

ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF DETECTING FRAUD INVOLVING EUROPEAN FUNDS

Ana-Maria BUZDUGAN

Stefan cel Mare University of Suceava, 720229, Romania

ORCID: 0009-0005-7529-401X

annabuzdu@yahoo.com

Elena HLACIUC

Stefan cel Mare University of Suceava, 720229, Romania

ORCID: 0000-0003-0601-748X

elena.hlaciuc@usm.ro

Abstract

Fraud or irregularities associated with the management of European funds represent a major risk to the European Union budget. In this study, we examined from a qualitative and exploratory perspective the potential role of artificial intelligence in supporting the detection of fraud involving European funds. The research is based on a bibliometric analysis of scientific literature indexed in the Web of Science database for the period 2013-2025, combined with a qualitative analysis of institutional reports issued by the OLAF and the EPPO for the period 2020-2024. The institutional reports are used to illustrate the current scale and evolution of fraud cases affecting European funds, while the academic literature is analyzed to identify relevant artificial intelligence techniques, research trends and implementation challenges. The findings indicate a growing academic interest in the use of artificial intelligence technologies-such as machine learning, data mining and anomaly detection-for financial fraud detection. However, the application of these technologies in the specific context of European funds remains limited and fragmented. The analysis also highlights data sources, uneven data quality, legislative differences between member states and restricted access to data on beneficiaries and public procurement. Based on these findings, the paper proposes a conceptual model that integrates artificial intelligence as a complementary analytical tool within existing anti-fraud frameworks, with an emphasis on risk-based analysis, data pre-processing and human validation. The study concludes that artificial intelligence can improve the detection of fraud involving European funds, provided that adequate investments are made in digital infrastructure, data governance, staff training and interinstitutional cooperation.

Keywords: European funds; fraud, artificial intelligence; fraud detection

JEL Classification: M42, M41

INTRODUCTION

The management of European funds is one of the essential pillars of the European Union's cohesion and development policies. The complexity of procedures, the high volume of transactions, and the diversity of actors involved lead to a vulnerable terrain for the emergence and growth of irregularities and fraud. With the number of projects financed by European funds on the rise, there is a growing need for modern and effective fraud detection tools, especially in situations where traditional methods of audit, control, and financial analysis are overwhelmed by the complexity of fraudulent schemes and the increasing volume of data.

Despite the growing number of studies on financial fraud detection and the increasing use of artificial intelligence in private sector applications, the literature addressing the specific context of fraud involving European funds remains fragmented and limited. Most existing studies focus either on generic fraud in financial statements or on national anti-fraud mechanisms, without sufficiently integrating institutional data sources, regulatory constraints, and the multi-level governance structure specific to European Union funds.

The purpose of the study is to identify the extent to which artificial intelligence can contribute to strengthening anti-fraud mechanisms at European level and what conditions are necessary for the effective implementation of an artificial intelligence-based model designed to detect fraud involving European funds. To achieve this purpose, the research pursues the following objectives:

O1. Identifying the main artificial intelligence technologies and tools used in financial fraud detection, with applicability in the management of European funds.

O2. Assessing the main limitations and challenges related to the application of artificial intelligence in this field, such as the lack of centralized databases, restricted access to information, and regulatory differences between Member States.

O3. Proposing a conceptual model that integrates digital technologies into the process of early identification of fraud risks, based on data already available at the institutional level.

By addressing these issues, we aim to contribute to the development of integrated perspectives on the modernization of anti-fraud systems and to strengthen the role of artificial intelligence in protecting the financial interests of the European Union.

I. LITERATURE REVIEW

Although the implementation of advanced technological solutions remains a central pillar in fraud detection strategies, a review of the literature reveals an emerging convergence. Researchers are increasingly investigating how organizational characteristics and human competencies underpin or can amplify the effectiveness of these tools (Cosmulese, 2024). In addition to technical solutions, recent literature highlights the importance of human factors, such as emotional intelligence, for organizational efficiency (Grosu et al., 2025), providing a relevant perspective for investigating the role of artificial intelligence in combating fund fraud.

We began this research by querying the Web of Science database to identify research trends on the use of artificial intelligence in the context of detecting fraud involving European funds. To this end, we used a Boolean search for the keywords "EU funds" or "European funds" or "structural funds" or "cohesion funds" or "EU budget" and "fraud" or "financial fraud" or "fraudulent irregularities" or "corruption" or "embezzlement" or "misappropriation of funds" and "fraud detection" or "fraud investigation" or "fraud risk indicators" or "forensic accounting" or "forensic investigation" and "artificial intelligence" or "AI" or "neural networks" or "intelligent systems" or "digital tools", obtaining a total of 44 publications, articles, reviews or papers from various fields of expertise, published between 2013 and 2025. Most articles were published between 2024 and 2025, which indicates a high level of research interest in fraud detection in recent years. This may be due to an increase in the number of fraud cases or to interest in the use of digital technologies for detecting them.

The most cited article, with 189 citations, is "Mining corporate annual reports for intelligent detection of financial statement fraud – A comparative study of machine learning methods" published in 2017 by authors Petr Hajek and Roberto Henriques.

