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Advancing Explainable AI for AI-Driven Security and Compliance in Financial Transactions

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Abstract : Explainable AI (XAI) has been delivering ground-breaking results in various domains. Emerging in parallel with the rise of powerful machine learning models, how to extend explainability to those black-box systems and promote its integrality have evolved into a blooming research field. Financial services are among the first to highlight the requirement for interpretable and fair algorithms, and the European Union has established the minimum regulatory and supervisory expectations for taking Transparency and Explainability of AI into national law. And XAI seems to be an inevitable future trend in anti-money laundering detection due to the booming applications of machine learning techniques.

Thereat, a novel and all-round XAI-Prompted AI-Driven Security and Compliance Platform for Financial Transactions is proposed, providing AI decision uncertainty and traces, disclosing feature attributions, and automatically generating data analytic compliance documentation. A comprehensive comparison of manifold interpretation methods is also conducted to yield salient results, suggesting that a model-specific and post-hoc algorithm can prominently outperform others in this special financial domain. Moreover, adopting the innovative language model to automatically generate explanations of the prediction target is also explored successfully. Fargo is an interdisciplinary team, composed of researchers across computer science, machine learning, natural language processing, and financial regulation. They communicate and cooperate to make Fargo transparent and clearly documented its model, data, techniques, methodology and results. They receive a financial transaction that is not classified as suspicious or unusual.

Keywords: Explainable AI, AI in finance, XAI, AI research, Black box, AI ethics, Interpretability, Transparency, Trust, Regulation, Financial compliance, Financial security, Financial transactions, Responsible AI, Heterogeneous ensembles, Feature selection.

1. Introduction

Explainable AI (XAI) is expected to play a transformative role in the exploitation of ML, including in AI-driven Security and Compliance (ASC). The potential benefits of XAI are discussed in the context of ambitious but realistic AI-related use-case implementations in the financial domain. The broad scope of the described work draws on research areas such as fairness, privateness, causality, ontological modelling, and the development and empirical assessment of XAI methods applicable to ML techniques.

The application of Explainable AI (XAI) can significantly foster autonomous Artificial-Intelligence (AI)-based decision-making in an array of high-stakes complex tasks that have increasingly become the privilege of human operators. After the Modelling and Prediction by Emerging Techniques in Time Series competition, the organisers reflected upon the predictive modelling methods contesting in this subject and remarked on the contrast with the application of simple models which are less subject to "black-box risks" and may be successfully employed in "high-stake business-related fields such as bank loans, market trading, asset enterprises, or healthcare".

A decade has since passed, during which a theoretical beachhead and a set of analytical methods and algorithms have been developed to be operationalised in computer systems.

Fig 1: Explainable artificial intelligence (XAI) in banking

1.1. Successful Implementations

Having begun the first security operations centre (SOC) in Ireland while working at one of the largest financial institutions globally has shown the slow progressions in compliance with respect to new data protection laws across the globe. The research on artificial general intelligence (AGI) has blossomed as has the development of artificial intelligence (AI) in the financial sector. Computer interfaces with clients have become quite common though they always necessitate human approvals. Faster implementation in other industries occurred, and in financial transaction networks for example has barely begun. Many developments are being hampered due to a lack of explainability. AI-driven decision-making systems can be trained to explain their outputs: using Explainable AI (XAI) methods. In recent years, a range of XAI tools have been developed and research has been active in many societal sectors. This is a new frontier in XAI research with unexpected results. Law enforcement has been forced to invest in a number of small deals with newly-merged AI companies born from academia. There are no proven models regarding big-ticket funding relative to the new AI graduates. If such models existed it would be against the established code of conduct for researchers to make a guaranteed profit. Other industries are adapting to this reality with heavy investment in their own AI advanced degree programs to guarantee well-trained candidates for roles in these future-looking industries. However emerging regulations could decrease competition as privacy laws mean startup draining patterns and phishing may finally stop post-acquisition. Furthermore, the introduction of stringent compulsory XAI regulations will make sales impossible for some. Hence, if you are researching FinTech strategies, it is now the time to shop around to save developing various options. A concept of combinatorial explainability regimes can be novel both not only for any granted AI in automatic transaction steps (trade taking systems) but any steps at any financial societal level too. To inspire public acceptance and trust across finance on these crucial AI-based settings one just needs at least a basic public understanding of these

Equation 1: AI Model for Predicting Risk or Fraud

$$f(\mathbf{X}) = \hat{y} \quad \text{where} \quad \hat{y} \in \{0, 1\}$$

where:

- $\hat{y} = 1$ indicates the transaction is likely fraudulent
- $\hat{y} = 0$ indicates the transaction is compliant.

