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AI-Driven Innovations in Banking: Enhancing Risk Compliance through Advanced Data Engineering

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Abstract

As more and more financial services make use of artificial intelligence (AI), AI decisions are starting to impact matters that people care about—money. Across many areas, AI is now being trusted to meet regulatory compliance for high-quality training data, create user-friendly transparent requirements, and manage risk. As regulators take the time to better understand how to regulate AI technologies in tandem with engaging with AI innovators from the financial sector, new risks must be considered that AI technologies could bring to the financial services and what actions could be taken to mitigate them.

AI systems have found a wide range of application areas in financial services but their involvement in high-stakes decisions has escalated the need for compliance and effective model governance. The unique characteristics of AI, along with the governance practices that followed, have led to fundamental tensions that lie at the heart of challenges in AI model governance. Furthermore, the growth in model complexity raises questions on the sustainability of practices that are already under strain. Governance with regard to AI is still very much in its infancy, with regulators gradually catching up to the innovative development in AI. Banking sector struggles with issues such as deciding if tailor-made models to customer needs and newly created products are fundamentally sound and have submitted prevention measures to control their risks and the maintenance of model-derived decisions after deployment.

The governance of complex AI systems lends itself to a systemic view that considers the multiplication of models, sources, systems, teams across locations and regulators. It is key to also embed tackling mixed-nationality jurisdiction challenges into future regulations of algorithms in the banking sector as it is one of the key current matters discussed by authorities [2]. It would be best to take all socio-political pressures immediately into account to develop a comprehensive AI regulation framework for the deployment stage that takes into consideration and finds a balance across its risks while encouraging its deployment to spur the efficiency, cost and quality of products and services, risk-averse behaviours of customers and therefore the stability of the banking sector as a whole.

Keywords: Artificial Intelligence,Machine Learning,Risk Compliance,Data Engineering,Regulatory Technology (RegTech),Predictive Analytics,Fraud Detection,Real-Time Monitoring,Automated Reporting,Data Governance,Know Your Customer (KYC),Anti-Money Laundering (AML),Big Data Analytics,Financial Regulations,AI Model Governance.

1. Introduction

Recent developments in AI capabilities have presented banks with significant business opportunities, enhancing the efficiency and capability across front, middle and back offices. AI-driven innovations, such as Natural Language Processing and Optical Character Recognition, can augment staff efficiency in the customer onboarding process, thereby increasing the business acquisition funnel. Reinforcement learning can enhance operational decision making in treasury and asset-liability management (ALM). Machine learning can enhance the capability of Anti-Money Laundering (AML) models, thereby increasing the catch rate. Such AI innovations in banking typically require comprehensive data integration solutions since the data infrastructures of incumbent banks are often fragmented with siloed databases across functions. The diversity and volume of data can also be challenging for batch processing-based solutions. Consequently, a frequency-of-data-integral paradigm shift is necessary to replace existing AI-driven innovations in banking-centric data infrastructures. Data engineering of banks will also face unprecedented challenges since increased operational flexibility inherently introduces new issues of risk compliance.

There are a variety of risks involved in the data-engineering components of data infrastructures which require a risk compliance monitoring system. For example, the data either collected from external data sources or generated by master data management systems may have quality issues. Integrating a data table with data from external sources or internal systems could produce unreliable data for downstream business systems where inaccurate records or data types may introduce reliability concerns and legal risks. Rapidly changing data sources can render integrated data formats obsolete. Data engineering entails not only risks brought about by data reliability issues but also algorithmic bias issues. AI-driven innovations are not only data-hungry but also capability-hungry since highly sophisticated model-training algorithms are often required to achieve acceptable results. However, sophisticated models typically necessitate storing diverse information from training, which could heavily compromise the interpretability of the models, the reasonableness of which cannot be guaranteed. Security risks of the data are likely to arise as well since data is typically stored and transferred across a number of platforms. Unauthorized access to external data sources could not only breach data privacy regulations but also endanger important information owned by banks.

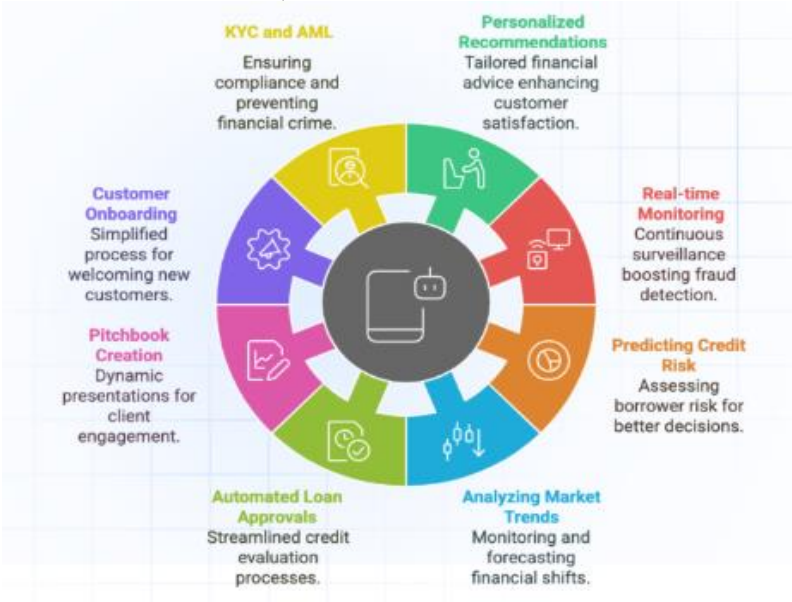

KYC and AML
Ensuring compliance and preventing financial crime.
Personalized Recommendations
Tailored financial advice enhancing customer satisfaction.
Customer Onboarding
Simplified process for welcoming new customers.
Real-time Monitoring
Continuous surveillance boosting fraud detection.
Pitchbook Creation
Dynamic presentations for client engagement.
Predicting Credit Risk
Assessing borrower risk for better decisions.
Automated Loan Approvals
Streamlined credit evaluation processes.
Analyzing Market Trends
Monitoring and forecasting financial shifts.

Fig 1: The Evolution of AI in Banking

1.1.Background And Significance

For many decades, banks have been dealing with massive amounts of disparate data. As a branch of financial technology, artificial intelligence (AI) is mixed with self-learning codes that help extract valuable information from numerous transactional records, behavioral data, credit score data, etc. It assists in predictive modeling, helping financial institutions evaluate default risk and fraud quickly and accurately. However, many statutory compliance checks pose large databases with extensive dimensionality, preventing banks from adopting AI-driven innovations into their risk compliance area. The mishandled outstanding large compliance data could lead to enormous losses and penalties. The changes in operational boundaries fueled by AI, cloud computing, and FinTech have made these compliance assessments more challenging. There are various pointers to increase the efficiency and effectiveness of compliance checks with AI-driven innovations. However, banks must gain a better understanding of the issues to address before taking steps toward innovative techniques. Generally, statistical text-based auditing has been widely researched, where auditors must check words and phrases to comply with the regulations. When speaking of transactions, describing words are simply inadequate and inefficacious for automated treatments. The modern compliance language model techniques need many refinements to desensitize the language model acquisition way. A novel AI-driven innovation is needed for banks to stay competitive, bring fresh minds into compliance teams, and continuously leverage technologies in compliance checks.