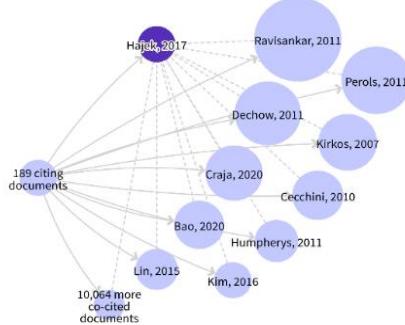


Figure 1. Co-citation map for the article "Mining corporate annual reports for intelligent detection of financial statement fraud – A comparative study of machine learning methods"

Source: Web of Science

The co-citation structure illustrated in *Figure 1* provides insight into the intellectual foundations of fraud detection research. The central position of the study by Hajek and Henriques (2017), together with its strong co-citation links to works focusing on revenue management, financial misreporting and analytical models, indicates that fraud detection research builds on a well-established literature that combines accounting theory with advanced analytical techniques. The density and proximity of the nodes suggest a high level of conceptual interconnection between the methodological approaches used for detecting financial anomalies and the broader field of financial fraud in the private and corporate sector with limited visibility of studies explicitly addressing public finance or European funds. This observation supports the need for a broader bibliometric exploration aimed at identifying how artificial intelligence concepts are connected to fraud detection in different institutional contexts. This study analyzed whether a better system for identifying financial fraud could be created using both data from companies' financial reports and information about managers' involvement in these documents (Hajek & Henriques, 2017). The most relevant research paper generated by Web of Science is "An international analysis of fraud detection in European structural and investment funds" published in 2024 by Baumgärtler et al. (2024) in the European Journal of International Management, presenting a complete semantic correspondence with the terms introduced in the Boolean formula, namely fraud, European funds, detection mechanisms. This study identified specific factors in each country that could help to detect fraud involving European funds more effectively.

In order to identify the research correlations regarding artificial intelligence in the context of detecting fraud involving European funds, a keyword co-occurrence analysis was performed on the publications retrieved from the Web of Science database (2013–2025), using the VOSviewer bibliometric software (see Figure 2).

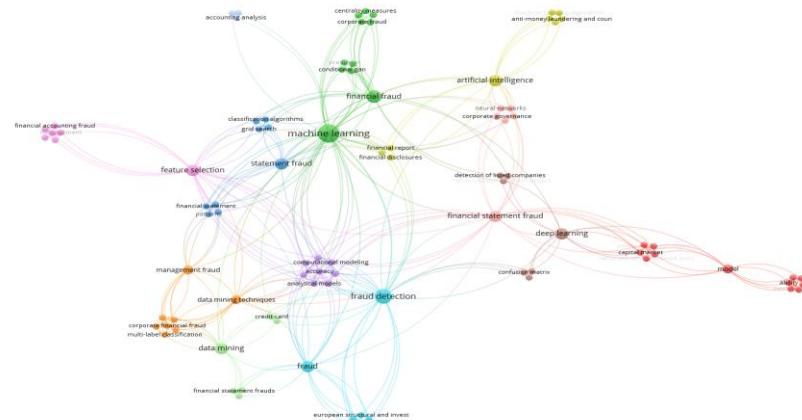


Figure 2 View co-occurrence cluster using all keywords

Source: Own elaboration with the help of VOSviewer

As shown in Figure 2, the analysis generated a total of 94 items grouped into 12 thematic clusters, reflecting the main conceptual and methodological directions in the literature. The central core is represented by the "*fraud detection*" cluster, which is closely connected to both fraud schemes involving European funds and technology-oriented clusters. Among these, "*machine learning*" emerges as the most frequently used concept, showing the highest number of occurrences and the strongest co-occurrence links with keywords such as "*data mining*", "*deep learning*", and "*artificial intelligence*". The research field is structured around this central core, highlighting the dominant role of predictive models, classification algorithms, and neural networks in identifying financial anomalies and fraudulent behavior. Several groups emphasize methodological aspects, including feature selection, overall learning models, and performance evaluation techniques, indicating the increasing sophistication of AI-based fraud detection systems. In parallel, institutional and governance-related groups incorporate concepts such as "*anti-fraud strategy*", "*corruption*", "*European Union*", and "*transparency*" linking technological approaches to the normative context of fraud prevention.

Overall, the connections between these groups suggest that, despite the widespread use of artificial intelligence in general fraud detection research, its specific application to fraud involving European funds remains relatively unexplored. This gap supports the relevance and novelty of the current research topic.

