes keywords into distinct clusters based on how authors have associated them, reflecting their co-occurrence (van Eck & Waltman, 2014). The results of the keywords co-occurrence analysis are presented in Figure 4. It shows the network of connections between the selected clusters. The subject of ML is widely developed in the literature, which results in a large number of papers and related keywords. In connection with the above, an analysis of the relationships of the main keywords was carried out, i.e., ML (yellow), anti-money laundering (red), crime (violet), finance (light blue), regulation (dark blue), and terrorism (green). In the analyzed literature, the most frequent keyword was ML, which is also the result of the search terms used.

Figure 4. Clusters indicating semantic relations between keywords discovered during the literature analysis based on merged Scopus and Web of Science databases (based on 1,135 papers)



Source: Author's own calculations.

Type of analysis: „citation" – countries analysis presents the relationship between particular countries when the author deals with IFF and ML. Unfortunately, due to the limitations of the VosViewer tool, in this case, it was not possible to analyze the combined Scopus and Web of Science databases, so the results were presented separately in the appendices (Tables A1 and A2).

The most cited countries in the Scopus database were the United States (2,158), the United Kingdom (1,794), Australia (1,035), the Netherlands (858), and Mexico (609). This is undoubtedly related to the volume of published documents in the following countries: the United Kingdom (146), the United States (144), Australia (78), the Netherlands (44), and Mexico (5).

The most cited countries in the Web of Science database were the United States (223), the Netherlands (142), Australia (129), England (127), Italy (77), and Canada (44). The results are similar to those in the Scopus database, and the lower number of citations and documents may be due to the smaller number of articles covered by Web of Science compared to Scopus.

The analysis of authors' impact on the body of IFF and ML literature was verified using citations from authors in VosViewer. Among the authors who contributed the most to IFF and ML topics according to the Scopus database were S. Rose-Ackerman (498 citations), B.J. Palifka (498 citations), M.A. Naheem (385 citations), B. Unger (357 citations) and M. Levi (295 citations). For a detailed overview of cited authors in the Scopus database cf. the appendix (Table A3). Meanwhile, among the top authors according to the Web of Science database were B. Unger (113 citations), J. Walker (78 citations), N. Raphaeli (55 citations), S. Melzer (39 citations), L. Shalley (39 citations), H. Fujiki (36 citations) and A.S.M. Irwin (36 citations). For a detailed overview of cited authors in the Scopus database cf. the appendix (Table A4).

The bibliometric analysis indicated the presence of studies examining the relationship between ML and generally defined criminal activity, along with the methods of combating illegal practices. A deep understanding of IFF and ML goes beyond the mere possession of knowledge in economics. The bibliometric analysis has revealed that the subject matter extends to computer and information science (data mining, machine learning, anomaly detection, graph neural networks), law (regulations, compliance, international law, legitimacy), and political science (governance, security, and prevention). To sum up, the current state of research indicates an interdisciplinary approach to the issues under study.

3.3. Textual narrative synthesis

The next step of the thematic synthesis conducted in this article is to undertake a textual narrative synthesis. This analysis facilitates the identification of exemplary methods employed for detecting and estimating IFF and ML and verifying the variables on which the authors based their papers. Furthermore, the various determinants utilized to assess the investigated phenomena were outlined. The conducted research not only aids in structuring the existing knowledge on the aforementioned topics but can serve as the basis for defining future developmental trajectories, particularly among the most prospective methodologies.

A textual narrative synthesis of 234 articles dedicated to calculating the value of IFF and proceeds of a crime subject to ML revealed some common features between the analyzed papers. Over the years, researchers have used various methods related to the estimation of IFF and ML (Tiwari et al., 2024a). The vast majority of research was based primarily on a theoretical approach stemming from the systematization of knowledge (33.3% of all papers) and case studies (3.8%). Machine learning techniques (22.2%) are a constantly evolving method, but "traditional methods" like statistical and econometric ones (14.5%) still play a significant role in the available literature. For this study, the blockchain analysis method (13.2%) was also identified as a separate calculation technique despite being related to machine-learning methods. Similarly, this applies to the distinction of the gravity-based model and its modifications (2.6%) from broader statistical and econometric methods. Other models accounted for 10.3% of all papers and consist of methods such as economic analysis (2.1%), risk-based approach (5.6%), trade-based ML (TBML, 2.1%), and Unified Modeling Language (UML) (0.4%). These methods were focused more on detection than estimation of IFF and ML.

