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The challenge of integrating Artificial Intelligence in Anti-Money Laundering

Le défi de l'intégration de l'Intelligence Artificielle dans la lutte contre le Blanchiment d'Argent

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Abstract : Digital transformation is radically changing the behavior of individuals, businesses and organizations in the financial field. The need to better understand customer needs, offer targeted products and services and manage risk more effectively pushes all operators in the sector to adopt a so-called data-driven model.
A data-driven approach means that business decisions, from marketing strategies to risk management, are based on data analysis and interpretation, rather than intuition or past experience. This involves the ability to collect, process, and use large amounts of data to gain actionable insights and make more informed and accurate decisions.
The data-driven approach is also revolutionizing the anti-money laundering (AML) sector, offering more effective tools to counter money laundering and terrorist financing.
In a scenario where traditional AML methods often rely on predefined rules and manual checks, which can be slow, expensive and ineffective in detecting suspicious activity, generating a high number of false positives and requiring further analysis by experts and increasing operational costs, AI becomes a powerful tool to interpret, learn and act on the basis of the information available. AI, in fact, feeds on data to function: the more data it has available, the more it is able to learn and improve its performance.
This research therefore aims to explore how the implementation of artificial intelligence tools in the field of anti-money laundering and countering the financing of terrorism is the most effective way to improve the performance of a system that, unfortunately, still struggles to identify and isolate resources and capital of criminal origin.
Through an in-depth analysis of current and future application of AI, the benefits in terms of transaction monitoring, money laundering risk assessment, identification of criminal networks and complex money laundering schemes will be assessed.
In addition, challenges related to AI implementation, such as data quality and management, privacy and cybersecurity, and the impact on employment, will be discussed.

Keywords: Anti-Money Laundering, Artificial Intelligence, Data-Driven.

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1. Introduction

Artificial intelligence (AI) is revolutionizing many industries, including the global financial system. Among the most interesting areas of application of AI are those of AML (anti-money laundering) and CFT (countering terrorist financing): they represent fertile – and partly unexplored – ground for the development and application of artificial intelligence, the real cornerstone of the construction of a new model of digital and interconnected reality.

In fact, in a scenario where traditional AML methods often rely on predefined rules and manual checks, which can be slow, expensive and ineffective in identifying suspicious activity, generating a high number of false positives and requiring further analysis by experts and increasing operational costs, AI becomes a powerful tool for interpreting, learn and act on the basis of the information available. AI, in fact, feeds on data to function: the more data it has available, the more it is able to learn and improve its performance.

Artificial intelligence (AI) can offer numerous benefits in the context of Anti-Money Laundering (AML) and Countering the Financing of Terrorism (CFT), significantly improving the effectiveness and efficiency of processes, including:

1. Improved accuracy and speed in detecting suspicious activity.
2. Process automation.
3. Better risk management.
4. Adaptability and continuous learning.
5. Cost reduction.
6. Improved regulatory compliance.
7. Greater ability to analyze and understand data.
8. Decision support.

but also have some disadvantages:

1. Implementation and maintenance costs.
2. Lack of transparency and interpretability.
3. False positives and false negatives
4. Resistance to change
5. Regulatory and legal challenges
6. Cybersecurity
7. Evolution of recycling techniques
8. Job losses

This work therefore aims to explore the adoption and impact of AI in AML (anti-money laundering) and CFT (countering terrorist financing), examining future challenges and opportunities and offering a comprehensive view of how AI is transforming the global financial sector.

2. Big Data and 6V

We therefore live in the era of Big Data, where the amount of information generated and collected is growing at an exponential rate.

We talk about Big Data when you have a dataset so large that it requires unconventional tools to extrapolate, manage and process information within a reasonable time. There is no reference dimension, but it is always changing, as machines are getting faster and the datasets are getting bigger and bigger.