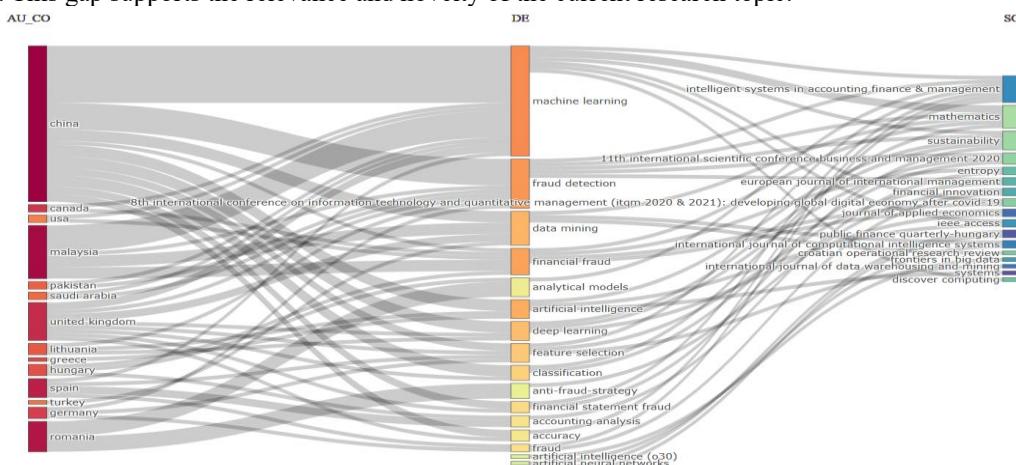


Figure 3. Map of the Three-Field Plot

Source: Bibliometrix (Biblioshiny)

The Three-Field Plot map indicates that the main contributions to methodological research on fraud detection come from countries such as China, Canada, and the US, countries that dominate the technology sector globally through research focused on machine learning, data mining, and artificial intelligence, published in journals such as IEEE Access, Entropy, and Frontiers in Big Data (Cosmulese & Macovei, 2024). In European countries such as Romania, Spain, Greece, and Germany, topics related to financial fraud, anti-fraud strategy, and financial statement fraud can be found in journals such as the European Journal of International Management, Sustainability, and the Journal of Applied Economics. The structure of the graph shows that studies on fraud detection involve an intersection between advanced technologies and

applied economic research, which includes analyzing financial statements, detecting accounting fraud, deviations, and irregularities, identifying fraud risks, auditing, and controlling the use of public funds, including their management.

Public financial information about companies and the content of annual reports can help identify companies that may be committing fraud, and analysts' estimates of revenue and profit can flag companies with suspicious behavior (Crain et. al., 2019). The literature presents several modern methods of fraud detection that use intelligent programs capable of analyzing data and identifying suspicious behavior, such as neural networks, decision trees, support vector machines, evolutionary algorithms, and automatic text analysis (Hajek & Henriques, 2017).

Regression analyses conducted at the EU member state level have revealed significant correlations between the fraud detection rate and indicators of fraud use and the level of irregularities, fraud monitoring, and the level of economic fraud monitoring transparency of an EU country (Baumgärtler et al., 2024).

II. RESEARCH METHODOLOGY

This research is part of an exploratory and applied research framework, with a predominantly theoretical orientation, which aims to identify and systematize the main approaches, technologies, and challenges related to the use of artificial intelligence in the detection of fraud involving European funds. Given that the application of artificial intelligence in this specific field is still in its infancy, particularly in the context of European public finances, the methodological approach aims to identify points of convergence between academic research, institutional practices, and the existing regulatory framework governing the protection of the European Union's financial interests.

The research was conducted in two main stages. In the first stage, a documentary and bibliometric analysis was carried out based on academic sources indexed in the Web of Science database and official documents issued by European institutions with responsibilities in fraud prevention and detection. The bibliometric analysis covered the period 2013-2025 and aimed to identify research trends, dominant themes, and methodological approaches related to artificial intelligence and fraud detection. The results were processed and visualized using VOSviewer and Bibliometrix software, which allowed the identification of groups of keywords that appear together and thematic research directions. The second stage consisted of a qualitative and interpretative analysis of the content of institutional reports and regulatory documents, focusing on cases of fraud involving European funds in the period 2020-2024. This stage aimed to examine existing fraud detection mechanisms, risk indicators, and institutional tools, as well as their limitations in the context of increasing data volumes and the complexity of fraud schemes. Particular attention was paid to the role of digital systems and analytical tools in supporting risk-based controls and early detection processes.

The method used was predominantly qualitative, with an emphasis on content analysis and triangulation of sources. The validation of interpretations was ensured by cross-checking academic results with institutional data and by integrating bibliometric results with qualitative information. This approach supports the development of a coherent conceptual model and provides a structured basis for future empirical research and the potential implementation of AI-based fraud detection models.

III. RESEARCH RESULTS AND DISCUSSIONS

Knowledge of the current situation regarding the evolution of the number of cases of fraud involving European funds is an essential starting point for assessing the effectiveness of existing detection mechanisms and for substantiating the need to use advanced analytical tools. In this context, the analysis of the evolution of fraud cases must be reported to the institutional framework responsible for identifying and investigating these practices at the European Union level.

At the European Union level, OLAF investigates fraud against the EU budget, corruption, and serious misconduct within European institutions and develops anti-fraud policy for the European Commission (European Commission, f.a.). Similarly, the European Public Prosecutor's Office (European Parliament, f.a.), which began operating in 2021, is an independent and decentralized EU body with powers to investigate, prosecute, and bring to trial persons accused of crimes affecting the EU budget.