As indicated above, the "systematization of knowledge" is the most popular method used by researchers (Anagnostou & Doberstein, 2022; Gilmour, 2023; Goecks et al., 2022; Krishnan et al., 2023; Umar et al., 2020; Unger & Van Waarden, 2009; Warikandwa, 2023). This group contains articles whose abstracts suggested the possible presence of models for estimating the scale of ML and IFF. It also contained papers in which the authors discussed data access, enabling them to conduct empirical research (Levi, 2020; Reuter, 2013). The frequent use of this method can also be attributed to the fact that the systematization of knowledge enables one to determine the current scientific achievements in a given topic, identify possible gaps, and set directions for further development (Anagdobrenostou & Doberstein, 2022; Brandt, 2023; Goecks et al., 2022).

The second major group of methods pertains to machine learning. Technological advances are causing more and more human activity to move into the digital sphere (Jensen & Iosifidis, 2023a). An illustrative example is the financial sector, which actively leverages the capabilities of artificial intelligence, extending them to additional AML areas: from data processing through know your customer (KYC) processes, customer due diligence (CDD) to transaction monitoring and customer risk scoring (Turksen et al., 2024). At the same time, this impacts the continuously increasing volume of suspicious transactions and activity reports submitted by obliged institutions to supervisory and law enforcement authorities (Clavijo Suntura, 2022). This has led to big data sets that are required to be processed by various institutions. A proposed solution by researchers for processing vast data sets involves applying automated data analysis techniques (Jensen & Iosifidis, 2023b). Among machine learning methods used for AML, we can distinguish supervised, unsupervised, semi-supervised, and reinforcement learning (Kute et al., 2021).

Supervised learning models (Alarab et al., 2020; Cunha & Brito, 2023; Krishnan et al., 2023) operate on previously labeled data. This means that someone or some process must apply these labels, for example, manually reviewing transactions and preparing datasets by tagging. Detecting ML consists of quantifying the extent to which a transaction (or a group of transactions) is similar to known fraudulent patterns.

Unsupervised learning (Krishnan et al., 2023) is a technique in which models are not supervised using a training dataset, such as a labeled set of transactions. Instead, the models find hidden patterns and insights from the data, which are then mainly used to detect unusual correlations. In the context of AML, the unsupervised method quantifies how a transaction (or group of transactions) diverges from the norm (Alarab et al., 2020). A combination of the above two categories is a semi-supervised algorithm.

Semi-supervised learning algorithms learn on both labeled and unlabeled datasets. The labeled datasets help the algorithm understand patterns and identify relationships. Unlabeled datasets teach the algorithm to identify and detect new patterns and those already trained (Ghalwash et al., 2020).

Reinforcement learning is based on a system of rewards and punishments and learns by interacting with the environment (Kute et al., 2021). This algorithm can be applied by optimizing the monitoring of financial transactions in real time. It means that the system can learn which transactions are suspicious, then prioritize them and minimize the number of false positives. As a result, the detection of illegal operations is improved.

Among the literature analyzed in this article, researchers employ methods like an unsupervised learning algorithm, such as the expectation-maximization (EM) algorithm and K-means clustering (Baek et al., 2019; Pettersson Ruiz

& Angelis, 2022). They were based on variables like cryptocurrency transaction data, average transaction value, the standard deviation of deposits, withdrawals, and transaction volumes (Baek et al., 2019). Other researchers used supervised learning algorithms (like Random Forest, Extra Trees, Gradient Boosting) (Alarab et al., 2020; Cunha & Brito, 2023; Huang et al., 2023; Lorenz et al., 2020; Serban et al., 2019), decision tree (DT) algorithms and the ID3 algorithm (Masrom et al., 2023; Tharani et al., 2024; Wang & Yang, 2007) in order to create AML rules or determine company's ML risk based on bank customer profiles. Part of the analyses (Alarab et al., 2020; Alarab & Prakoonwit, 2024; Alkhatib & Abualigah, 2023; Xia et al., 2022) was based on Graph Convolutional Network and Long-Short--Therm Memory Neural Networks (LSTM) (Lokanan, 2022; Wan & Li, 2024), financial transaction data and historical transaction relationships (Sousa Lima et al., 2022). Also worth noting were the Amaretto model (Labanca et al., 2022), an adaptation of eXtreme Gradient Boosting (XGBoost) (Elmougy & Liu, 2023; Vassallo et al., 2021), graph neural networks (GNN) or optimization algorithms (Gray Wolf-Bat, hybrid Gray Wolf-Bat) and distance algorithms (Levenshtein, Jaro–Winkler distance). They were successfully used on customer data or sanction lists and can be useful in identifying suspects (Serban et al., 2019).