In 2001, Doug Laney , then vice president and service director of the company Meta Group, described in a report the 3V Model related to the 3V's of Big Data: Volume, Speed and Variety. A simple and concise model to define new data, generated by the increase in information sources and more generally by the evolution of technologies. Laney's paradigm was then enriched by the variables of Veracity and Variability and for this reason we speak of the 5V of Big Data. Over the last few years, however, a sixth V has been added, focused on the value generated by data:

- Truthfulness, where Veracity of Big Data, means the quality and reliability of data
- Volume, where volume means the large amounts of data or in strong growth
- Speed where Speed means how quickly the Data generated and captured is collected
- Variety where Variety is defined as data that is heterogeneous in terms of source and format
- Variability, where variability means the mutability of meaning based on context
- Value, where Value means the source of economic and financial value

2.1. The 6 V's of Big Data

1) Volume: The term "big data" is ambiguous, as the different entities obliged to comply with anti-money laundering legislation have different data storage and analysis capabilities. What might be overwhelming for a smaller local or regional obligated entity is just a drop in the bucket for a multinational organization. When determining the volume of big data that obligated entities can handle, they need to look at both their internal systems and the types of data they are working with.

2) Speed: When obligated entities examine the amount of big data they have and continue to collect, they should then consider the speed at which it can be used. The speed of generation, collection, and updating of big data are the main issues that obligated entities will encounter with big data. Today, big data is being generated at an almost incomprehensible rate. According to Forbes, 90 percent of all data in the world was created in the last two years alone, and we currently create about 2.5 quintillion bytes of data per day. It is estimated that by 2025, this figure could reach 463 exabytes per day.

3) Variety: The variety of information available to obliged entities is what has spurred the growth of big data. Big data in the financial sector refers to two types of data: structured and unstructured. Structured data is easy to understand (think numbers, text, etc.), commonly used data collected from customers, including: Name, Address, Income, etc. This type of personal data and information is easily categorized and organized into tables and graphs for immediate consumption and analysis. But the biggest benefit of big data is the unstructured content now available. Unstructured data is the unconventional information that obliged entities can collect and use to impact all areas of the business, such as contracts, fraud detection, and customer experience. This information comes from data analytics and machine learning focused on content from social media, multimedia, written reports, and even wearable technologies. The so-called Internet of Things (IoT) now allows obliged entities to use unstructured data to paint an increasingly complete picture of each customer and to gain deeper insights into overall operations. And because they're generated by devices and platforms that never shut down, operators have 24/7/365 access to an uninterrupted supply of unstructured data.

4) Truthfulness: Truthfulness is defined as conformity to facts, so in terms of big data, truthfulness refers to the trust and reliability of such data. When dealing with big data, this is in a way a double-edged sword: because there are so many large amounts of data generated from so many disparate sources, some

big data is unreliable by default. As volume, variety, velocity, and value, as well as the other V's of big data, increase, veracity is more prone to decrease. There is always a slight margin of error with large data sets, but being able to process them and still make the most accurate decisions possible is critical to leveraging big data in AML/CFT. As in any industry, obliged entities must apply an innate skepticism to verify their data and the information they provide.

5) Validity: While data validity may seem similar to data veracity, in this case, we're asking, "How related does this data relate to the questions and results I'm looking for?" Undoubtedly, there are countless methods for creating and collecting data, each of which has its own advantages and limitations. When collecting big data, it's important to match the right data sets to the appropriate activities. In addition, obliged entities should install consistent data practices, so that every analysis and report receive the same treatment, therefore improving accuracy.

6) Value: The value of big data has a twofold consideration: is the data collected good or bad, and do obligated entities make informed, business-driven decisions based on the valuable insights generated by all this data? Because big data is generated in large quantities, the quality of the data can be diluted. Obliged entities should focus on good data. But what makes good data? Good data is first and foremost accurate. They are also reliable and consistent, allowing operators to continue making data-driven decisions rather than one-time estimates. The value of big data goes beyond good and bad data; it also concerns what obliged entities do with it. AML/CFT big data can be leveraged to make accurate decisions about specific risk assessment, but it can also influence business initiatives.