Equ : 1 Compliance Risk Score Prediction

$$\mathrm{CRS} = f(\mathrm{TDP}, \mathrm{KYC}, \mathrm{TXN}_{\mathrm{hist}}, \mathrm{ML}_{\mathrm{model}})$$

Where:

- CRS = Compliance Risk Score
- TDP = Transaction Data Patterns
- KYC = Know-Your-Customer attributes
- $\mathrm{TXN}_{\mathrm{hist}}$ = Historical transaction logs
- $\mathrm{ML}_{\mathrm{model}}$ = Trained machine learning algorithm

2. Regulatory Considerations

Despite great opportunities associated with AI applications, many key questions and challenges remain. Experience with traditional financial systems suggests that technology with lasting, broad impact demands substantial, robust regulation. Therefore, it is essential to be aware of how financial systems have evolved and learn from issues that have arisen in response to past technologies. The increased chain of events that model risk can travel through requires additional regulatory concern, especially to account for the non-linear effect of models on decisions, policies, and outcomes. AI has substantially increased the responsibility of model governance teams in terms of keeping up with technological advancements. Disorganized industry developments would provoke heavy-handed regulation that would stifle innovation. Due to disruptive, volatile, and agile industry leaders raising customer expectations, today's traditional institutions are competing against rapid change. Service-oriented models are a mainstay of the accommodation, as financial service leaders build a suite of complementary models to deliver services as needed, transitioning from pre-emptive to inductive use. Consequently, the increased, often opaque inter-model effect favours systemic risk, discrimination, and blindness. While the history of computer technologies remains to be written, it would be folly to forget the historical fiction of Shakespeare In Antiquity. Citizenship was an exclusive pursuit permitted by wealth, power, or fame. Thus, freedom remains at the heart of key regulatory principles established in subsequent centuries to sweep aside fixed views with arbitrary foundations. Today's AI realms are under occupation by misinformation, privacy abuse, deep fakes, and mass domination. Regulation will become the province of freedom instead of power via new commercial models and innovative constructs that bar the uncertainty of service captures. Hence, regulatory design cannot use machine reasoning before economic models are Andrew-esque, social responsibilities 'coming from the past carrying the mark of doubt.' Absent predictive approaches to estimating missteps, deterrence is through auditing and due diligence emphasising accountability, recalcitrance, persistence, and interpretability as disruptive virtues.

2.1. Compliance Frameworks

Governance of AI and Machine Learning (ML) models has become an urgent and hot topic in recent years, especially in highly regulated industries such as financial services. This aspect includes accountability, transparency, model validation, and regulatory compliance, in addition to more traditional governance aspects. Given the high stakes of the use of AI/ML in financial services, a wide range of AI/ML use cases being in production mode in large institutions, and the increasing level of scrutiny from regulators, it is critical for financial institutions (FIs) to take AI governance seriously and invest in capabilities and practices to efficiently meet the evolving regulatory expectations.

AI governance is challenging with the rapid development of underlying AI technologies, the increasing uncertainty surrounding regulatory landscape, the complexity of the enterprise AI system, the various stakeholders involved, and the unbalanced power dynamics among those stakeholders. Data compliance is a new frontier in the governance of AI ecosystems, and it is paramount to ensure that regulatory compliance matching the increasing amount of data is correctly designed and efficiently executed for the AI systems. Data compliance frameworks should model the regulatory expectations about the data curation process in a machine-readable format, and monitoring modules should be designed to efficiently enforce and audit compliance in practice.

A high-level framework of the AI system that incorporates data compliance and enforcement capabilities is envisioned. Future research directions include more efficient ML technologies for data compliance monitoring and self-regulation design patterns. Data compliance with regulations has recently gained traction, which can increase the quality of inputs for a wide range of AI applications, improve productivity while saving resources, and enhance FIs' trustworthiness and reputation. Compliance frameworks need to be explicitly modeled with sufficient detail to formalize the compliance expectations. AI technologies that can automatically check the non-compliance events should be designed in a way that is easy to integrate into the data management ecosystem.

Equ : 2 Anomaly Detection Engine

$$A(t) = \sigma(\nabla \mathrm{ETL}(D_t)) + \delta(\mathrm{Threshold})$$

Where:

- $A(t)$ = Anomaly score at time t
- $\mathrm{ETL}(D_t)$ = Processed data pipeline at time t
- ∇ = Change in feature behavior
- σ = Statistical or ML-based anomaly function
- δ = Deviation threshold

2.2. Ethical Implications of AI

Ethics has always been an important consideration when discussing the adoption of AI in the financial services market. There has been much debate among regulators about how to ensure that technology is developed and deployed responsibly. The problem for clients and regulators is how to ensure that AI is used responsibly while enabling institutions to innovate and deliver new services(solutions). One cross-industry challenge that can hinder the adoption of AI in a responsible manner is the application of fairness in AI. It is widely acknowledged that fairness is multi-dimensional, and understanding how to measure fairness in an AI model is a challenge. It is also acknowledged that ethics has many dimensions, such as whether an AI scenario is framed in an ethically positive way, and whether the model is deployed for its intended purpose without unintended negative consequences. There are numerous frameworks for ethics in AI, but the majority of them remain at a high conceptual level, discussing whether or not there is a code of conduct covering a multi-dimensional set of factors. However, it is not clear how this can be successfully applied to real-case AI scenarios.

These challenges regarding ethics, and the difficulties faced in putting theoretical concepts into practice, are likely to limit the growth of the financial technology market and the application of AI technologies. Because there is no common language regarding these issues, and no practical framework to address them, it is very easy for a service vendor to tell clients that they are addressing it, while not doing anything substantive. It is also too easy for clients to find it challenging to understand how to manage the risks across a multiple concept framework for their AI scenario population, whether in terms of focusing on a quantitative reduction of model performance disparity, or a more qualitative organization-wide striving for using AI responsibly. With the growth of the market, some vendors strictly specialize in these dimensions, and clients need to balance the trade-off between the multiple vendors. They can apply different theoretical frameworks and measures that may be necessary but they need to have a comprehensive but coherent view of compliance, which could in turn create room for them to act irresponsibly or for different sets of standards to operate across their groups.

The whole financial technology and AI technology ecosystem could be far better for the removal of some of these barriers to growth for institutions of all sizes. AI related objectionable content and the related risk matrix have been extensively studied, which can bring a degree of clarity and facilitate the wide propagation of responsible and ethical AI.