A familiar method – blockchain analysis – was based mainly on transaction data (transaction history). It should be noted that criminals are developing increasingly sophisticated techniques (Lazarus, 2025). Examples include chain hopping, which involves rapidly converting assets between multiple blockchain networks to avoid tracking, and mixing services that aggregate funds from multiple users to obscure transaction traces (Kushelevitch, 2024). To further emphasize the severity of the situation, according to the Hacken (2024) report, losses due to blockchain-related exploits have reached \$2.9 billion, highlighting the growing complexity of financial crimes in the Web3 ecosystem. Researchers propose implementing advanced blockchain analytics based on machine learning in response to evolving threats. Models such as GNN and their extensions like Graph Convolutional Networks (GCN), Graph Attention Networks (GAT), or Heterogeneous Graph Neural Networks (HGNN) dominate AML analysis (Cheng et al., 2023; Ferretti et al., 2024; Guo et al., 2023; Pocher et al., 2023). According to (Lo et al., 2023), the Inspection-L model showed the highest performance in self-supervised anomaly detection, outperforming other methods in addressing blockchain anonymity challenges. The purpose of such methods was to create rules for detecting anomalies such as outliner detection or rapid movements of funds. The authors relied on cryptocurrencies, account balances, and transaction values (Farrugia et al., 2020; Oad et al., 2021). Researchers frequently evaluated their models using datasets such as Elliptic, Elliptic ++, Bitcoin-

Heist, and the Ethereum Phishing Dataset (Cunha & Brito, 2023; Elmougy & Liu, 2023; Tharani et al., 2024; Yang et al., 2023). The above research contributes significantly to improving the precision of AML systems and reducing the occurrence of false alarms while monitoring suspicious activity.

One recurring vulnerability of machine learning methods is the need for more interpretable and explainable machine learning models. While many algorithms achieve high accuracy, their "black-box" nature often complicates their adoption in highly regulated institutions, such as financial or regulators, where transparency in decision-making is fundamental (Kute et al., 2021). Current models designated to detect ML are often trained on limited, specialized datasets, raising concerns about their generalizability to broader, real-world transactional data.

A solution worth considering for data confidentiality is the creation of research centers within individual institutions. Cooperation between financial institutions, regulators, and researchers might be based on creating projects in research groups and workshops or conferences. Such research groups would undoubtedly bring value added to the development of new systems or the automation of current processes. The results of such cooperation could be programs for real-time detection of suspicious behavior and its direct reporting to law enforcement agencies. These systems would respond to strategic requirements and follow current trends. Close cooperation between experts from different environments, focused on building and testing benchmark datasets and methodologies, could ensure that models are properly adapted. One of the key barriers to collaboration between researchers and practitioners is regulations restricting data sharing and processing. Establishing a secure data-sharing framework, such as public-private partnerships (PPPs) or anonymization techniques, can help mitigate these concerns while ensuring compliance with legal requirements.

Another group of methods were those from the fields of statistics and econometrics. Articles classified in this group utilized methods such as statistical analysis of capital flows with AML measures (Loayza et al., 2019), least squares methods (Javaid & Arshed, 2022), analysis using Pearson's correlation coefficient (Al-Kasawnih, 2019), or the Multiple Indicators Multiple Causes (MIMIC) method (Saenz & Lewer, 2023; Schneider, 2010). The latter contributed most significantly to quantifying the ML scale, as it enables the estimation of latent ML phenomena based on observable variables such as the number of suspicious transactions and tax gaps (Saenz & Lewer, 2023). Conversely, Principal Component Analysis (PCA) methods facilitated the construction of AML indices (Tiwari et al., 2021). The authors' data were obtained from financial institutions (mainly banks) and national or international statistical bodies. Using international statistics (such as the quality of the education system, the level of bureaucracy in the countries concerned, the size of the shadow economy, financial flows, and cash turnover), the researchers attempted to estimate the volume of ML.