3. The (IN)efficiency of traditional AML Models

In the era of big data, therefore, all the players in the anti-money laundering system are now aware, on the one hand, of the digitization of exchanges, relationships, transactions and assets and, on the other, of the fundamental role played by the ability to attribute meaning (and to do so quickly and securely) to the data obtained from the "digital migration" of this boundless wealth of information.

It is now evident that the traditional approach to AML/CFT shows limitations in the face of the evolution of money laundering and terrorist financing techniques. Especially:

- Over-emphasis on formal compliance: Over-emphasis on regulatory compliance can lead to a bureaucratic and inefficient approach, with resources focused on standardized control activities instead of a targeted risk assessment.
- High number of false positives: Strict rule-based models often generate alarms for legitimate transactions, overwhelming analysts and making it difficult to identify real suspicious activity.
- Difficulty in identifying complex patterns or transactions: Money laundering and terrorist financing techniques have become increasingly sophisticated, making it difficult to identify complex patterns or operations through transaction monitoring alone.
- Dependency on structured data: Traditional models rely primarily on structured data, ignoring valuable information that may be present in unstructured data such as emails and documents.
- Lack of cooperation and information sharing: Lack of cooperation and information sharing between financial institutions and competent authorities can hinder the detection and prosecution of financial crimes.
- High cost: Deploying and maintaining rule-based systems can be expensive, requiring significant investments in hardware and software

According to some research, traditional AML models generate about 98% of "false positives" in reports: to date, the "manual management" of alerts based on the use of static models still prevails, which is able to cause an "overload" of work for compliance teams. In recent years, in order to cope with the growing number of reports "constrained" to human analysis, financial institutions have taken on more and more resources in the compliance area, with a significant increase in costs, which, however, has not been followed by a corresponding improvement in efficiency.

This conservative approach does nothing but dissipate resources compared to the most high-risk cases, effectively neutralizing the function of financial intermediaries in the entire architecture of the anti-money laundering system.

The picture outlined, therefore, highlights how the monitoring system (of transactions, but also of subjects) is afflicted by a marked imbalance between investments and available data, on the one hand, and, on the other, a concrete ability to analyze and manage them efficiently: the use of artificial intelligence allows these critical issues in the sector to be overcome.

In recent years, traditional AML models have evolved towards more sophisticated approaches, such as using artificial intelligence and machine learning. These new models are able to analyze large amounts of data and identify complex patterns that may be missed by traditional systems.

4. New AML Models

A "modern" approach to the fight against money laundering (AML) and terrorist financing (CFT) evolves to overcome the limitations of traditional models and is based on a combination of advanced technologies, sophisticated data analytics and international collaboration. This approach focuses on preventing, detecting, and responding to illicit activities more effectively and efficiently.

Here are some of the key elements that characterize it:

1. Risk-Based Approach (RBA)
    - Risk assessment: Financial institutions identify and assess money laundering risks specific to their business, customers, and geographies.
    - Proportionate measures: They take control and due diligence measures proportionate to the level of risk identified, concentrating resources where they are most needed.
2. Artificial Intelligence (AI) and Machine Learning (ML)
    - Anomaly detection: AI/ML algorithms analyze large amounts of data to identify patterns and anomalies that could indicate recycling activities, even complex and hidden ones.
    - Continuous improvement: ML models learn and adapt over time, improving their ability to detect new forms of recycling.
3. Big Data Analytics
    - Multiple data sources: Different data sources are used, both internal (transactions, customer information) and external (news, social media, government databases), to gain a more comprehensive view of risk.
    - Efficient processing: big data technologies allow large volumes of data to be processed quickly, identifying relevant patterns and links.
4. Process automation
    - Operational efficiency: Automation reduces manual work, speeds up analysis and reporting, and allows analysts to focus on more complex tasks.
    - Reduced errors: Automation reduces the risk of human error and improves the accuracy of AML processes.
5. Collaboration and information sharing

- Information sharing: Financial institutions collaborate and share information with each other and with the relevant authorities to better identify and combat money laundering.
- Public-private partnerships: Public-private partnerships are created to improve the fight against money laundering.