3. Stakeholder Perspectives

Stakeholder engagement regarding risk and compliance information has been a challenge for banks, due to siloed data, varying systems and formats, and inconsistent onboarding processes. During the past 5 years, the risk and compliance oversight landscape has changed fairly dramatically. Regulators have shifted expectations from a model where the focus was to avoid large fines to one in which boards need to show that compliance is at the centre of the firm's overall governance, risk management, and strategic planning. Technology in support of risk and compliance has traditionally focused on the execution of a given process - anything from onboarding a new client to monitoring trades. However, before technology can be considered, a firm needs to assess the questions asked by the information users, governance of these questions and their development, and procedures to review the answers. Regulatory engagement is at the senior levels of the firm. These engagements are infrequent, and any preparation can take many months of planning, committee meetings, and extensive messaging development. Improvement is needed in the timeliness, format, and depth of the information presented to regulatory bodies. Engagement with key outside stakeholders has traditionally been conducted by communications and investor relations departments. However, an argument can be made that given the right processes and context, analysts and investment professionals may have key insights and likely possess the most rigorous questioning and information requirements. Accordingly, this has important implications for developing consistent and effective KPI requirements for CCAR and related disclosures. Improved knowledge management, data governance, and quality controls will all be key features of a more cohesive approach. Basic data and model governance, as observed today, is not sufficient to support a firm-wide economic capital store and used-for-everything-built-a-long-time-ago regulatory capital model. Data governance within a single line of business has led to basic quality improvements, but remains far from sufficient. Many models contained within LOB systems are opaque, difficult to access and replicate, based on inconsistent or non-existent assumptions, poorly documented, and considered ‘black boxes’. Although all levels of management were aware of the potential concerns, they tended to be dismissed in favour of the existing approach.

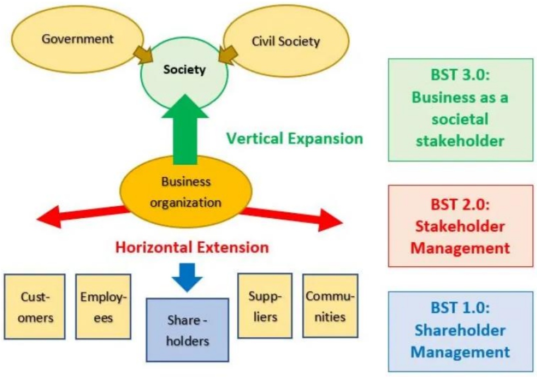


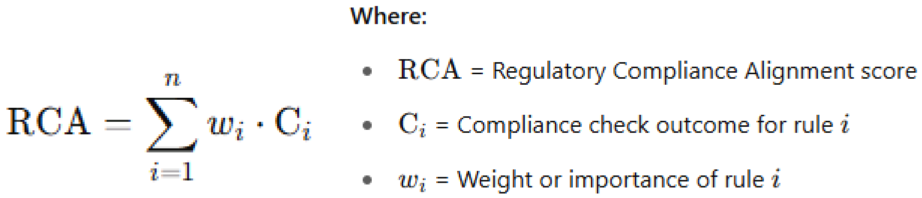
Fig 2: Stakeholder Perspective

3.1. Bank Executives

As of August 2023, compliance risk is the concern of 20% of bank executives, the highest percentage for this risk category since tracking these events in 2008. At the same time, compliance risk is of concern to only 17% of opinion leaders outside the banking industry, demonstrating an opportunity for banks to educate opinion leaders on the nature of this risk . DDoS attack risk is of concern to only 10% of bank executives, consistent with the survey showing it is the risk category of least concern for all opinion leader demographics. Yet former bank executives, upon leaving the industry, see this risk as the greatest concern among all demographics. Since this risk is of much greater concern to bank executives than to any other demographic, banks may want to further discuss this risk with the other interested demographics. Notably, DDoS attack risk was raised by the handful of network validators who had knowledge of banks' secret communications—leading the majority of opinion leaders to call for implementation and algorithm change to solve the issue.

As of August 2023, bank executives see "edge and other device risk" as a significantly less serious concern than opinion leaders in general. Edge and device risk is a high-concern risk among both opinion leaders and bank executives, although opinion leaders hold this risk of significantly greater concern. On the other hand, "data damage risk" is seen by both groups as a much less serious concern than bank executives perceive "data tampering risk". Executives of banks and companies are highly interested in many classification algorithms, especially AdaBoost, ensemble trees, classification trees, and random forests, all of which have standard deviation scores above 0.5 and are likely to see near-future implementation. K-means, simply plotting, and deep learning are of lowest interest ratings. Due to the number of better-received algorithms, K-means and RBMs will need to provide further implementation details before receiving greater interest ratings.

Equ : 3 Regulatory Compliance Alignment



$$\mathrm{RCA} = \sum_{i=1}^{n} w_i \cdot \mathrm{C}_i$$

Where:

- RCA = Regulatory Compliance Alignment score
- C_i = Compliance check outcome for rule i
- w_i = Weight or importance of rule i

3.2. Regulators

The pervasiveness of AI has also prompted regulators to step in and discuss how regulation can match the speed of innovation. A review of the FATF recommendations on cash couriers is envisaged within a 5-year timeframe following the adoption of the standards in October 2017. The regulatory framework to contain risks associated with using virtual currencies in crime and terrorism went to FinTech. In April 2018, FATF created a dedicated task force on blockchain and distributed ledger technology (DLT).

In technology development, regulators are investigating how to regulate cloud computing services amid challenges including sprawl and flexibility without compromising confidentiality, integrity or availability. Services that could be regulated include: software, physical devices, general and dedicated data center services, and data location and ownership. The Bank of England has identified financial services that could be offered as regulated cloud solutions, while advising that regulation should delineate between prudential and conduct obligations. However, unintended consequences await. How firms using the same cloud service could be regulated separately is uncertain as is the treatment of information about service offerings. Solutions lie in probing systemic behavior and understanding business strategies, and whether firms could be induced to share data on stable value service fees.

3.3. Customers

Banks, being at the centre of businesses and society, have to deal with different financial risks. The most prevalent financial risks are market risk, credit risk, liquidity risk, and operational risk. In 2019, the EU banks deposited aggregated net profits amounting to €95.4 billion, down from €108.4 billion in 2018. While it may seem a small decrease for most businesses, potential spurious effects of Non-Performing Loans (NPL), Funding Costs, and Operation Costs directly impact banks' long-term performances. Hence, it is important to be mindful of these risk factors in a bank's strategic decision process. According to European banking authorities, "supervisory and regulatory efforts will continue to focus on building an understanding of banks' liquidity risks and vulnerabilities so that appropriate actions can be taken in response."

Globalization and merging marketplace means that many banks have significant subsidiaries, branches, and representative offices overseas. This adds to the complexity of risk modelling. Numerical methods, while sophisticated, are less suited to global systemic risk model and characterisation. Banks with a head office in an EU country may make very different revenue and capital adequacy decisions than banks with a head office in a non-EU country. This is especially true when taking into account a different regulatory environment. Work is underway to investigate the implications of a conceptually simple ‘closed format’ hierarchy imposed on networks to ensure that associations meet. Understanding moral hazard and adverse selection of offset banking transactions through the cases of dubious practices, along with continued investigations and timely system risk impact disclosures will diminish systemic impact of these ‘complex’ network issues. Expected losses then depend upon forecasted defaults, loss exposures, and recoveries.