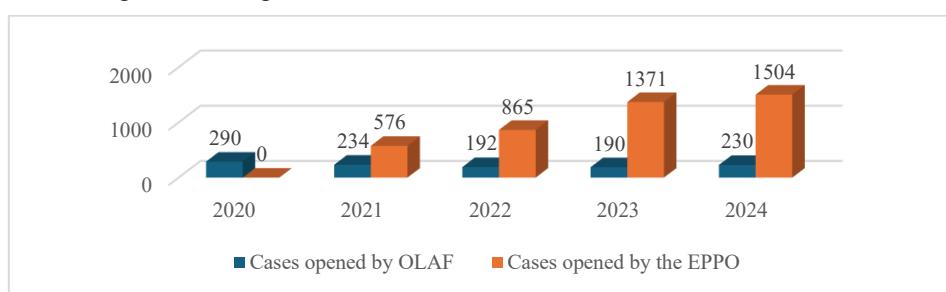


Figure 4. Evolution of the number of cases opened by EU structures with powers to detect fraud involving EU funds, 2020-2024

Source: Own elaboration based on information taken from the European Commission website

The evolution presented in Figure 4 reflects not a reduction in fraudulent activity, but a redistribution of institutional responsibilities following the establishment of the EPPO. While OLAF's caseload decreased due to its preventive and administrative role, the sharp increase in cases handled by the EPPO indicates a growing number of criminal investigations involving fraud, corruption, and misappropriation of EU funds. This trend suggests an increase in both the volume and the complexity of fraud cases, particularly those requiring judicial investigation. In this context, traditional control mechanisms based on ex-post verification and manual checks become increasingly insufficient. The current situation highlights the need for more advanced analytical approaches capable of identifying fraud patterns at an early stage and across large datasets, thereby supporting risk-based controls and targeted investigations.

Methodologically, this supports the need for analytics that can screen large numbers of projects ex ante, link dispersed signals across authorities, and prioritize scarce investigative resources through risk scoring. Hence, AI-enabled anomaly detection is relevant not as a replacement for legal assessment, but as a front-end triage layer that improves targeting and timeliness.

Member States shall apply the same measures to combat fraud affecting the financial interests of the Union as they apply to protect their own financial interests (European Union, 2016). For example, Romanian national legislation (Law 66, 2011) provides for a series of fraud indicators to be taken into account, based on the principle of good practice, in order to identify indications of possible fraud in situations where the risk assessment indicates a high risk of fraud.

There are four types of fraud indicators, which are as follows:

Table 1. Fraud indicators

Indicator	Description	Role	Detection method
1. Single-factor indicators	- simple alarm signal, an error, a deviation from internal controls, or unusual transactions, such as: a double payment, an invoice without supporting documents, an unusual transaction;	- quickly alerts and triggers spot checks;	- manually, through audit controls, direct observation;
2. Compound indicators	- combines several factors that individually do not raise suspicion, but together signal a risk, such as a high-value transaction with a new beneficiary and an urgent payment;	- detects complex fraud; - useful in overall risk assessment and prioritization of controls;	- semi-automatic, using statistical formulas;
3. Random indicators	- random selection of transactions for detailed verification, such as monthly sampling of 10% of payments;	- can detect hidden or atypical fraud;	- manual or automated, using sampling methods, which can sometimes be generated by software;
4. Model-based indicators	- uses algorithms or artificial intelligence to compare behavior, such as: AI systems can detect deviations in public procurement processes.	- can detect subtle anomalies in real time from a large volume of data;	- automated, through intelligent systems: machine learning, neural networks;

Source: Adapted after Crain et al., 2019

Next, Figure 5 shows the stages of fraud detection, integrating both classic financial analysis and modern investigation methods, such as the use of digital means, data mining, artificial intelligence, and digital forensics, to detect complex fraud hidden in large volumes of transactions or in digital environments (including cryptocurrencies). Data collection represents the foundation of the entire process, as the quality and completeness of the collected information directly influence the effectiveness of subsequent analyses.



Figure 5. Stages of fraud detection

Source: Ali et al., 2024, p. 543

The analysis of financial documents enables the identification of initial anomalies and risk indicators, which can then be further clarified through interviews aimed at understanding the context, decision-making processes, and potential motivations behind suspicious activities. The final stage, involving the use of digital techniques, plays a critical role in modern fraud detection by allowing the processing of large volumes of structured and unstructured data, identifying hidden patterns, and uncovering complex fraud schemes that may not be detectable through traditional methods alone.