One method used by researchers (Perez et al., 2012; Roman et al., 2022; Roman & Schaefer, 2023; Walker & Unger, 2009) related to statistic and econometric techniques was the gravity-based model and its modifications. The estimates were based on an adaptation of a gravity model derived from physics to estimate the volume of international trade exchange, which John Walker (1999) introduced in 1999 to estimate the scale of ML. The gravity model describes the geographic distribution of criminal proceeds that require laundering to conceal their illegal source (Ferwerda et al., 2013). The transfer of funds between countries depends on the "attractiveness" of the destination country and the distance between them (Walker & Unger, 2009). Authors extended this model with variables such as FDI (foreign direct investment) flows, international trade, AML regulations, number of criminal proceeds, membership in SWIFT and the Egmont Group, and other geopolitical considerations (Ferwerda et al., 2013; Perez et al., 2012; Roman et al., 2022; Roman & Schaefer, 2023). The data sources were mainly based on discrete variables but sometimes included information from national financial intelligence units (FIU) and law enforcement agencies. For example, Ferwerda et al. (2020) relied on Suspicious Transaction Reports (STRs) data from the authorities in the Netherlands. STRs (or their equivalents) are submissions by reporting entities to their respective FIUs and verified by FIU's analysts. These reports include information about the transaction, among others: originator (sender) and destination of the transaction (beneficiary), the value of the transaction, the timestamp, and a description of suspicious activity. Using transaction data empowers authors to conduct IFF estimations and identify the main high-risk areas (Khan et al., 2018).

A key challenge facing traditional statistical and econometric models in estimating IFF is their limited ability to adapt dynamically to the emergence of new factors or variables. As these models become increasingly complex with additional variables, challenges with multicollinearity, endogeneity, and the significance of individual parameters arise (Feridun, 2024). This can lead to the need to frequently reevaluate model assumptions and parameters, reducing the responsiveness of such models to real-time changes in financial crime. Therefore, a critical research gap is a comparative analysis of these methods. In particular, it would be valuable to assess the effectiveness of econometric approaches, such as the gravity model, compared to machine learning-based models in estimating IFF. Such a comparative study could illuminate the strengths and limitations of each approach, providing insights into improving both the accuracy and adaptability of financial crime detection methodologies.

Research using the risk-based approach (Akartuna et al., 2024; Islam & Nasir, 2020; Riccardi et al., 2019; Tropina, 2014) aimed to identify clients and financial transactions with increased risk. This involved verifying the clients' identities and the payment methods, as well as quantitative variables, including, among others, income from illegal markets and the intensity of cash transactions.

In other papers, particularly those involving economic analysis (Biagioli, 2008; Lillo et al., 2017; Solaiman, 2016), the authors focused on the following variables: market data, archival data on amnesties for criminals, trends and directions of ML. Studies based on TBML (Cassara & Poncy, 2015; Marzouk, 2022; Milon & Zafarullah, 2024; Umar, 2023) used factors like interviews, information about bank clients and their transactions, AML regulations, exploratory research, TBML practices, and country risk. Irwin et al. (2012), in their study based on the methods of Unified Modelling Language, utilized variables such as 184 typologies of ML and terrorist financing containing financial transactions and interactions between entities. Meanwhile, papers based on case studies (Di Nicola & Terenghi, 2016; Schneider, 2004; Verrier, 2020; Woda, 2007) used proceeds-related criminal cases (POC) from the Royal Canadian Mounted Police management information system as well as interviews, court records, and police reports.