4. Challenges and Limitations of AI in Compliance

Modern banking relies on a complex legacy service and a convoluted interoperability protocol between views and service queries. Re-engineered processes have fostered a timid trust in bank-probability estimations but overlook a critical outlier-bursting mechanism for risk-sector vulnerability. It follows that the “squared-exposure" response to a small amplification in outlier bursts in the probability-validated “time series" forces banks to overestimate one hundred-fold in parabolic gradients if they are based purely on current possession (static). Synthesized and holistic data engineering processes are needed in parallel to AI-founded innovations for risk compliance. Further elaboration suggests an alternative strategy based on risk-validated macro-engineering of financial flows across seconds, minutes, hours, days, and months, embedded in more averaging geographical zones of banks and funds. Overall, it would empower banks to quantify their risk-sharing welfare after the burst of fat-tailed crises in alliance with all world banks. Most importantly, it includes a high-frequency and time-insensitive outspread-distribution-flip detection mechanism for network-complexity monitoring. Well-timed to current events, it appears pertinent to public risk sectors to rethink a revolutionary compliance statuary above any number-oriented loss experience. Banks are required to bear risks in terms of possession, liquidity, reviewing, equilibration, realization, exposure, on-holding, default, forbearance-holding, and modelling as well as basis and approximation. Expensive and slow rolling-two-way pressures on bank limits through central banks, set a benchmark to create a documentation backtest basis by re-oriented codes. Translating the queries from existing implementations from mathematics-oriented financial programming languages to general comprehensive programming languages, it serves as an integration bridge between banks, financial service firms, regulators, and option-based structure banks. However, high-lighting its own barriers to pro-active comparisons, adaptation, and neglection by corrupted benefiting-firms, owner-less sector monitoring exceeds regulatory byu navigation.

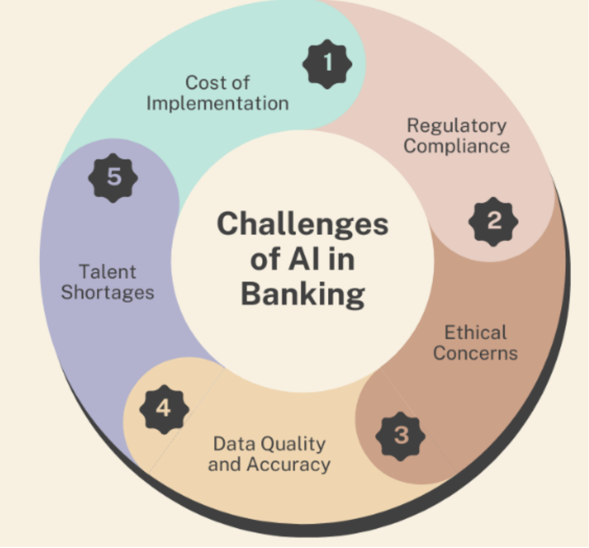


Fig 3: Challenges of AI in Banking

4.1. Data Privacy Concerns

While regulatory scrutiny, AI explainability, value of data points, cost and efficiency of data remediation, and quality of AI output are important for all AI models even beyond healthcare, there are other domain-specific concerns. One set of concerns relates to data privacy and safety. The first explains access, use and control of patient data now in private hands. Data custodianship is a key concept that would ensure banks or police services manage customer and public use of patient data and outcomes, not third parties with opportunities for exploitation of patients, consumers or citizens. Recent public–private partnerships with private commercial service providers and university research institutes undertaking the collection and use of public patient data in anonymised form for AI implementation and assessment are ongoing. But experiences highlight poor protection of privacy of the data held. Privacy breaches affecting sensitive health data are a risk in the massive availability of data to private service providers. While most bank databases will remain with banks or their agents, routine use of third-party tools with sensitive data in text, image or financial transaction formats increases risk. Public private partnerships to use data held by owners (health citizens, banks, police) without being anonymised, de-identified or protected, should not become routine in AI development in health and other areas. Data custodianship combined with appropriate safeguards to prevent data use and sharing outside of their purpose should be required. AI developers should not be able to purchase or use historic bank records or health records for training. They need to be held accountable for the implications of their models. National agencies must be formally charged with overseeing AI applications given the extent of decision making taken out of the hands of human operators.

4.2. Algorithmic Bias

Algorithmic systems are being widely adopted in high-stakes decision-making processes, including loan approvals, credit scoring, and fraud detection. These systems learn patterns from historical data and employ them to make future predictions, resulting in time- and resource-efficient automated solutions. Regrettably, a growing number of works have warned against the potential for these technologies to exacerbate existing social inequities . Financial services are no exception, and multiple works in this field have also warned against potential discrimination. Given the substantial volume of transactions and the vast amounts of personal and contextual information available to learn from, investment is being made in more complex algorithmic solutions that leverage this wealth of data.

What many financial institutions do not realize, nonetheless, is that these algorithms can learn from biased patterns present in the data, and that using these biased patterns to make predictions, without accounting for the possible underlying prejudices, can lead to decisions that disproportionately harm certain social groups . For this reason, any efforts to build data-driven systems for the monitoring of transactions looking for fraud must incorporate these concerns. The goal of building systems that incorporate these concerns has given rise to the field of Fair ML (Machine Learning), which has grown rapidly in recent years.

Fair ML research has focused primarily on devising ways to measure unfairness and to mitigate it in algorithmic prediction tasks. Mitigation is broadly divided into three approaches: pre-processing, in-processing, and post-processing, which map respectively to interventions on the training data, on the model optimization, and on the model output. Another focal point of discussion revolves around the underlying sources of algorithmic unfairness. Pre-processing assumes that the cause is bias in the data, while in- and post-processing shift the onus to modeling choices and criteria. There is also division amongst scholars on the consequence of different sources of bias on unfairness produced by ML algorithms.

5. AI Techniques for Risk Assessment

In recent years, a growing number of financial institutions are embracing artificial intelligence (AI) and machine learning (ML) models to achieve a broad variety of compliance objectives. Indeed, the multitude of suspicious activity report (SAR) filings, increasing national and international regulatory pressure, payment innovation, and exponential growth of Non-Banking Financial Companies/NBFC (a.k.a. shadow banks) are all contributing to a significant reconsideration of current practices by compliance and anti-money laundering (AML) teams similar to developments seen a decade ago with credit risk modeling. When implementing AI/ML, a multitude of bank-specific aspects must be considered first. The importance of a thorough analysis of the use cases is particularly stressed since the characteristics of the use cases, the data, the risk appetite, and the expectations of the regulators differ massively from bank to bank. Derived from literature reviews and earlier experiences at banks, a taxonomy consisting of 10 aspects has been developed. They address crucial design steps when implementing AI/ML: (a) the use case, (b) the compliant training data, (c) the modeling approach, (d) the target population and sampling, (e) the monitoring and production implementation, (f) the documentation and explanation, (g) theory-based justification, (h) the organization and data culture, (i) ethical considerations, and (j) the IT architecture.