Table 2. Mechanisms for combating fraud involving European funds

Mechanisms		Description	Benefits
The EU's anti-fraud magnifying glass program	AFIS (Anti-Fraud Information System)	- IT system managed by OLAF that enables the rapid and secure exchange of information on fraud between national and EU authorities.	- improves cooperation between member states; - enables faster identification of cross-border fraud schemes; - increases the efficiency of anti-fraud investigations.
	IMS (Irregularities Management System)	- a system integrated into AFIS through which authorities report irregularities and suspected or confirmed cases of fraud related to European funds.	- ensures uniform reporting of irregularities; - supports the monitoring of the use of EU funds; - facilitates risk analysis and the prevention of future fraud.
The fair taxation package		- a set of EU measures aimed at combating tax evasion, simplifying tax systems, and improving cooperation between tax administrations.	- reduces tax evasion and abuse; - increases tax transparency; - supports fairer and more efficient tax systems;
Central electronic payment information system		- an electronic system that collects information on cross-border payments to help tax authorities accurately monitor VAT obligations.	- improves control of cross-border payments; - reduces the risk of VAT fraud; - supports rapid detection of irregularities in B2C transactions.
Early Detection and Exclusion System (EDES)		- an EU system designed to protect the EU's financial interests by identifying and excluding economic operators involved in fraud, corruption, or other irregularities from contracts financed by the EU budget.	- prevents high-risk entities from accessing European funds; - contributes to the correct and efficient use of the EU budget;
ARACHNE		= an IT tool developed by the European Commission, used for data collection and enrichment, which supports managing authorities in administrative controls and management verifications of structural funds.	- helps identify risks of fraud and irregularities; - improves the efficiency of administrative controls; - enable the analysis of large volumes of data and the prioritization of high-risk cases.

Source: Own elaboration based on information taken from the European Parliament website

Although these tools strengthen coordination and risk signaling, their effectiveness varies across Member States as they rely on heterogeneous upstream reporting practices. Tools designed for information sharing mainly improve visibility, while risk assessment tools critically depend on data completeness and consistent identifiers across procurements, payments, and beneficiaries. Consequently, an AI model built on these infrastructures should explicitly address data gaps, document quality, and entity resolution across systems; otherwise, it may amplify false positives and shift the workload rather than reduce it. However, access to information and cooperation between institutions, as well as the lack thereof, lead to the risk that fraud attempts, irregularities, and even fraud itself remain undetected.

Table 3 presents certain techniques and tools used in fraud detection, found in the specialized literature and based on studies by authors.

Table 3. Fraud techniques and tools encountered in the literature

Authors, year	Techniques, fraud tools
Schreyer et al., 2018	- using autoencoder neural networks to spot weird entries in the logbook; - applying link analysis to identify (sub)groups of accounts in the general ledger with a degree of risk;
Nursanswi, 2024	- in-depth examination of financial data: involves gaining a clear understanding of the commercial context, industry, and external factors that may influence an organization's financial situation. - forensic accounting supports the identification of suspicious transactions by analyzing unusual trading patterns, anomalies in financial flows, and any irregularities that may signal the existence of fraud risk.
Ali et al., 2024	- anomaly detection, forensic auditing, and data analysis; - collection of financial information from companies, such as income statements, balance sheets, and transaction logs using XBRL standards implementation; - use of digital forensics tools such as EnCase (Guidance Software) and FTK (AccessData); - identifying patterns and detecting anomalies in financial data sets using advanced data analysis tools such as Tableau and SAS Analytics; - using judicial audit through the IDEA application, developed by CaseWare Analytics, to analyze financial documents in order to identify anomalies and signs of fraud;

	<ul style="list-style-type: none"> - report-based analysis, which involves comparing key financial indicators such as profit margins, liquidity indicators, and turnover rates; - sequential analysis, which tracks the order and evolution of data over time to identify unusual patterns by applying cumulative sum methods to detect significant changes in the factors analyzed; - statistical analysis, performed using methods such as regression analysis and chi-square tests, used to highlight significant relationships and deviations in the data.
Adejumo & Ogburie, 2025	<ul style="list-style-type: none"> - the use of data analytics, artificial intelligence, and blockchain technology by forensic accountants to identify and prevent fraud; - the application of big data analytics and artificial intelligence-based tools to detect irregularities and anomalies in financial statements.
Hossain, 2025	<ul style="list-style-type: none"> - integrating traditional investigative methods with advanced technologies; - using data mining methods to track suspicious financial movements hidden in the complexity of international transactions. Integrating tools based on artificial intelligence;

Source: Own elaboration based on the articles studied

Literature consistently highlights the growing importance of data analytics and artificial intelligence in strengthening fraud detection mechanisms, particularly in response to the increasing volume and complexity of financial transactions. Traditional forensic accounting tools are often insufficient to address these challenges, which has led to a shift toward advanced analytical models capable of processing large data sets and identifying complex fraud patterns (Ali & et al., 2024).

A recurring theme in recent studies is the applicability of AI-based models in high-risk areas such as public procurement, where large financial flows and information asymmetries increase exposure to corruption risks. Research highlights that transparent digital platforms and predictive analytical tools can support the early identification of risk signals and enable timely intervention by regulators, thereby reducing the likelihood of escalation and financial losses (Baumgärtler et al., 2022; Zhu et al., 2024).

In addition, artificial intelligence techniques, including anomaly detection models and neural network architectures, demonstrate superior performance compared to conventional risk assessment approaches by identifying hidden patterns and adapting to dynamic market conditions. These capabilities enhance financial security by detecting fraudulent activities in real time and improving regulatory oversight (Islam & et al., 2024; Lokanan, 2022; Oko-Odion, 2025).