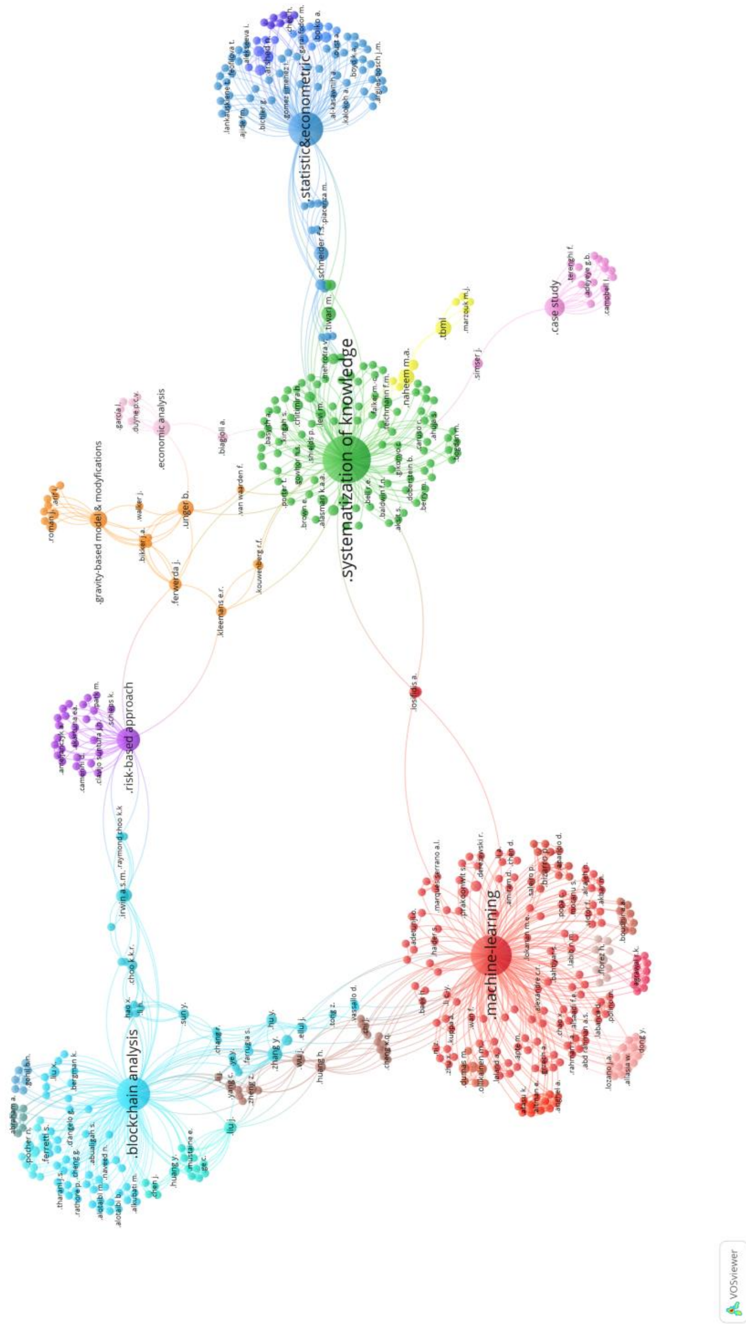
A systematic literature review has identified various methods for detecting and estimating IFF and ML, ranging from supervised and unsupervised machine learning techniques to econometric models and risk-based approaches. Although these methodologies contribute significantly to fraud detection and ML prevention, several important limitations can be identified. Starting with the systematization of knowledge undoubtedly supports the synthesis of a large amount of research (Goecks et al., 2022). This process facilitates the identification of research gaps, available methods, and variables. Moreover, it can help propose regulatory solutions (Brandt, 2023). However, it does not identify new techniques but instead describes existing ones (Jensen & Iosifidis, 2023a; Llaque Sánchez et al., 2023; Tiwari et al., 2024a; Warikandwa, 2023). The case study allows for detailed correlations and the creation of suggestions for regulators but has a limited ability to generalize conclusions. (Schneider, 2004; Verrier, 2020). The economic analysis method is best at assessing the impact of ML on the economy through the application of macroeconomic perspectives but will not be effective for detecting individual fraudulent transactions (Lillo et al., 2017; Unger, 2013). TBML and risk-based approaches are suitable for assessing transaction risk and identifying suspicious trading patterns. However, researchers using these methods face difficulties obtaining complete risk data and high monitoring costs (Cassara & Poncy, 2015;

Koo et al., 2024). The UML method is appropriate for the design of analytical architecture and facilitates communication between reporting institutions and law enforcement agencies. Nevertheless, the modeling of execution conditions for suspicious transactions is not entirely precise (Irwin et al., 2012). Statistical and econometric methods perform well in quantitative analysis, hypothesis testing, and trend prediction (Kalokoh, 2024; Levchenko et al., 2019; Li et al., 2024; Tiwari et al., 2021) and analysis of the attractiveness of countries for IFFs (Khan et al., 2018; Roman & Schaefer, 2023). However, they are dependent on the quality of the input data (Saenz & Lewer, 2023), may not be able to follow the dynamic changes in real systems (Bojnec & Fertő, 2018; Reite et al., 2023), and have difficulty grasping complex integrations (Babatunde & Afolabi, 2023). Machine-learning methods, especially those based on blockchain analysis, are very successful at the automatic detection of suspicious transactions, automatic scaling, and rapid adaptation to new ML techniques (Masrom et al., 2023; Nayyer et al., 2023; Pocher et al., 2023; Shadrooh & Norvag, 2024; Tertychnyi et al., 2022; Wan & Li, 2024). They are suitable for handling large volumes of data, with a low vulnerability to errors due to human interference (such as computational errors). Unfortunately, they have large computing requirements, which translates directly into maintenance costs (Wan & Li, 2024), risk of misclassification (Cheng et al., 2023), and difficulties in interpreting the results due to the models acting as "black boxes" (Koo et al., 2024; Pocher et al., 2023).