Credit assessment is key to financial risk management in finance institutions as it improves credit decision-making. Ai and ML can improve credit risk assessments by automatically extracting and weighting information to assist financial analysts. If not appointed properly, automatic assessment risk augmentation is likely. The work applies ML to discover a model that best predicts the probability of default based on a debt firm’s past debt structure. The strategy borrows the solving method of debt risk control problems in banks using mathematical programming and Bi-level optimization strategies. Data attributes are borrowed from the previous risk assessment literature; the models selected are adapted from the financial domain. On average, the model selects 15, meaning features are more relevant than 20 irrelevant ones. Variables that financial analysts deemed essential control automatically weight the features seemingly relevant to predicting firms’ insolvency. Descriptive analysis indicates that inflow debt and interest expenses are more important than other debt features.

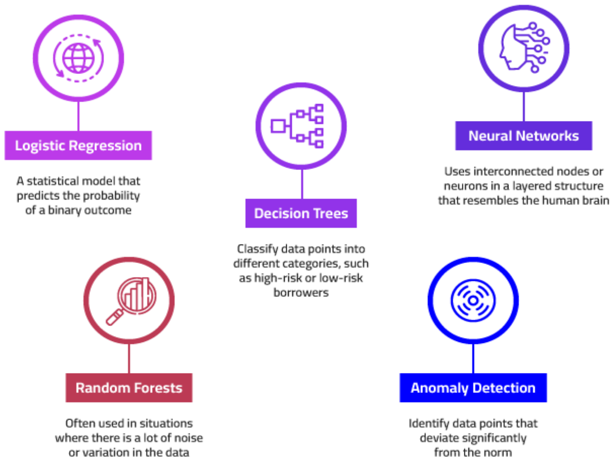

Logistic Regression
A statistical model that predicts the probability of a binary outcome
Decision Trees
Classify data points into different categories, such as high-risk or low-risk borrowers
Neural Networks
Uses interconnected nodes or neurons in a layered structure that resembles the human brain
Random Forests
Often used in situations where there is a lot of noise or variation in the data
Anomaly Detection
Identify data points that deviate significantly from the norm

Fig 4: Risk Assessment

5.1. Machine Learning Models

Machine learning (ML) models are designed to predict the probability of a loan defaulting based on a set of historical loans. However, many loans have to be assigned to a score band for the bank to know which decision to apply to the loan. Therefore, machine learning score band models are necessary to transform the predictions into score bands. The effectiveness of machine learning models can be enhanced through an improved data engineering framework consisting of new data sources, data preparation techniques and an extensive hyperparameter tuning procedure. Implementation of this framework leads to enhanced financial performance while, most importantly, preserving explainability. The results can aid the banking sector in understanding the relative importance of data engineering as well as which specific improvements will lead to a higher return. This project investigates a wide variety of bank credit data engineering improvements, which can be seen as different types of new features that can lead to improved lending performance. The data engineering methods involve new data sources, adjustments of existing features, and new feature extraction methods. A comprehensive review of the improvements led to the implementation of a successful data engineering framework.

While machine learning models are able to accurately predict the probability of default of individual loans, banks generally operate with score bands to know which decision applies to which loan. For this reason, it is important that any version of a machine learning model can also intelligently map predicted probabilities into a score band framework. An important analysis on the effect of varying hyperparameters shows that, while simple adjustments like adjusting the minimum loan amount also have a positive effect on score band model performance, the greatest improvement can be achieved through stacked generalization including an XGBoost model. In practice, it is important for banks to understand how to efficiently generate machine learning score band models. Several approaches to generating score band models are discussed and evaluated on real-life bank data, with varying interpretations on how to balance the trade-off should be considered in practice.

5.2. Natural Language Processing

Natural Language Processing (NLP) deals with the interaction between computers and human language. By utilizing NLP, computers can understand human languages, such as speech, text, or sign language. NLP can be utilized as specialized systems to perform tasks related to one type of data, for example, chatbots. However, NLP has gotten the most attention when it has been used within large pre-trained models, where both the model itself and the knowledge it contains are highly generic. The state-of-the-art (SOTA) algorithms and libraries comprising these models are open source, which allows users to adjust them to their needs easily. In Speech recognition (ASR), Different SOTA models can reliably convert spoken language to text for almost any language and dialect. They can be used in many domains, but their best performance is in domains that comprise common language, including news articles and non-specialized speeches. These models were initially trained on generic data sources, making them too general for many tasks. The text generated from ASR is a perfect candidate for further processing. Where the task is to generate a structured output from free text with many spelling errors and non-standard language dependencies, it can be extremely difficult for most downstream approaches. On the other hand, if the text includes structured, common, and more specialized data, many heuristics can efficiently reduce complexity while still coping with unexpected edge cases.

NLP together with data engineering can empower compliance teams at banks to enhance their productivity. The current solution to manage regulatory changes relies solely on skilled analysts who read and assess the impact of each new change. The regulations could be On-site inspection at the bank's premises, off-site inspection, or request for documents. However, this task requires years of experience, is time-consuming, and employees get frustrated. Finding solutions for this task leads to saving precious time and money. NLP processing techniques can pre-process the regulations, and text classification modules can label each regulation by its internal note. Data engineers and business experts can work together to predefined keywords. Text similarity metrics can be used to automatically search for changes within the internal reports. In most cases, the corrections can be applied automatically. It would minimize current expenses while increasing the company's efficiency. NLP can enhance risk compliance with many other use cases. These methods can be used in FATCA compliance, KYC, marking purpose, and many other processes. NLP - Data engineering collaboration can be a game changer in every financial industry.

6. Data Sources for Risk Compliance

Fulfilling compliance obligations while maintaining competitiveness is indispensable for Enhancing Risk Compliance Financial & Banking sectors. However, the exponential rise in regulatory expectations and need for compliance inhibits the ability of conforming firms to remain competitive. Today, organizations have access to richer and diverse data than ever before, however existing processes lack the agility and automation to derive insights from the available data. While these insights could help to improve compliance, done manually, such processes can consume several weeks. Compounding the problem, organizations do not holistically assess regulatory risk and typically treat each regulation as siloed. This leads to missed opportunities for interpretability and transparency of risk, which, if captured, could drastically reduce compliance costs. This paper proposes to harness cutting edge data engineering techniques including Natural Language Processing (NLP) and Process Mining (PM) to derive actionable insights at scale across the risk compliance life cycle, thereby enabling organizations to be both competitive and compliant. AI-Driven Innovations in Banking Risk Compliance.