6. Focus on customer due diligence (CDD)

- Customer identification and verification: Stricter measures are taken to identify and verify the identity of customers, especially those at high risk.
- Continuous monitoring: Customer monitoring is continuous to detect changes in their behavior or activities that could indicate increased risk.

7. Holistic approach

- Process integration: AML is integrated into all business processes, from risk management to compliance, to ensure greater effectiveness.
- Training and awareness: Staff are properly trained and sensitized about money laundering risks and AML procedures.

In summary, the modern approach to AML is based on a combination of advanced technologies, innovative methodologies and increased collaboration to effectively counter money laundering in an ever-changing financial environment.

In the era of big data, therefore, all the players in the anti-money laundering system are now aware, on the one hand, of the digitization of exchanges, relationships, transactions and assets and, on the other, of the fundamental role played by the ability to attribute meaning (and to do so quickly and securely) to the data obtained from the "digital migration" of this boundless wealth of information.

In this sense, the FATF (or FATF, Financial Action Task Force) itself – i.e. the intergovernmental body that deals with the fight against money laundering and the illicit financing of terrorism – underlines the importance of big data analysis through artificial intelligence and technological solutions based on machine learning and other AI-based technologies. As described at the beginning of the July 2021 Report "Opportunities and challenges of new technologies for AML/CTF ", these techniques make it possible to strengthen the existing system for monitoring and reporting suspicious transactions, as well as to implement customer due diligence (CDD) and risk assessment.

5. Data-Driven approach to Anti-Money Laundering

The data-driven approach to anti-money laundering (AML) combined with artificial intelligence (AI) represents a significant evolution in the way financial institutions and other entities approach the fight against money laundering and terrorist financing.

A data-driven approach to AML relies on collecting, integrating, and analyzing large amounts of data from different sources. This data is used to identify patterns, anomalies, and relationships that could indicate money laundering activity.

Artificial intelligence, especially machine learning, offers advanced capabilities for data analysis and automation of AML processes. AI algorithms can be trained to recognize complex and subtle patterns that may escape human analysis.

The integration of a data-driven approach with artificial intelligence in AML allows to improvethe accuracy of controls. In fact , AI algorithms can identify suspicious activity with greater accuracy than traditional methods, reducing false positives and focusing on truly suspicious activity. Traditional methods of AML, often based on predefined rules and manual checks, tend to generate a high number of false positives. These are reports of suspicious activity that are not, causing unnecessary expenditure of resources on investigations and distracting analysts from real money laundering cases.

5.1. AI: Accuracy and Efficiency

Artificial intelligence, especially machine learning, offers several benefits to improve accuracy in AML:

- Recognition of complex patterns: AI algorithms can be trained to recognize complex and subtle patterns in data that could indicate money laundering activity. These patterns might be difficult to spot with traditional methods.
- Continuous learning: AI algorithms can continuously learn from new data and adapt to changes in money laundering techniques, constantly improving their ability to identify suspicious activity.
- Reduced false positives: With the ability to recognize complex patterns and continuously learn, AI can significantly reduce the number of false positives, allowing analysts to focus on real money laundering cases.
- More precise risk assessment: AI can be used to develop more sophisticated risk models that take into account a wide range of factors and data to assess the money laundering risk associated with specific customers, transactions, and products. This allows institutions to focus their resources on the areas of highest risk.

Additionally, AI can automate AML processes, such as verifying customer identities, tracking transactions, and reporting suspicious activity, reducing manual work and improving efficiency.