While the literature analyzed in this paper seems already deeply developed, some gaps still deserve further exploration. Most of the studies rely on transaction data provided by financial institutions (Reite et al., 2023; Tertychnyi et al., 2022) or publicly available blockchain data (Alkhatib & Abualigah, 2023; Elmougy & Liu, 2023; Ferretti et al., 2024). Public data sets such as Elliptic Dataset, Bitcoin Heist Dataset, or Ethereum phishing dataset (Tharani et al., 2024) are compliant with GDPR and enable low-cost testing of algorithms, but may affect the quality of analysis by not covering the full range of real financial fraud are compliant with GDPR and enable low-cost testing of algorithms, but may affect the quality of analysis by not covering the full range of real financial fraud. Real financial data have limited access as they are often covered by strict regulations such as privacy. However, their use improves the effectiveness of models (Cheng et al., 2023; Koo et al., 2024). Analyses based on integrating multiple data sources (reporting institutions, law enforcement, adverse media, or blockchain transactions) in real time are worth conducting in the future. Nevertheless, data anonymization and privacy are significant challenges. Most of these data contain financial secrecy clauses that are not publicly available. Adequate anonymization of test data still poses a significant challenge in regulation. Noticeably, there is a growing demand for artificial intelligence models to provide transparency in decision-making processes (Kute et al., 2021). Machine learning methods are suitable for handling large volumes of data, with a low vulnerability to errors due to human interference (such as computational errors). Nevertheless, the interpretability of these methods and their adequate anonymization still pose a significant challenge in terms of regulation.

The final phase of this study involves the development of a bibliometric visualization, presenting the connections between the authors and the techniques they utilized. The results of a textual narrative synthesis of 234 articles were imported into VosViewer software (Eck & Waltman, 2011). The results are shown in Figure 5. It illustrates the following clusters: the systematization of knowledge, machine learning, economic analysis, blockchain analysis, TBML, case study, statistic, econometric, risk-based approach, and gravity-based and its modification model. Systematization of knowledge often provides a starting point for further research. Focusing on theoretical assumptions is a prelude often used by researchers to identify gaps and directions for further research. This relationship is also confirmed in Figure 5 because connections between authors focusing their research interests on theoretical approaches, and their occurrence in other clusters can be observed. Some of them have pursued case studies (Otusanya & Adeyeye, 2022; Schneider, 2004; Woda, 2007) as well as statistical and econometric methods (Babatunde & Afolabi, 2023; Hanif et al., 2023; Wronka, 2022). Others have focused on risk-based methods (Akartuna et al., 2024; Cindori & Slovic, 2017; Ferwerda & Kleemans, 2019; Koo et al., 2024), blockchain (Alkhatib & Abualigah, 2023; Cheng et al., 2023; Cunha & Brito, 2023; Oad et al., 2021; Phetsouvanh et al., 2018), and even advanced machine-learning techniques (Alexandre & Balsa, 2023; Altman et al., 2023; Jullum et al., 2020; Nayyer et al., 2023; Pettersson Ruiz & Angelis, 2022; Sheu & Li, 2021).

Figure 5. A collection of methods used in the authors' analysis to estimate IFF and ML based on 234 papers



Source: Author's own calculations.

4. Discussion

One of this article's primary objectives is to systematically organize the vast body of existing knowledge in the fields of IFF and ML, especially existing methods of detection and estimation of research topics. This review integrates an extensive array of sources to capture and reflect the current trends in this continually evolving field.

This paper provides detailed guidelines for conducting a systematic literature review, facilitating identifying best practices across multiple dimensions of the research field, including regulatory frameworks, economic impacts, and technological advances. Sections two and three describe the methods and steps required to replicate this research, enabling future scholars to track emerging trends in detection techniques and variables. Such a process is crucial because the dynamic nature of financial crimes and regulatory responses requires regular updates to research methodologies. Sequentially, through an application of screening, thematic synthesis, and textual narrative synthesis, this review identifies not only current gaps but also highlights successful strategies used in various jurisdictions, which analysts in obliged institutions, regulatory bodies, FIUs, and law enforcement agencies can leverage.