In recent years, the financial services industry has seen the swift adoption of Artificial Intelligence (AI). The AI-based applications used in the financial services industry range from algorithmic trading and credit risk scoring to real-time fraud detection and sentiment analysis for customer feedback. Bank branches, insurance agencies, and financial advisory firms are increasingly digitizing their decision-making processes and turning to innovative AI techniques. Nevertheless, industry players have much to understand, regulate, and govern about this powerful tool that has the potential to transform the industry. The recent proliferation of machine learning-based AI (ML AI) in financial services has led to the development of input data-driven models with significantly more complex applications. The deployment pipeline for AI-powered products has also shifted dramatically, following on-demand software development best practices. Outputs from such complex ML AI models are intrinsically encoded data representations rather than either formulas or feature importance values. These phenomena change the nature of model risk management and compliance activities fundamentally. On one hand, model agnosticism is required for effective governance. On the other hand, black-box models pose significant hurdles to meeting today’s model risk management requirements. Industry-wide challenges and the practitioner’s perspective on prioritization of the challenges and suggested practices have yet to be a subject of academic inquiry. This work aims to respond to these observations by providing better understanding about AI model risks and governance, exploring novel solutions to the unique challenges associated with AI models.

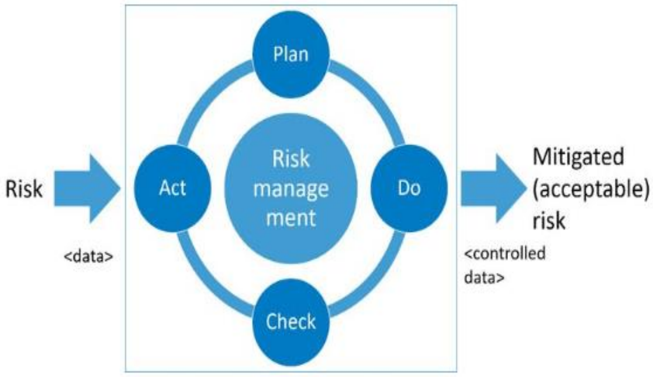


Fig 5: Data Sources for Risk Compliance

6.1. Internal Data

The ability to make sophisticated judgments based on mountains of data has greatly improved with the advent of big data technology and the accessibility of unprecedented computing power. The financial services sector continues to be poised to benefit from cutting-edge tools, whether effective forecasting across asset classes or building a more in-depth understanding of market sentiment based on social media. However, banks’ usage of new technologies continues to lag behind other industries, adherence to manual processes and Excel spreadsheets hindering efforts to stimulate performance and capture efficiencies. Challenges are mounting; margins are being pressured by cryptocurrencies, fintechs, and increasing regulation. Banking organizations face both a superb opportunity and an urgent necessity to expand their investment in AI-augmented business models. Furthermore, CEOs are sponsoring intensified efforts to transform their banks into more intelligent enterprises. This report will offer some actionable insight to guide leaders in directing their investments in a high-impact manner.

A firm deploying AI in their organization can benefit in four main ways: augmenting a bank's workforce and using AI to multiply human capabilities; automating manual and repetitive tasks in the back offices to contain costs; offering clients more personalized service and targeting products to the clients that will derive the most value; increasing the accuracy of models of behavioral risk and improving compliance monitoring by analyzing data wherever it is stored and however it is structured. For example, AI can help target products to the clients that will derive the most value by cross-selling and enhancing loyalty, making retention efforts more effective. Machine learning models can detect not only the level of propensity to buy but the most valuable products, which can then be targeted for retention strategies. In response to pricing, human intervention is required not only to open a dialogue but to apply judgment around sentiment and tone, and who to target and what offer to communicate. By automating targeted approaches to win back customers at risk of churn, efforts can be more effective and potentially less costly.

6.2. External Data

Challenges in AI evaluation usually relate to the quality and availability of banking data and the ability to interpret model results. The potential liabilities surrounding algorithmic bias and discrimination necessitate establishing internal policies to limit these risks. Trust and transparency are paramount in implementing AI technology into core business applications, necessitating the explainability of the bank's choice of technology. Banks should address clients' concerns on model performance, non-discrimination, accountability, and redress regarding the provision of credit products, service-charges, and their exclusions. Banks should also address their own concerns on development choices regarding equity and inclusion for monitoring the eventual decisions arrived at by AI-based applications on counter-offers to clients.

Banks are still exploring and establishing the necessary governance mechanisms, internal processes, and capable personnel to fulfil their obligations to clients and regulators alike. A facilitation of information sharing regarding both opportunities and risks in AI via trade and industry associations might be warranted. Completing the ongoing alignment of the AI product offering with the existing prudential and conduct regulations is essential for general model governance . In addition, there are plentiful opportunities to innovate novel AI-based competitive service offerings that augment current practices across the banking industry, as the continuous exploration of ML models by regulators and banks illustrates.

7. Data Engineering Practices

Data Engineering practices for AI-driven Regulatory Compliance applications can be grouped into three areas of concerns: Anomaly Data Management, Privacy Preservation, and Explainable Data Management practices. Data Engineering practices that do not either directly modify the data-based characteristics or analyze data for model input features are out of the scope. Practitioners interested in a wider view on Data Engineering can refer to.

Anomaly Data Management practices are data processing techniques for better data accuracy and consistency by controlling and filtering the unwanted data points. Commonly seen data anomalies could be defined as: Semantic notes, such as impossible properties, incorrect timestamps, or names. Missing value notes, such as incomplete Hedge/IncrementBankPosition values. Value outlier notes, such as deposit or withdrawal amount threshold checks. Posting volume note, such as a too large number of postings for a report in validation. Data Quality Note, such as too many to fix/validate data points for the last month's reports. Standard Data Hygiene practices, such as Cross source data matching, Periodic pattern checks. Practitioners are encouraged to define a hierarchy or categorization to better manage these notes. More specific guidelines on these practices could further encourage collaboration-oriented deployment and discussions within the knowledge-clustering groups of a financial compliance team.

Privacy Preserving Data Engineering practices process the data in a privacy-friendly way that is designed to protect sensitive features. These practices both ensure compliance with connection disclosure regulation and mitigate side-channel risks of sensitive features. Common counterfeit disclosures can be summarized as: Differentially Private Noise Injection. Encryption-based, which includes Only Secrets Sharing and Homomorphic Encryption. Data Desensitization / Aggregation / Swapping / Binning. Data Synthesis / Simulation or Generative Method. Each method might be appropriate for different elements in a transformation pipeline depending on the context.

Consequently, both domain/technical experts and non-domain specialists go through a costly but unfortunately necessary process of reverse engineering the deep learning models and the SQL queries that generated the training/test data before they are able to cooperate in improving the knowledge of the bank. Effective interfaces between the systems, which would allow a co-creation process, are needed, but AI/ML systems are currently still too brittle and a hostile environment for domain experts to interact with. In a specific application, methods and techniques need to be developed that extract effective explanations and insights to be able to feed and employ neural net-based predictive or generative models.

Additionally, the output of the AI/ML systems need to interface with the expert engineers, generating knowledge among them and letting it propagate downwards, or upwards.