2. Understanding Explainable AI

The broader objective of this article is to bring to light the importance of explainable AI (XAI) in AI-driven security and compliance, particularly in the context of financial transactions. Before plunging into the depth of the discussion, this Section l discusses some basic principles and taxonomy of XAI. The upcoming Section 3 sheds light on some of the innovative advances and significant findings in the realm of XAI for AI-driven security and compliance across various applications. Layperson acceptance of AI technologies has actively grown surrounding strategic sectors, in part source by the better understanding and trust fostered through explanations, but deep learning (DL) methods frequently maintain opaque decision-making policies. To subdue this inadequacy, an array of explainable AI approaches have been analyzed and proposed, usually working on complicated models post-hoc via approximated explanations, such as gradients.

The success of AI, including model capabilities for understanding, reasoning, and generating data, is required to be explainable, which is typically validated when the trust and feasibility in AI systems are built. Recognizing this need, several AI approaches that favor transparency and interpretability have been analyzed and proposed to engender AI that can give reasons for its outputs. This is subject to improved decision-making with transparency, but also fosters trust between the developers and end readers. Nonetheless, a great deal of the AI practices, fundamentally deep learning (DL) models, often retain opaque decision-making policies. Generally, DL models posit tremendous complexities, flexibility, and nonlinearities, which transpire in enormous numbers of parameters, layers, and operations in demand to learn a complex and abstract representation. As a consequence, the low-level human-understanding could not analyze the intricacies of DL models and infer their behavior in a logical manner.

Another reason for increased research on the development of AI- and ML-based tools on risk management and compliance for financial service providers is the information asymmetry in favor of financial intermediaries vs. their clients. Efficient financial regulation is important to protect clients, ensure fairness and sustainability of the financial sector, and overall, trust in the banking system. For these reasons, financial intermediaries, such as wealth managers, portfolio managers, and commercial banks, have to fulfill a number of explicitly prescribed due diligence tasks. Happening continuously in the background of each 'typical' commercial transaction, it is necessary to filter out the rare problematic ones while dealing with a substantial set of common and legitimate payments. Machinery is used to detect problems. Commercial banks and money-changer offices are legally required to detect potentially unlawful transactions, such as money laundering or as a transfer of assets related to terrorism at an early stage within their reach.

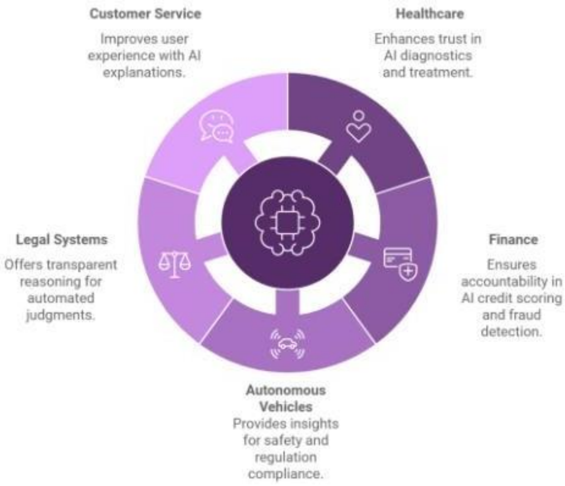

Fig 2: Understanding Explainable AI

2.1. Definition and Importance

Financial service providers are among the most strictly regulated businesses in the world. Recent history has seen a steep increase in financial regulation worldwide, which can be seen as a response to the 2007-2008 financial crisis. The EU, through the implementation of the European Market Infrastructure Regulation (EMIR), then mandated the use of innovative technologies. Financial service providers are using electronic payment systems, which will also facilitate the shift towards 'big data' analysis with AI tools. Innovative approaches are being discussed to improve the filtering and interpretation of the huge amounts of data commercial banks have to deal with. For Swiss banks, the automation of risk-related tasks as a project-level adoption is particularly interesting. These tasks should be tackled in line with the trend towards more machine learning (ML) applications.

2.2. Current State of Explainability in AI

The success of artificial intelligence (AI) methods, particularly deep learning and deep neural networks, has driven their wide adoption across various sectors. Deep learning methods, known for their capability to process large-scale data and comprehend complex patterns, have gained wide adoption in many businesses and are swiftly being implemented in new areas as well. One of the paramount challenges with current AI methods in finance is that they are fundamentally non-transparent and tough to interpret. The opacity of the AI models is particularly critical for AI systems used in high-stakes applications or with strict compliance requirements. This has driven investigations into designing and deploying explainable AI (XAI) methods.