Despite these advantages, literature also points to significant challenges associated with AI adoption, particularly in terms of data quality, algorithmic bias, transparency, and regulatory compliance. Ethical and legal considerations, such as data privacy and compliance with data protection regulations, underscore the need to maintain active human oversight. Consequently, AI should be considered a complementary tool that enhances, rather than replaces, professional judgment in fraud detection processes (Bhagat, 2024; Dulgeridis et al., 2025).

To highlight the key differences between traditional methods of detecting fraud involving European funds and those based on artificial intelligence, based on the studies reviewed, the table below presents a comparison of their main characteristics and implications.

Table 4. Comparison of traditional methods vs. AI-based methods in detecting fraud involving European funds

Indicators	Traditional methods	AI-based methods
Institutions involved	- control institutions in each Member State (audit, Court of Auditors), OLAF, EPPO;	- The European Commission (created the ARACHNE, AFIS, IMS, and e-SMEC systems, which involve digital technologies in their use);
Applicable legislation	- GEO 66/2011; - article 325 TFEU; - internal procedures adopted by each Member State;	- Charter for the introduction and application of ARACHNE risk rating tools in management controls; - Government Emergency Ordinance 70/2022;
Tools used	- manual verification based on sampling;	- machine learning; - neural networks; - data mining;
Volume of data analyzed	- based on physical documents;	- AI can analyze extensive databases;
Rapid identification of fraud	- manual analysis is time-consuming;	- AI can identify anomalies in real time;
Identified fraud patterns	- red flags; - the experience of controllers;	- can detect hidden patterns;
Level of human involvement	- requires the active presence of controllers at all stages;	- requires human validation;
Fraud prevention	- controllers act by sampling, or after an irregularity occurs;	- can detect signals that have led to fraud in the past;

		- can identify beneficiaries, contracts, or projects that have characteristics similar to those of fraudulent projects;
Associated risks	<ul style="list-style-type: none"> - Each controller may interpret an irregularity differently, which may lead to human error. - Analysis complicates the physical process of fraud detection. 	<ul style="list-style-type: none"> - AI must be checked and updated regularly to avoid serious mistakes;

Source: Own elaboration based on the articles and laws studied

Based on the above, we believe that the implementation of artificial intelligence supports the process of detecting fraud involving European funds. In this regard, investments in staff training and digital infrastructure modernization are essential (Socoliu, 2024) because artificial intelligence requires trained human resources and databases structured in the most efficient and accurate way possible.

The use of digital infrastructure, especially by incorporating artificial intelligence into it, can transform the way control institutions collect data and identify types of fraud. The effectiveness of these technologies depends on data quality, access to information, and cooperation between institutions, and the lack thereof leads to the risk that attempts at fraud, irregularities, and even fraud itself will go undetected.

Based on the information presented in this article, we have outlined a structure to assist future research in creating a model for detecting fraud involving European funds (Figure 6).

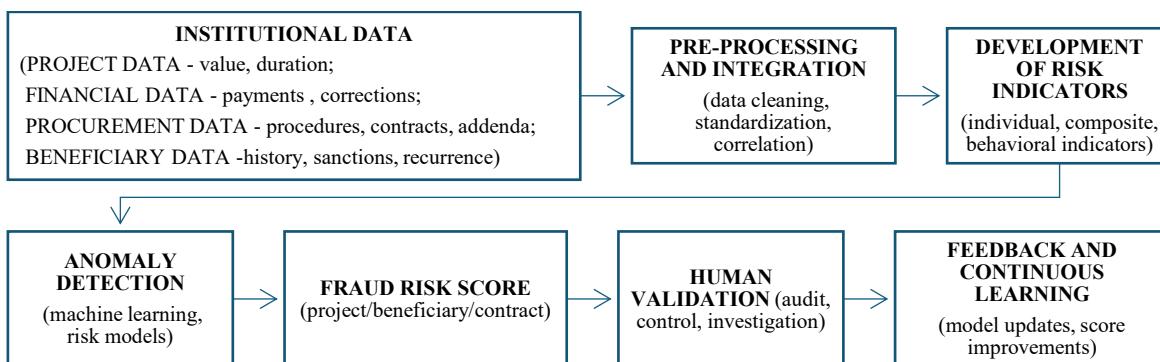


Figure 6. Conceptual model for fraud detection

Source: Authors' elaboration

Figure 6 summarizes the main conclusions of the study in an operational form and proposes a conceptual model for detecting fraud involving European funds, based on the use of artificial intelligence. The model is based on institutional data, which accurately reflects the categories of information currently used by managing authorities, control bodies, and anti-fraud institutions. This includes data on projects (value, duration), financial data (payments and corrections), public procurement data (procedures, contracts, addenda), and data on beneficiaries (history, sanctions, recurrence). The structure of this data is consistent with existing mechanisms, such as ARACHNE, IMS, and OLAF and EPPO reports, discussed earlier in the article, and highlights the fact that the proposed model is based on information already available at the institutional level. The preprocessing and data integration stage directly addresses one of the main challenges identified in the study, namely the lack of centralized and homogeneous databases, as well as the variable quality of the reported information. This stage includes data cleaning, format standardization, and correlation of entities from different sources, which is essential to ensure the consistency of the analysis. As the analysis of institutional reports and literature shows, without proper preprocessing, the use of artificial intelligence risks generating distorted results or a high number of false alarms.