By automating tasks that once required a lot of manual effort, you can now:

- Customer identity verification (KYC): AI can automate customer identity verification by analyzing identity documents, biometrics, and other information. This reduces the time and cost associated with manual verification and improves process accuracy.
- Transaction monitoring: AI can monitor transactions in real-time to identify suspicious activity. AI algorithms can be trained to recognize complex and subtle patterns that could indicate money laundering, allowing institutions to intervene promptly.
- Suspicious activity reporting (SAR): AI can automate the generation of SARs, reports that financial institutions are required to submit to the relevant authorities in the event of suspicious activity. AI can analyze data and identify transactions that meet the criteria for reporting, reducing manual work and improving regulatory compliance.

In addition, the automation of AML processes through AI allows a:

- Reduced manual work: AI can automate repetitive and time-consuming tasks, freeing up AML teams for more strategic tasks, such as analyzing complex cases and developing new strategies to combat money laundering.
- Increased speed and efficiency: AI can process large amounts of data much faster than humans, allowing institutions to identify and report suspicious activity more quickly and efficiently.
- Improved accuracy: AI algorithms can be trained to recognize complex and subtle patterns that may be missed by human analysis, improving the accuracy of identifying suspicious activity and reducing false positives.
- Cost reduction: Automating AML processes can reduce operational costs associated with manual labor, data processing, and regulatory compliance.

5.2. AI: Complex snd Sophisticated Money Laundering schemes

One of the most significant benefits of combining the data-driven approach and AI in AML is the ability to identify complex and sophisticated money laundering schemes that, with traditional methods, could easily be missed, through:

- Intricate pattern analysis: AI algorithms, especially machine learning algorithms, can analyze massive amounts of data from different sources (financial transactions, customer information, identification data, public records, news, social media, etc.) to identify complex patterns and subtle correlations that could indicate money laundering activity. These patterns might be difficult or impossible for the human eye to identify or through predefined rules.
- Anomaly recognition: AI can recognize anomalies in data that could suggest suspicious activity. For example, it can identify transactions that deviate significantly from a customer's normal behavior, or sudden changes in transaction volume or frequency.
- Dynamic adaptation: Unlike systems based on fixed rules, AI is able to continuously learn and adapt. This means that it can evolve over time to identify new forms of money laundering, as criminals develop increasingly sophisticated techniques.
- Customer behavior analysis: AI can create customer risk profiles based on customer behavior and identify changes that could suggest money laundering activities. For example, if a customer routinely transacts in small amounts suddenly starts making large transactions, AI can flag this anomaly as a potential indicator of money laundering.

The world of money laundering is constantly evolving. Criminals are constantly developing new techniques and strategies to evade controls and launder illicit proceeds. A static AML approach, based on predefined rules and manual controls, is likely to be quickly overtaken by these new challenges.

The integration of a data-driven approach with artificial intelligence offers a fundamental advantage in a scenario where criminals are constantly developing new techniques and strategies to evade controls and launder illicit proceeds. A static AML approach, based on predefined rules and manual controls, is likely to be quickly overtaken by these new challenges.

AI algorithms can be continuously updated and refined (continuous adaptation) based on new data and new money laundering techniques, allowing institutions to quickly adapt to changes in the criminal landscape, making AML systems more resilient to new challenges and threats, more effective in the long term because they can keep up with the evolution of the criminal landscape, and with a consequent reduction in the risk of being "surprised" by new money laundering techniques. This is done through:

- Continuous learning: AI algorithms, especially machine learning algorithms, have the ability to continuously learn from new data. As new data on money laundering activities is collected, algorithms can be "trained" to recognize new patterns, techniques, and trends.
- Upgrade and refine: AI models can be continuously updated and refined based on new data. This means that the AML system can evolve over time, becoming increasingly effective at detecting new forms of money laundering.
- Recognition of new techniques: AI can be used to analyze data and identify new money laundering techniques that may not have been predicted by traditional systems. This allows institutions to anticipate the moves of criminals and adapt their counter-strategies accordingly.
- Real-time adaptation: In some cases, AI can be used to analyze data in real-time and immediately adapt controls and monitoring strategies in response to new threats or suspicious activity.