There are numerous different methods which can potentially render a deep learning model more transparent. These methods intend to help people gain better insights about how a black-box model produces its outputs or predictions, which shall arguably make those AI models more trustworthy and approachable for end-users. It is noticed that explaining a deep learning model is not an exact science; instead, it is mostly an empirical process and largely relies on data sufficiency. After extracting kernel-based features, they are fed into a Naïve-Bayes ensemble model trained on bootstrapped samples and annotated words are used to simulate the local explanation in the text domain. Finally, the salient features or most important model predictors are applied to interpret the deep learning model. On the whole, the intention of different explanation methods is to spotlight the most important patterns learned by the model and to rationalize how they influence the AI model's predictions in a way that most users can apprehend.

3. AI in Financial Transactions

Efficient financial regulation is paramount to the success of the financial sector. Since the financial and economic developments in the last four decades, concerns regarding the stability, efficiency, and compatibility of the financial sector have increased. In comparison, the financial sector's size has multiplied manifold. Financial institutions leverage developed technologies to generate insights, automate processes, and improve decision-making from the vast amount of data they hold. However, advanced technologies are often construed as opaque keeping their decision-making process 'black boxed'. Hence, to make AI systems for financial services more transparent, many recent AI/ML developments focus on the research area of eXplainable AI (XAI). Financial intermediaries face the challenge of providing accurate and timely explanations to their clients about individual decisions taken by the AI system. The main objective of this paper is to provide a compact survey of and insights into addressing this challenge from the standpoint of explainability research. For the ensuing explanation, concepts like risk classification task as part of supervised machine learning, leading to the initial development of a financial-based binary classification model, and the use of Explainable Artificial Intelligence (XAI) through SHAP values for interpreting a black-box AI-based model is included. Also, a feedback evaluation study with domain experts from the business unit for improving the interpretations sheds light on those findings. Encouraged by the results in the given experimental study to provide insights for financial-based risk management tools and future research directions under compliance with data protection. Large, privacy-conscious Swiss financial intermediaries are required to announce how the algorithmic decision generated has been reached. However, this is not sufficient for customer trust in the system as it is essential for financial intermediaries to be sure about the rationale behind AI-based decisions.

An analysis of the historical development of XAI, its current popular applications in finance for compliance, explaining beneficial client outcomes, and risk management with pitfalls is provided. Besides, regulatory and research prospects that await discussions about the challenges, opportunities and potential development of XAI are newly understood.

3.1. Role of AI in Fraud Detection

In the era of digital banking, the importance of ensuring the security and integrity of financial transactions and activities has become more critical. Activities related to financial fraud, particularly in online banking and credit card transactions, impose severe threats to the global economic system. It is estimated that billions of dollars are lost every year due to fraudulent activities carried out within the financial sectors. In consequence thereof, financial institutions have conducted and continue to undertake rigorous research to combat and to identify financial fraud. One of the prevalent domains that is the subject of extensive research is bank-related financial fraud.

Bank account fraud may take many forms, ranging from unauthorized funds transfers to account takeovers. Although there are straightforward ways of detecting fraudulent schemes using traditional rule-based banking mechanisms that set a predefined threshold for each type of transaction, it is also possible that more subtle and fraudulent transactions are overlooked. Therefore, precise understanding and mitigation of these threats require thorough research, which should be underpinned by rich and diverse datasets. Given the vast amount of data available to financial institutions, machine learning (ML) technologies have been broadly adopted in the quest to develop effective systems that can detect bank account fraud. Generally, the fraud detection systems in bank systems use machine learning models in conjunction with a considerable amount of historical transaction data to identify the potentially fraudulent activities.

The success of machine learning algorithms significantly depends on the datasets used for training. Depending on the nature of the data and the type of fraud, diverse machine learning algorithms are adopted. However, in certain domains, datasets of bank account transactions may pose a challenge in devising a robust fraud detection system using machine learning approaches. Financial institutions usually possess their proprietary historical transaction data, from which they train machine learning models with the goal of recognizing potentially fraudulent activities. However, different financial institutions often face distinct fraudulent patterns. That is, machine learning models which were trained on a particular historical transaction dataset may not generalize well to fraudulent schemes in a different sector.