Adopting a multidimensional approach, this article goes beyond a simple survey of detection and estimation methods. It offers a holistic view of the entire spectrum of literature related to IFF and ML, covering different dimensions such as the AML framework, the effectiveness of regulations, the roles of different actors, and the economic impact of IFF. This allows those interested in the subject to focus on specific dimensions of knowledge relevant to their requirements, whether on legal aspects, technological innovations, or economic factors. The broad scope of this review allows the identification of emerging trends and best practices from different regions, making it a worthwhile tool for improving national and international responses to financial crime.

Thematic synthesis allowed us to answer the question: What is the current state of knowledge on IFF and ML? The dimensions identified in previous research (Tiwari et al., 2020) and incorporated into the thematic synthesis (AML framework, regulations and their effectiveness, the role of actors and their relative importance, impact of ML on the economy, new ML opportunities, IFF and ML detection, scale of IFF and ML) show a wide range of issues related to IFF and ML. Over the years, the number of publications on IFF and ML has expanded, confirming the relevance of these phenomena. This is primarily due to the implementation of novel legislation in the field of AML/CFT and scholars' examination of its efficiency. The topic gained popularity due to technological advancements, including Web3, blockchain, and artificial intelligence, which have transformed the landscape of financial transactions and fraud detection (Hacken, 2024).

The topics addressed by the authors in the context of ML have evolved over the years. Originally, IFF or ML were only signaled as additional areas of research concerning crime in general. Then, the authors focused on a more in-depth exploration of the subject. Over time, AML recommendations have emerged, but new threats such as terrorism, VAT carousels, and cybercrime have also appeared. Similar conclusions have also been reached by Tiwari et al. (2020, 2024a).

To comprehensively cover the subject of IFF and ML, the authors of the reviewed papers employed an interdisciplinary approach to foster mutual inspiration across different scientific fields. For example, understanding the IFF and ML phenomenon requires knowledge of legal sciences in order to analyze current regulations. Knowledge of the physics, geography, and economics sciences enables the creation of an appropriate gravity-based model for IFF estimations. Preparation of an appropriate machine learning method requires extensive and advanced knowledge in the field of computer science. Subsequent studies should also rely on the cross-fertilization of knowledge to develop methods suitable for addressing the identified research gaps (Biagioli, 2008; Ferwerda et al., 2020).

The textual narrative synthesis enabled the identification and systematization of research methods utilized by authors in previous studies. It answered the following questions: What are the methods of detecting and estimating IFF and ML in the literature? and What variables/proxies were used to estimate IFF and ML? The results of the textual narrative synthesis showed that the literature in question is still based mainly on the systematization of knowledge and case studies. The main problem raised by the authors using the method of systematization of knowledge was the lack of access to data, enabling quantitative research. Part of the research was based on statistical and econometric methods, for which authors used the following variables: total tax rate, diversion of public funds, amount of confiscated money, cash used per capita in criminal activities, the number of prosecuted persons criminal activities such as drug dealing, illegal weapon sales, increases in domestic crimes as well as official GDP per capita and the effectiveness of the legal system (Schneider, 2010). Noteworthy is the gravity-based model and its modification, which holds particular interest. These methodologies employed variables such as GDP, the distance between pair of countries, common language, colonial history, Egmont Group, and SWIFT membership, corruption perception index, discrete data of number and value of transactions between pair of countries (Biagioli, 2008; Perez et al., 2012; Roman et al., 2022). Some authors (Ferwerda et al., 2020) based their studies on STR data obtained from the authorities in the Netherlands. The next category of methods the authors employed comprises machine learning techniques, particularly those based on blockchain analysis. These have undoubtedly been a growing trend, especially in the past two years. Examples of variables used in these methods include data based on virtual currency transactions (transaction amount and value, the average value of transaction differences, variance of those values, timestamp, number of transactions per address, standard deviations of amounts deposited and withdrawn, number of linkages between addresses, transaction glocalization). Among the databases used by the authors were both actual blockchain databases (Elliptic, Ethereum Blockchain, BitcoinHeist) and synthetic datasets (AMLSim, fraud detection simulations). The detection and estimation of IFF and ML are conducted using methods like supervised learning algorithms (DT, RF, LR, SVM, XGBoost, GCN, GAT, HBOS, LTSM) (Elmougy & Liu, 2023; Yang et al., 2023), unsupervised learning algorithms (IF, DeepAutoencoder, Elliptic Envelope, GNN Local Outliner Factor), especially in blockchain analysis (Cunha & Brito, 2023; Yang et al., 2023), for which authors relied on similar data like in machine-learning techniques methods.