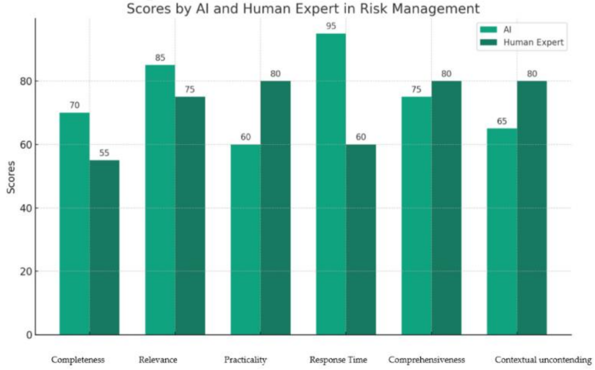


Fig 6: Navigating the Power of Artificial Intelligence in Risk Management

7.1. Data Cleaning and Preparation

To gain the trust of data-driven solutions aimed at improving decision-making in business processes, organizations and domain experts must have uncontested access to the company's data. However, in many large companies, data lakes and data warehouses can become disorganized and poorly documented over time, hampering state-of-the-art data-driven approaches. With similar issues, banks and financial institutions are obligated to use technologies to improve regulatory compliance. The growing importance of risk compliance, prompted by intensifying regulatory requirements in recent years, underscores the necessity for continuous investment in technology and personnel by banks to implement such technologies proficiently and on a sufficient scale. Current approaches typically involve the repeated execution of similar tasks for many transactions. Given the standardized structure of data warehouse systems, this essentially involves the repeating execution of the same operations, which requires repetitive configuration and sufficient computational resources. Any accidental discrepancy in the configuration would irreversibly alter the underlying data, leading to an incorrect solution. Consequently, building an AI-based decision support system in such an environment often lacks interpretability and robustness. Furthermore, domain experts tend to view such proprietary top-down solutions as a black box and are unlikely to trust the output unless supplied with unequivocal standards and interpretability.

In order to gain trust in data-driven solutions, domain experts and organizations have to have uncontested access to the company's data. This is usually done by giving the experts read access to the SQL queries that are used to extract the needed data. However, in many large companies and banks, an understandably complex and expressive query language can be used to mine data from a vast number of interconnected databases. When these companies grow over time, regulations are enacted, or new services are introduced, the data lake/data warehouse vanishes, and the documentation is likely to become outdated .

7.2. Data Integration Techniques

Risk and compliance mitigation through data engineering is a multi-step process, which includes various steps like Data integration, Data storage, Data cleansing, Data transformation and Data generation (input to analytics). Data integration is the process of obtaining and analyzing data from different sources and combining it to provide a unified view to the user. It is a crucial step of the ETL process, where the data is cleaned, filtered and loaded into a data warehouse for analysis. Data integration involves three steps: Data extraction, Data transformation and Data loading.

Data extraction is the process of obtaining the data from different sources. Data extraction involves various techniques and approaches like Commercial Tools, Middleware Tools, Custom Tools etc. In commercial tools, the application vendor builds integration capabilities as part of the application package. In middleware tools, some tools available in the market act as middleware to extract data from source systems and load it into the DW.

In custom tools, the integration team builds the integration capabilities as part of the project. The consultants use existing ETL tools to extract the data from data sources and load into the DW. This process involves ETL workbench/configuration settings and scripts to invoke and run them at a scheduled time. In scripting and coding, some teams write coding using scripting languages to extract data from the data sources. In COTS tools, some teams use applications like Targit, TIBCO, etc. These tools may require some initial configuration but significantly reduce the effort and improve quality and performance.

Data transformation is the process of converting the extracted data into a relevant data format for analysis. Before loading the data into the data warehouse, the transformation process is usually performed. It does not have any explicitly defined format or standard. As a result, there is great variation between the expectations provided for DW transformation. Based on the experience in writing transformation documents, broad categorization of the transformation document into useful format is specified.

8. AI-Driven Risk Monitoring Systems

An enormous volume of new risk and compliance obligations has arisen as a result of recent responses to various financial disasters in developed markets. Thus, an expanding number of institutions are under obligations to report to regulators, often on questions that differ significantly from one institution to the next. In vast organizations, regulatory reporting processes are often labor intensive: they require an exorbitant amount of analyst hours per report.

Firms are building automated reporting systems to track and display information in any format that may be found useful, to fuse together diverse elements of compliance and recent risk events, and to trigger monitoring processes. For instance, incorporating advanced natural language processing, decision trees, and graph databases, along with mandatory paper trails of all actions, and rules to ensure avoidance of undesirable actions, lowered exposure to case-by-base analyses, along with the human ability to follow trails when they do arise.

Risk managers and compliance officers will also be assisted by advanced graph technologies, cloud-based aggregation of all available data from siloed operations, and semi-structured NLP pullers of documents of potential interest on an ad hoc basis. Banks are no longer constrained to examine a slice of their past data thousands of times: they can examine it all at once. Each document will now be examined by swarm analyses. The bigger datasets will allow risk managers and compliance officers to examine events' potential systemic impact and what follows after them throughout regions (such as anticipated reductions in equity prices), maxima, verifiability against expectations, and subsequent decline timelines. Surface observations will filter down to what to check and who should be asked for a comment.

9. Case Studies of AI in Risk Compliance

This section describes some example case studies to showcase the power of using Data Engineering and AI technologies in ensuring compliance with risk regulations in the banking domain.

9.1 Case Studies Overview A few case studies from various firms, using Data Engineering artifacts and advanced analytics to enhance their performance, are described in this section. All the case studies have contributed to building/deploying a solution using AI along with Data Engineering and visualization techniques. All the case studies presented in this section are focused on regulatory compliance associated with risks in the banking domain. In particular, regulations associated with wholesale credit risk and its monitoring are discussed.

9.2 Measuring Fairness & Compliance for Pooling in Wholesale Credit Risk Regulation The modernized simplified regulatory framework involves assigning risk weights to an asset pool based on the different credit risk drivers assigned to collateral while creating it. Since these guidelines involve making several decisions on credit risk drivers, compliance against this regulation is defined as defending decisions related to these credit risk drivers and consequent forecasting of granular asset pool loss curve. Measurable fairness metrics are constructed from the lens of the defined compliance problem. These metrics identify deviation against compliance rules thus helping banks manage their workflow. A separate lineage based quantitative assessment approach is also communicated to assess the kind of investigation needed on deviations from the compliance metrics. The methodology is applied to a case study on an illustrative pool making decisions on four key credit risk drivers. Results indicate the need to investigate potential bias on one of the driver decisions. Further auditing on lineage, expected function used, and insights on high variance weight is indicated. The proposed solution identifies to the granularity of assets those decisions which need attention.