Fig 3: AI in Financial Fraud Detection

3.2. AI for Compliance Monitoring

The financial sector is transforming significantly due to technology innovations such as network connectivity, automation, big data, cloud computing, distributed ledger technologies, and AI. Currently, financial transaction processing activities are fully digitized, and the majority of these activities have been automated except for a few manual steps. Processes involved in financial transaction processing and monitoring need scalable and super efficient solutions that can process data in real-time in a trustable way. There are typically patterns that can be associated with both anomalies and normal activities in financial transaction data, which are however hard to distinguish. As such, AI-driven solutions would enable the identification and prediction of potential vulnerabilities, threats, and risks emerging from or affecting financial processes. The use of AI models in financial blockchain networks is driven by security and compliance concerns to safeguard transactions, data, and assets. Therefore, mechanisms that can ensure trust in the predictions made by AI models are required. However as the AI techniques become more sophisticated, there are bigger concerns for AI accountability, transparency, and fairness due to the use of complex algorithms and big data.

Concerns regarding trustworthy practices with AI execution can be stated as nonconformance with internal corporate governance. AI systems can be adapted to protect and secure themselves because the execution of AI systems in production environments can have substantial regulation and compliance implications. Violations could result in reputational loss and regulatory fines. AI algorithms are opaque data-driven that can put forward risks of fairness, causality, security, and deception. Over the lifecycle of an AI model, changes can be made in a data-drift, model-drift, process-drift causing degradation to the AI model. Extensive, accurate and reliable documentation is a prerequisite for validation and broader usage. Missing or inadequate documentation can raise regulatory exposure. Re-generating lost artifacts is nearly impossible for complex, dynamic or large-scale models.

Equation 2: Explainability of AI Model

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)]$$

where:

- N is the set of all features in the transaction,
- S is a subset of features excluding x_i,
- $f(S \cup \{i\})$ is the prediction with the feature x_i included, and
- $f(S)$ is the prediction with the feature x_i excluded.

4. Challenges in AI-Driven Security

The financial services industry has always been an area of special focus, where disclosure and other regulation can play a significant role. Important model governance activities must be taken into account if models implementing AI are to be considered safe and thorough. Transparency from providers of such models between the training data, pre-processing and network adjustments is also necessary, which can be compared with standard, pre-existing models. Examples for adversarial action or reduced data may be examples of AI effort requiring such disclosure and regulatory measures. Similarly, systems may be examined from AI discovering irregularities, concerning potential legal or regulatory infringements, but the system design may remain free from revealing rules of control. While GDPR and the Berlin Principles have been initial efforts toward necessary regulation, more specific measures are required to deal with proprietary matters and to secure financial resources. Conceptual guidelines offering transparency in proprietary PII, both in the learning process and at runtime, may also be beneficial. Ensuring security has long been subjected to discussion with the rise of AI. The main potential threats to the success of AI within the security and conformity domains, however, do not come from the highest.

Fig 4: Challenges of Artificial Intelligence in Finance

4.1. Data Privacy Concerns

Often sensitive to data privacy concerns in financial service companies. Concerns are growing, as AI/ML models are increasingly used in business decision-making. Privacy concerns arising from business models that inadvertently influence sensitive categories such as race are well publicized. But other concerns are equally relevant and less so. Immunity to Brauner analysis, adversarial examples, and other similar concepts draw attention to the fact that models are doing the unexpected for reasons that are opaque but disclosable. To a lesser degree, it may seem unfair that even sophisticated statisticians cannot understand why a model denies a customer's mortgage application due to what seems to be statistical discrimination. However, up to this point, litigation of such circumstances is only a small trickle. Instead, while much less newsworthy, financial services companies have unique needs for explainable AI/ML, driven by transparency obligations, compliance needs arising from regulators, and business decisions that require a careful audit trail of modeling decisions. Concerns about the quality of the model and the scope of the data may seem similarly important to all users. Balancing needs for explainability is a fundamental tension that cannot be resolved by prudent management. In addition, needs for compliance arise from fairness considerations in business decisions and regulatory requirements such as model risk management. With such complexities, it is worthwhile to take a holistic view of what explanation means. Recent events give an impetus to document these needs in a focused manner and to consider the coding and modeling opportunities to advance the state of the art in financial services companies that are relevant to explainable AI. The principles of the BCBS 239 Explainability standard related to the modeling and data quality domain are discussed. Not all of the principles are of direct interest to explain AI, but compliance challenges outlined to frame discussion are holistic for the full text and modal patch standard covered in all domains. Therefore, the principles of BCBS 239 are considered mainly in a wider context.