5.3. AI: Sophisticated Risk Models

AI can be used to develop more sophisticated risk models that take into account a wide range of factors and data to assess the money laundering risk associated with specific customers, transactions, and products.

Risk assessment is a crucial element of AML processes. It consists of identifying and assessing the money laundering risk associated with specific customers, transactions, products, or services. An accurate risk assessment allows institutions to focus their resources and efforts on the areas of highest risk, thereby optimizing the effectiveness of AML controls. Integrating a data-driven approach with artificial intelligence (AI) transforms risk assessment in several ways:

1. Analysis of a wide range of data: AI is able to process and analyze massive amounts of data from different sources, including:
   - Structured data: financial transactions, customer information (KYC), identification data, etc.
   - Unstructured data: news, social media, survey reports, etc.

This ability to analyze a wide range of data allows you to gain a more complete and detailed view of money laundering risk.

2. Identifying complex patterns: AI algorithms, especially machine learning, can be trained to recognize complex and subtle patterns that may be missed by human analysis. These templates may include:
   - Behavior patterns: Identifying changes in customer behavior that could indicate suspicious activity.
   - Transaction patterns: Identify transactions that have unusual or suspicious characteristics.
   - Network models: Identification of connections between entities that may be involved in money laundering activities.
3. Dynamic risk assessment: AI-powered risk models can be continuously updated and refined based on new data and new information available. This allows institutions to quickly adapt their risk assessment to changes in the criminal landscape and identify new threats early.
4. Personalization of risk assessment: AI can be used to develop customized risk models for specific types of customers, transactions, or products. This allows institutions to assess risk more precisely and take appropriate control measures.
5. Automate risk assessment: AI can automate the risk assessment process, reducing manual work and improving efficiency. This allows institutions to focus their resources on more complex and strategic activities.

The integration of a data-driven approach with artificial intelligence (AI) therefore significantly improves risk assessment in AML. AI enables institutions to analyze a wide range of data, identify complex patterns, assess risk dynamically and individually, and automate the risk assessment process. This results in greater accuracy, efficiency and effectiveness in the fight against money laundering.

6. Models in comparison

Table no. 1

Differences between traditional and data-driven approaches

Characteristic	Traditional approach	Data-driven approach
Data management	Limited volumes, mainly transactional and basic customer information	Large volumes of data from different sources, including transactional data, customer information, social media, news, and external databases
Analysis	Manual, based on predefined rules and fixed thresholds	Automated, based on artificial intelligence and machine learning algorithms
Pattern identification	Limited to simple, predefined schemas	Identify complex and hidden patterns by analyzing large volumes of data

False positives	High number of false positives due to strict rules	Reduce false positives with machine learning and more sophisticated analytics
Adaptation	Slow and stiff, with difficulty adapting to new recycling techniques	Dynamic, continuous adaptation through machine learning and constantly updating models
Effectiveness	Limited, with difficulty in tackling complex recycling schemes	Increased effectiveness in combating money laundering thanks to comprehensive, real-time analysis
Costs	High due to manual analysis and report management	Potentially lower due to automation and resource optimization
Human resources	Heavy reliance on AML experts for manual analysis	Greater focus on data analysis skills and management of AI systems

Source: Author

7. AI: Risks and Opportunities

While the absolute centrality that the AI-based approach can also assume in terms of ascertaining and suppressing money laundering and, in general, financial crime cannot be overlooked, at the same time it is necessary to consider the potentially critical aspects and limitations of machine learning models, which could undermine their reliability and consequent usability.

A particularly delicate phase is constituted, in fact, by the creation of datasets: incomplete, obsolete, irrelevant training data, or inaccurate collection techniques, or, again, a disproportion between the data used for the training of the algorithm and those subjected to actual analysis can compromise the analysis through machine learning. In addition, the risk of cognitive bias in the construction of the algorithm and, even more, the error in the interpretation of the information obtained can make the use of machine learning tools useless.