Notwithstanding the seemingly advanced research in analyzed literature, as indicated by researchers (Ferwerda & Unger, 2021), none of the current methods used to estimate IFF and ML scales are fully effective or have been validated by official international organizations dealing with AML. Textual narrative synthesis showed some dependencies between individual studies, identifying their common features (models and measures used).

5. Conclusions

Although the existing research on IFF and ML literature appears to be well--developed, it is essential to emphasize the ongoing need for a continuous follow-up of newly published articles and to monitor which research gaps remain unaddressed. Based on the findings of this study, it would be worthwhile to systematize knowledge further by conducting a quantitative analysis through a meta-analysis of the relevant literature. Such a meta-analysis could compare the methods used, the variables applied in calculations, the models employed, and the results obtained. Its results would benefit not only scholars but also practitioners in financial institutions, law enforcement, and regulatory bodies by supporting the automation of their analyses and enhancing the capabilities of their artificial intelligence systems.

The findings also present practical implications aimed at supporting regulators in effectively addressing ML and IFF. There remains a research gap in the practical solutions offered to LEAs by the scientific community, which would allow an ongoing response to new ML methods. This will enable researchers to estimate the scale of IFF and ML worldwide and by individual geographic regions and sectors.

A particularly noticeable trend over the past two years has been the application of machine learning methods in improving the detection of suspicious behavior. This sends an important signal to academics and practitioners, including law enforcement agencies, regarding the direction of the AML system. Increased cooperation in working groups, conferences, and practitioner lectures is crucial. Sharing information about models and methods by researchers and access to actual (or synthetic) data for model testing is essential, although it requires appropriate regulation. As a result, effective models will be able to react quickly to emerging risks, thus contributing to the reduction of IFF and ML phenomena.

Summarizing, defining the most suitable method and tools for accurately calculating the amount of IFF and proceeds from ML remains challenging. These challenges stem from several key factors: the complexity of ML processes, the continual emergence of new criminal methods, variations in legal and regulatory frameworks, limitations in data availability and quality, and the diversity of methodologies and variables used. This review underscores the critical need for further research to refine methods and identify novel variables capable of addressing the rapidly evolving threats in the fields of IFF and ML. The advancement of a valid model requires the appropriate selection of variables, the standardization of their source, and the scale of the research (from local to global).

Despite the important findings, this study has some limitations. Firstly, the WOS and Scopus databases do not always contain publications exclusively from leading journals, which may affect the completeness and quality of the collected literature. It is recommended that future research be more selective in the choice of sources. Targeting literature from publications of a higher quality standard will provide more accurate views of the issues analyzed. This approach may increase the reliability of the results and provide a stronger basis for practical recommendations for researchers and regulators. The second limitation is the restricted access to key sources held by libraries with limited public access. Although this paper encompassed all available studies, 81 were excluded from textual narrative synthesis due to a lack of access to the full-text articles.

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Appendices

Table A1. Ten most cited countries via Scopus

Ord. No.	Country	Documents	Citations
1	United States	144	2,158
2	United Kingdom	146	1,794
3	Australia	78	1,035
4	Netherlands	44	858
5	Mexico	5	609
6	Canada	44	569
7	Germany	40	480
8	China	46	427
9	Switzerland	30	422
10	Italy	50	395

Source: Author's own calculations.

Table A2. Ten most cited countries via Web of Science

Ord. No.	Country	Documents	Citations
1	USA	21	223
2	Netherlands	5	142
3	Australia	5	129
4	England	12	127
5	Italy	6	77
6	Canada	5	44
7	Japan	2	36
8	Austria	1	35
9	Singapore	3	34
10	South Korea	3	32

Source: Author's own calculations.

Table A3. Ten most cited authors via Scopus

Ord. No.	Author	Documents	Citations
1	B. J. Palifka	1	498
2	S. Rose-Ackerman	1	498
3	M. A. Naheem	24	385
4	B. Unger	12	357
5	M. Levi	9	295
6	J. Ellul	2	222
7	J. Wu	5	172
8	G. Azzopardi	1	169
9	S. Farrugia	1	169
10	P. Alldridge	3	168

Source: Author's own calculations.

Table A4. Ten most cited authors via Web of Science

Ord. No.	Author	Documents	Citations
1	B. Unger	2	113
2	J. Walker	1	78
3	N. Raphaeli	1	55
4	S. Melzer	1	39
5	L. Shelley	1	39
6	H. Fujiki	1	36
7	A. S. M. Irwin	2	36
8	G. Ardizzi	1	35
9	J. A. Bikker	1	35
10	H.-H. Chang	1	35

Source: Author's own calculations.

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