4.2. Bias and Fairness Issues

As with any machine learning system, relying on biased patterns to learn to make predictions, without accounting for the possible underlying prejudices in the data, can lead to decisions that disproportionately harm certain social groups. Notably in financially important industries, such as healthcare and especially financial services, this is a key problem – and the development of tools that can learn to manage these potential pitfalls are a high-profile area of ML research. The goal of developing robust and accurate ML systems that are able to account for and minimize the amplification of bias has been widely embraced by both the research community as well as legislative actors.

5. The Need for Explainability in Financial AI Systems

Since their dawn, the success of artificial intelligence (AI) systems, such as deep ensembles, has led to their widespread adoption across various industries. Representations in hidden layers of neural networks, employed by deep ensembles, allow complex patterns to be learned and have the potential to encode temporal and transactional behavior in a chain of financial transactions. Finance is among the latest sectors to adopt AI technologies. Financial AI systems can be used to infer the risk associated with financial transactions or to detect fraudulent behavior. However, because of their inherent lack of explainability, AI-transformed solutions raise significant concerns. A behavior based on the hidden representation of deep ensembles cannot be explained in a human interpretable manner, which can make the financial AI system unreliable in the context of the law. This project aims to address this critical issue by providing explainable AI for AI-driven security and compliance in a chain of financial transactions. The behavior of complex financial AI systems is explained to human interpretable models that might be considerably simpler. The overall view is that a financial system could be used as a decision maker to trigger a risk flagged or financial AI system could be used as a detector for some potential fraudulent behavior, ideally in real time. Meanwhile, XAI-driven models can interpret the behavior of DAI, contributing to improving the transparency of the legal processes being considered.

Fig 5: Explainable AI

5.1. Trust and Transparency

Trust and Transparency: XAI Implementation in a Real-Time System for Explainable Data Governance on Financial Transactions
Reinforced by the 2008 financial crisis, there has been ever-increasing oversight and regulations for financial intuitions' data infrastructure and handling. One of the challenges faced by banks in implementing explainable AI to meet such obligations is the so-called ontology drift: instruments, transactions, and customers change over time, creating a need for the financial ontology to frequently adapt. This text presents an investigation of such needs with respect to financial data governance on transactions, and a solution implemented in a system. The explainable AI interfaces provided aim to assist in the potential problem for a designated 'compliance officer' in maintaining a comprehensive, automated, and evidence-augmented data governance system for their financial institution.

5.2. Regulatory Requirements

Financial transactions are an ideal target for fraudulent activities. Advanced AI/ML solutions can help detect these fraudulent activities, thereby safeguarding the integrity of the financial system and the protection of the consumer. However, these solutions can significantly fail by identifying innocent behaviors or not recognizing the TDs (true detections). Thus, the need for explainability is now a high research priority in order to unveil the functioning of these opaque algorithms and provide proper proof and trust to such functioning. Unveiling credit card transaction behavior in different circumstances helps in explaining the behaviors and decisions of AI/ML algorithms developed to monitor their integrity such as detecting money laundering and fraudulent transactions. Such behaviors can be related to unfairness, unanticipated results, unexpected outcomes, incorrect classifications, and beneficial lawful transactions erroneously classified as illegal or false positives. Additionally, they can help to convince domain expert auditors in companies and financial organizations, the whole compliance chain, court experts, judges, etc., as to why and how the AI/ML decision-making process led to a specific behavior or a conclusion.

Protection against misuse and fraudulent activities in the financial system is necessary to preserve its integrity and to prevent the existence of hidden financial risks. In this regard, a good way to identify suspicious and illegal activities is through the analysis and follow-up of financial transactions. Such transactions are generally monitored and analyzed by financial institutions in order to detect money laundering, terrorist financing, fraud, theft, etc. The monitoring of other credit card transaction behaviors not necessarily typical of fraudulent behavior but which some people may think so or are interesting because they may be finally classified as criminal falls into the interest of privacy. Such observations from the monitoring of banks in collaboration with law enforcement agencies can lead to behaviors of an innocent but curious or highly jealous person that can easily be misinterpreted. The plain analysis of credit card exclusive transaction behaviors should be properly understood to avoid such misinterpretations. Regulatory requirements Current developments in the paradigms that regulate machine learning are reshaping financial markets, especially concerning the Fintech domain, with fresh demands for interpretability and fairness on the models' deployment and decisions. Exaptation theory offers tools to comprehend the transformation of equipment or knowledge for a new purpose. This paper employs OECD guidelines and Exaptation to examine the reshaping process, uncovering how the frazzled fabric of a unique setup of national regulations and European Directives was completely overhauled, accepting a hotchpotch of constraints into fully-fledged governance domain. The fintech firm becomes the "detrimental test case" acting as an unexpected entropic force on the environment and other subjects, and Meta-Learning models hypothesize how it may respond by influencing the epigenetic regulations toward a trade-off mechanism. Due to the dearth of tested signaling between departments and regulatory gaps, a new system emerges that increases firm's opacity and the regulatory efforts/interventions required, fostering, as a sort of "regulatory feedback" mechanism, a secretive enclave detrimental to the chaotic financial ecosystem as a whole.