Similarly, the lack of transparency in the processes of automation of analysis and decisions – i.e. the use of so-called "black box" algorithms – is another factor of distrust towards new technologies: transparency is essential and financial institutions must commit to using technologies that are not only efficient, but also understandable and reliable.

In summary, AI offers great potential to improve the effectiveness and efficiency of AML systems, but it is important to be aware of its limitations and challenges. A balanced approach that combines AI with human oversight and traditional controls is critical to mitigating risk and ensuring compliance with AML regulations.

Below is a SWOT analysis of artificial intelligence (AI) used in anti-money laundering (AML):

Table no. 2

SWAT analysis

Strengths	**Weaknesses**
Greater accuracy in detecting suspicious activity than traditional rule-based methods. Improved efficiency and reduced false positives, saving time and resources for AML analysts. Ability to analyze large amounts of data and identify complex patterns that may not be apparent to humans.	Potential reliance on training data, which can be incomplete or biased, leading to inaccurate or discriminatory results. Poor explain ability of decisions made by AI models, which can make it difficult for AML analysts to understand and validate alerts.

Adaptability to evolving money laundering techniques, allowing financial institutions to stay ahead of criminals.	High upfront implementation costs and the need for specialized expertise to develop and maintain AI systems. Possible vulnerabilities to manipulation or cyberattacks, which could compromise the integrity of AML systems.
Opportunity	**Threats**
Continuously improving the accuracy and efficiency of AML systems through machine learning and real-time data analytics. Integration with other technologies, such as social media analytics and blockchain, to gain a more holistic view of customer activities. Development of new AI-based tools and solutions to address emerging challenges in the AML industry, such as cryptocurrency-related money laundering. Increased collaboration between financial institutions, regulators, and technology companies to share information and best practices.	Possible over-reliance on AI, which could lead to a reduction in human vigilance and a weakening of traditional AML controls. Difficulty keeping up with evolving AML regulations and new AI-based money laundering techniques. Ethical and regulatory concerns related to data privacy, discrimination, and accountability for decisions made by AI. Competition with criminals who could use AI to develop more sophisticated and hard-to-detect money laundering methods.

Source: Author

8. Conclusions

The data-driven approach and artificial intelligence certainly represent a significant opportunity to improve the effectiveness and efficiency of AML processes. By harnessing the power of data and advanced technologies, institutions can reduce risk, increase compliance, and combat money laundering more effectively.

The implementation of artificial intelligence tools in this sector is the most effective way to improve the performance of a system that, unfortunately, still struggles to identify and isolate resources and capital of criminal origin. In particular, the possibility of pooling huge amounts of data, already collected and archived through interoperability between subjects and databases, represents the best way to increase the quality of performance in the sector.

However, the targeted investment, both by the financial intermediaries and by the supervisory authorities involved, must be accompanied by the proactive participation of the legislative bodies, which have the task of finding the balance between the objectives pursued through technological innovation and, on the other hand, the protection of rights from opaque and unverifiable systems, harbingers of potential discrimination against certain groups of customers and compressions of the spaces of freedom of each individual.

In addition, over-reliance on machine learning models can lead to a reduction in human vigilance with the risk of losing skills and critical analysis capabilities, and a weakening of traditional AML controls. The implementation and management of AI systems require new technical skills that AML analysts may not possess, creating the need for professional training and updating, therefore increasing costs, as well as hiring AML analysts with skills in AI and data analysis, which are not easy to find in the labor market.

Important ethical issues, such as data privacy, discrimination and accountability for decisions, should not be forgotten. It is essential to take a responsible and transparent approach, ensuring compliance with regulations and ethical principles.

Ultimately, the effective and sustainable implementation of the data-driven approach in AML requires a holistic view that takes into account not only the technological aspects, but also the implications for human resources, organization and ethics. Only in this way will it be possible to fully exploit the potential of AI to combat money laundering more effectively and efficiently.

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