9.3 Monitoring Compliance of Asset Pool with Safety Norms Safety norms require that the credit risk associated with pooled assets does not exceed pre-defined limits. Consequently, pools with similar asset characteristics must exhibit the same kind of safety. Previously these safety norms were monitored using data engineering techniques. This motivated the automation of safety norm compliance monitoring against the recent regulation on the compliance of asset pool safety. Recommendations to monitor pool compliance with relevant metrics are discussed.

9.1. Successful Implementations

There are considerable obstacles in the implementation of AI technology. The current lack of data at all levels of bank forecasting is a potential obstacle to the promotion and use of artificial intelligence. The development of artificial intelligence in risk management must take into account the principles of data processing. In this respect, various banks have established the technology and complete frameworks. The most fascinating one includes Wells Fargo Bank, which founded a financial subsidiary to focus on risk allergic transactions in the non-bank channel. Anti-financial crime, model risk management, business intelligence, etc., have their respective team and technical frameworks to provide technical safeguards for specific business lines. Such technology platforms are mainly joint collaborations across departments that bring together multiple data analytics tools, aiming to develop a good business practice of using artificial intelligence analytics to arouse bank-wide ecosystem effect together. Meanwhile, SunTrust Bank built a model musium to encourage the approval and modification of the applicant model, data sources, exclusion conditions, and interpretability, which made it easier for the AI risk management team to understand the entire working model and build a safeguard track. Commercial banks at various levels should establish their own automatic analysis system according to their business and risk-control characteristics so that advanced analysis talent, models, and results could be provided. The largest global financial institutions have been working to keep up with the technological advances that drive fintech competition. The AI-based solutions created by investment and commercial banks can accurately predict changes in regulatory trends and significantly reduce the manpower needed for compliance. These AI solutions demonstrate impressive performance gains, often achieving an efficiency increase of 90% while maintaining accuracy or even outperforming previous non-AI compliance solutions. Beyond regulatory compliance, banks invest heavily in fraud detection solutions based on machine learning. It reduces risk exposure by employing incremental learning on large datasets to identify and reject false transactions. Bank statements in PDF form can be accurately analyzed and inserted into internal accounting systems using deep learning-based document image processing technologies.

9.2. Lessons Learned

As the financial services sector rapidly embraces and advances AI to improve customer engagement, risk management, trading strategies, compliance, and efficiency, the range and criticality of the decisions made by AI have dramatically increased. This increased usage has driven an intensified focus on the need for compliance and effective model governance. Not only the financial services regulator, but also regulators in multiple industries have issued guidelines and reminders to firms on managing the risks of models used in their operations, especially AI models. Simultaneously, governments and regulators are striving to introduce and implement regulations on model risk governance of AI and advanced machine learning. Understanding the emerging challenges and opportunities under the need for AI model governance controls and regulations is critical for the financial services industry and regulators.

Model governance, otherwise known as for AI model risk management, is the internal risk management and regulatory compliance process that all models are generally required to go through, and ensure that the models are deployed for their intended usages, properly designed, implemented, deployed, and monitored. In the financial services sector, this process must meet both internal and external governance policies. This risk management and compliance process had evolved with the modeling frameworks used in finance, driven by decisions faced by increased model usage and regulatory scrutiny. It might struggle with the big differences in underlying characteristics of the AI and ML models; thus, another paradigm shift is required to safeguard against the hidden new risks brought to the banks by the rise of the newest modeling frameworks and help capture their opportunities.

10. Conclusion

The financial services sector is among the first to adopt big data analytics to make informed decisions. Financial giants have pioneered big data solutions to anticipate demand patterns and improve wealth management services. Betterment has disrupted investment services through precision-focused robo-advising that uses machine learning. By focusing on investments, they ignore essential banking regulations and anti-money laundering (AML) obligations. This focus on short-term profitability has consequences. Banks must comply with various laws, rules, and regulations meant to contain inherent misconduct risks. Banking is high-stakes because benign decisions affect millions, often in outside stakeholders. Banks cannot afford reputational risks given the costs of non-compliance frequently exceed the profits from misconduct . A critical point of improving risk compliance is an advanced data engineering (ADE) pipeline as the backbone of risk sensitivity. It consumes risk data, transforms it into the format necessary to accommodate compliance applications, and exposes the transformed data to those applications. A sophisticated ADE pipeline is the only guarantee to provide good quality data. AI-driven innovations are applied to large-scale data integration and cleansing steps to forecast and mitigate risks in anticipation of compliance applications.

Risk data coming from risk engines usually have little concern for compliance applications. Non-compliance models have more constraints than compliance models to be risk-sensitive. This prescription cannot feed non-compliance applications. The first task necessary to transform risk data into compliance data is integration. A banking environment typically uses a vast number of risk engines. Risk engines from different vendors would not only store data in different systems but also use different time, currency, and amounts. All of these vary between risk engines and application systems within a bank. The integrated data must undergo transformations to accommodate non-compliance applications. This task primarily focuses on converting risk data into data formats suitable for compliance rules, usually grammar-compatible formats and event-based time formats. Moreover, data cleansing increases the trustworthiness of compliance data further, automating the identification of erroneous data. Bank executives must ensure identification and rectification in the AD pipeline. Data on instruments in the compliance data set must undergo cleansing, the central focus of which is identifying anomalous data.

10.1. Future Trends

Technologies supported by artificial intelligence (AI) are rapidly changing various organizations, including financial institutions (FIs). While using AI has several advantages related to customer engagement, it also creates new challenges. Regulatory compliance is a key responsibility of FIs, especially in dealing with anti-money laundering (AML) and terrorist financing (TF). As new technologies develop, it is crucial to embrace innovations to detect related unprecedented risks. This examines the role of AI-driven data engineering in enhancing risk and compliance in the banking sector. Credible data management and engineering are prerequisites for the successful development and implementation of AI technologies. Thus, this analyzes the AI-enhanced data engineering process in banking innovations from the data-driven paradigm view. The focus is on identifying key tasks in the data engineering process, their importance for enhancing risk compliance capabilities, and future trends in AI-driven banking innovations.

The material critical to the analysis is collected from the online database of public documents and expert reports published between 2019 and 2023 by major international banks and related technology firms. Since many banking innovations are proprietary, research can only be conducted on publicly accessible authoritative documents. The search includes keywords such as “artificial intelligence,” “data engineering,” “risk compliance,” “Terrorist financing (TF),” and “Anti-money laundering (AML).” The retrieved documents illustrate the benefits, challenges, and use cases of employing AI-enhanced data engineering innovation for AML as a priority use case. The restrictions on subject information make it unsuitable for empirical interviews with practitioners.

Collectively, the AI-enhanced data engineering process is a critical development of data analytics that embraces innovations in data management, engineering, and architecture. Specifically, the connotation of AI-enhanced data engineering is twofold: reviewing the data engineering procedure and embracing AI in the data engineering cycle. To enhance risk compliance capabilities, it is essential to identify specific tasks of the AI-enhanced data engineering process to ensure that the necessary data is acquired, integrated, and analyzed for model operations, inferences, and interpretations. These tasks are key to successful data management and engineering projects that build credible data foundations for AI modeling.

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