Equation 3: Compliance with Regulatory Constraints

$$\mathcal{L}_{comp} = \sum_{i=1}^{m} 1\left(\mathbf{X}_i \notin \mathbf{C}\right)$$

where:

- m is the number of transactions evaluated,
- $\mathbf{X}_i$ is the feature vector of the i-th transaction,
- $\mathbf{C}$ is the regulatory constraint set,
- 1 is the indicator function, which equals 1 if a transaction

6. Conclusion

In this manuscript, the authors argue that the success of AI-driven applications in finance, and especially those handling security and compliance tasks where even small errors can have significant consequences, may be dependent on their ability to explain their decisions. AI-powered financial systems have historically been associated with “black boxes” but, as discussed in their review of the literature, explainable AI is a growing, interdisciplinary subfield that aims to shed light on how these systems operate in order to enhance their acceptance in (and compliance with) regulated industries such as finance. While a large body of literature has emerged examining XAI in finance, in this manuscript the authors delve deeply into how AI, and especially XAI, are being used within financial applications to process transactions. There are four sub-areas of finance and XAI use that are focused on: (a) the automation of anti-money laundering tasks and the rise of a surveillance culture, (b) the use of XAI to enhance the oversight and governance of AI systems (especially data quality and governance models), (c) the origins of the XAI field – the “black box” problem and existing legal frameworks, and (d) the rise of AI-driven privacy threats and the increasingly importance of data protection impact assessments. Finally, a model of human-AI interaction is described wherein explainable AIs are theorized not to provide an end product but enter into an ongoing dialectic with users. Communally negotiated explanations become a function of different societal interests and field dependencies, thereby reinforcing symbolic, economic and epistemic asymmetries. It is held that explanations in this framework are not value-neutral but subject to plugin normativity.

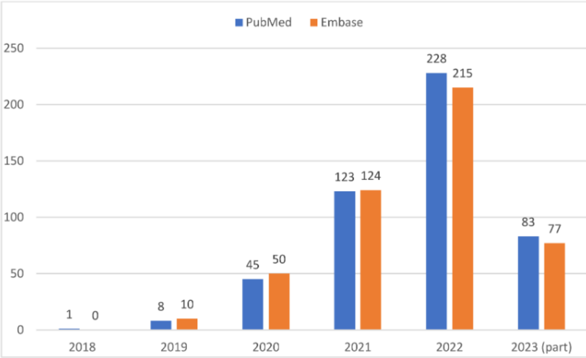

Fig : Explainable Artificial Intelligence (XAI)

6.1. Future Trends

Business impacts of the COVID-19 pandemic remain uncertain, fintech and the adoption of distributed ledger technology for financial services are expected to expand rapidly. There is a growing market focus on AI-driven compliance, risk measurement, and explanation of complex machine-learning models. In the realm of distributed financial database systems, blockchain is a sandbox for understanding machine learning models. Use of machine learning and of AI-driven compliance and risk management has growth potential in the context of blockchain in international finance. In theory this can augment FinTech efficiency but has been developed in limited explanatory ways. A research agenda for AI-driven financial compliance and risk management in the realm of blockchain hubs is introduced.

The explainable artificial intelligence for AI-driven financial compliance and risk measurement on blockchain for AI-Driven Security and Compliance in Financial Transactions Problem is defined research challenges, solutions, knowledge transfer, and project goals. A later study is enumerated by proposing a set of preliminary research questions and executing a scoping review. In addition to filling these gaps, it is hoped that the commentary will assist academic researchers and members of financial compliance and regulatory agencies in regulating emerging market behavior. AI-driven compliance and risk management are enabled on blockchain by providing an under-researched literature review and directions for network systems with at least one direct connection to hubs with a Layer-1 strategy. Piece provides a comprehensive understanding of the frontiers of blockchain in terms of basic properties, design principles of its derivatives, and the development landscape of blockchain hubs.

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