Based on the integrated data, the model moves towards building risk indicators, a stage that bridges the gap between traditional audit methods and modern technologies. Individual, composite, and behavioral indicators reflect both the warning signs provided for in national and European legislation (e.g., Law No. 66/2011) and the patterns identified in forensic accounting and fraud detection studies. This stage is fully consistent with the classification of fraud indicators presented earlier in the article and allows them to be translated into quantifiable variables that can be used by artificial intelligence models. The next level of the model is represented by anomaly detection, achieved through the use of machine learning techniques and risk models. At this stage, artificial intelligence analyzes the indicators built to identify deviations from normal behavior, atypical patterns, or combinations of high-risk factors. In line with the conclusions of the literature reviewed, this process is not intended to establish the definite existence of fraud, but to support the early identification of situations that require further verification.

The result of the analysis is expressed as a fraud risk score, calculated at project, beneficiary, or contract level. This score allows cases to be prioritized and supports a risk-based approach to audit and control activities, contributing to a more efficient use of institutional resources, which is highlighted as necessary in the context of the increasing number

and complexity of cases investigated by the EPPO and OLAF. The human validation stage plays a central role in the model, reflecting the study's conclusion that artificial intelligence should be a complementary tool to professional judgment, not a substitute for it. Auditors, controllers, and investigators analyze the risk scores generated by the model and decide on appropriate measures, ensuring compliance with the legal framework, ethical principles, and transparency requirements. Finally, the model integrates a feedback and continuous learning mechanism, through which the results of controls and investigations are reintegrated into the system. This component allows the model to be progressively adapted to new patterns of fraud and reflects the future research directions identified in the conclusions of the article, namely the development of artificial intelligence models capable of learning from accumulated institutional experience.

In conclusion, the proposed conceptual model demonstrates that the use of artificial intelligence in detecting fraud involving European funds is feasible and relevant, provided that there are an adequate digital infrastructure, quality data, and interinstitutional cooperation. It provides a solid basis for future empirical developments, such as testing on real data, implementing pilot projects, or expanding to advanced predictive models, thus contributing to the modernization and streamlining of systems for protecting the financial interests of the European Union.

IV. CONCLUSIONS

This study examined, from a qualitative and exploratory perspective, the potential role of artificial intelligence in supporting the detection of fraud related to the management of European funds. The analysis combined a review of academic literature with an examination of institutional reports issued by OLAF and the European Public Prosecutor's Office, which were used to illustrate the current scale and evolution of fraud cases involving European funds.

The analysis of OLAF and EPPO reports highlights a significant increase in the number and complexity of fraud investigations in recent years, particularly since the EPPO became operational. These findings provide an empirical context for understanding the growing pressure on existing control and audit mechanisms. In this context, bibliometric analysis reveals a parallel increase in academic interest in AI-based fraud detection techniques, particularly machine learning, data mining and anomaly detection. However, the literature remains largely focused on generic financial fraud or private sector applications, with limited attention to the specific institutional and regulatory environment governing European funds. This confirms the existence of a research gap at the intersection of financial intelligence public finance, and European anti-fraud systems.

Overall, institutional evidence on the evolution of fraud cases and the literature on AI-based detection methods suggest that traditional control mechanisms, largely based on ex-post verification and manual procedures, are increasingly challenged by the volume and heterogeneity of available data. Artificial intelligence does not appear to be a solution to fraud per se, but rather a support tool capable of improving early risk identification, case prioritization, and analytical capacity within the existing institutional framework.

At the same time, the study identifies several structural limitations that constrain the practical implementation of artificial intelligence in this area, including fragmented data sources, uneven data quality, legislative differences between member states and restricted access to data on beneficiaries and public procurement. These constraints, documented both in the literature and in institutional reporting practices, underscore the need for investment in digital infrastructure, data governance and interinstitutional cooperation.

Based on these findings, we propose a conceptual model that integrates artificial intelligence into the fraud detection process as a complementary analytical layer. The model emphasizes data preprocessing, the operationalization of fraud indicators into measurable risk variables and the need for human validation in interpreting results. This approach is consistent with the legal and ethical requirements governing fraud investigations and reinforces the role of professional judgment. The study demonstrates that artificial intelligence can contribute to improving the detection of fraud involving European funds, not by replacing institutional controls, but by supporting them in an environment characterized by an increasing volume of investigative work. Future research should focus on empirically testing the proposed model using real institutional data, evaluating its performance across different member states and refining data integration mechanisms to enhance the effectiveness of European anti-fraud systems.

REFERENCES

1. Adejumo, A., & Ogburie, C. (2025). Forensic accounting in financial fraud detection: trends and challenges. *International Journal of Science and Research Archive*, 14, 1219-1232. <https://doi.org/10.30574/ijrsa.2025.14.3.0815>;
2. Ali, A., & et al. (2024). Forensic accounting techniques in detecting frauds. *Journal of Ecohumanism*, 3, 543-558. <https://doi.org/10.62754/joe.v3i5.3922>;
3. Baumgärtler, T., Eudelle, P., & Gallud-Cano, J. G. (2024). An international analysis of fraud detection in European structural and investment funds. *European Journal of International Management*, 22(2), 198-229. <https://doi.org/10.1504/EJIM.2024.135943>;
4. Baumgärtler, T., Eudelle, P., & Gallud Cano, J. (2022). Fighting fraud and corruption in European structural and investment funds. *Palgrave Macmillan Cham*. https://doi.org/10.1007/978-3-031-19051-3_3;
5. Bhagat, N. (2024). Artificial intelligence challenges and its impact on detection and prevention of financial statement fraud: a theoretical study. *Demystifying the Dark Side of AI in Business*, 60-80;
6. Cosmulescu, C.G., Macovei, A.G. (2024). Artificial intelligence - strategic applications across sectors. International Scientific Conference on Accounting, ISCA 2025, 14 Edition: Collection of scientific articles, 14 Edition, April 4-5 2025. Chișinău: ASEM, pp. 99-103. <https://doi.org/10.53486/isca2025.12>

7. Cosmulese, C. G. (2024). Evoluția competențelor resurselor umane în organizațiile de afaceri prin integrarea inteligenței artificiale. *Proceedings of International Scientific Conference on Accounting, ISCA 2024, 13 Edition, 5-6 aprilie 2024, Chișinău. ASE* (pp. 203-208).
8. Crain, M. A., Hopwood, W. S., Gandler, R. S., Young, G. R., & Pacini, C. (2019). *Essentials of forensic accounting*. John Wiley & Sons, London, UK.
9. Dulgeridis, M., Schubart, C., & Dulgeridis, S. (2025). Harnessing AI for accounting integrity: innovations in fraud detection and prevention. *Working Paper: IU Discussion Papers – Business & Management, IU Internationale Hochschule*. <https://doi.org/2750-0683>;
10. European Commission. OLAF report. https://anti-fraud.ec.europa.eu/index_en;
11. European Parliament. Combating fraud and protecting the financial interests of the European Union. <https://www.europarl.europa.eu/factsheets/ro/sheet/32/combaterea-fraudei-si-protejarea-intereselor-financiare-ale-uniunii-europene>;
12. European Union. (2016). *Treaty on the Functioning of the European Union*. https://eur-lex.europa.eu/eli/treaty/tfeu_2016/art_325/oj/eng;
13. Grosu, V., Melega, A., & Bores, A. (2025). Emotional Intelligence and Its Implications for Firm Performance: A Bibliometric Analysis. In *Emotional Intelligence and Networking Competencies: Implications for Effective Leadership* (pp. 1-14). Cham: Springer Nature Switzerland.
14. Hajek, P., & Henriques, R. (2017). Mining corporate annual reports for intelligent detection of financial statement fraud – a comparative study of machine learning methods. *Knowledge-Based Systems*, 128, 139-152. <https://doi.org/10.1016/j.knosys.2017.05.001>;
15. Hossain, M. (2025). Forensic Accounting in Financial Crime Investigation. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.5255487>;
16. Islam, T., & et al. (2024). Artificial intelligence in fraud detection and financial risk mitigation: future directions and business applications. *International Journal for Multidisciplinary Research*, 6, 1-23.
17. Law 66. (2011). *Law No. 66/2011 on the prevention, detection, and sanctioning of irregularities in the acquisition and use of European funds and/or related national public funds*;
18. Lokanan, M. (2022). The determinants of investment fraud: a machine learning and artificial intelligence approach. *Frontiers in Big Data*, 5. <https://doi.org/10.3389/fdata.2022.961039>;
19. Nursansiwi, D. (2024). The role of forensic accounting in detecting financial frauds. *Accounting Studies and Tax Journal (COUNT)*, 1, 111-116. <https://doi.org/10.62207/brkz8497>;
20. Oko-Odion, C. (2025). AI-driven risk assessment models for financial markets: Enhancing predictive accuracy and fraud detection. *International Journal of Computer Applications Technology and Research*, 14(4), 80-96;
21. Schreyer, M., & et al. (2018). Detection of anomalies in large scale accounting *Data using Deep Autoencoder Networks*. <https://doi.org/10.48550/arXiv.1709.05254>;
22. Socoliuc, M. (2024). The impact of digital technologies on the fight against tax evasion-a fundamental analysis. *The USV Annals of Economics and Public Administration*, 24(2, 40), 142-156;
23. Zhu, S., & et. al (2024). A financial fraud prediction framework based on stacking ensemble learning. *Systems*, 12 (12). <https://doi.org/10.3390/systems12120588>;