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Financial Innovation through AI and Data Engineering: Rethinking Risk and Compliance in the Banking Industry

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Abstract: The banking industry has applied automated technologies since the late 1970s, focusing on transactional, low-risk, and volumes of business-type tasks. Several banks are now investing in research and programs for intelligent data engineering to help eliminate less predictable and consequential low-impacts tasks in human and decision-making intensive processes. Functions that are needed to be augmented by data engineering's intelligence capabilities to help improve productivity, performance, and customer service quality in these areas include investment decision-making, wealth advisory, loan issuance, model risk monitoring, model validation, regulatory compliance, market risk assessment, and credit loss estimation. However, it is unclear how the new opportunities of innovation through intelligent technologies would be implemented in existing domains without augmenting quest tools and technologies in terms of managing augmented traditions, organizational, and institutional dilemmas and challenges, and what implications the new opportunities would pose to rethink fraud-catching, risk estimating, trading, corporate colloquialism model-led change processes, treasury management, and risk-compliance management. This concern arises from the fact that financial system technologies' prior investments and developments are already sufficiently complex and complete.

There may be an AI and data engineering-enabled revamping of data lifecycles in the banking and finance industry. The proposed adaptation may be substantially broader than the narrowly defined opportunities within well-defined and low-contest markets and domains typically approached in automating sector-specific applications. Available privacy, regulatory compliance, fairness, transparency, and explainability issues and such are already well-known in practice. The analysis suggests opening up high-consequence areas for banking and finance experts to augment their competitive intelligence to engineer robust and reliable domains or trading engines to monitor and mitigate extreme risk events for systemic risks while rethinking and reconstituting trust in sequential rules and risk choices in addition to inputs. Future work should provide in-depth analyses of the aqualism implications and apply the approach to other industries where data engineering and intelligent technologies may have a similarly profound impact.

Keywords: Financial Innovation,Artificial Intelligence (AI),Data Engineering,Risk Management,Regulatory Compliance,Banking Technology,Predictive Analytics,Machine Learning in Finance,Real-time Risk Assessment,Compliance Automation,Fintech Disruption,Big Data in Banking,AI-Driven Decision Making,RegTech Solutions,Digital Transformation in Finance.

1. INTRODUCTION

Historically, a proliferation of moving parts was associated with economic complexity. Notably, metrics of economic growth were the number of allowed parts times their heterogeneity. In the end, the desired complexity is the productivity gain with the current level of complexity and risk mitigation seen as too big of a challenge to handle. Additionally, because it is too complex, algorithms to maintain these complex systems cannot self-improve. There are emerging questions targeting risk management which include the chasm opened by a new type of algorithm devoid of the grounding of formula-hardened algebraic models. It shapes the next generation of financial products, business models, operational models, and risks. These products manipulate data via software functions trained by enormous data sets outside outdated neglectable compliance checks. It ultimately leads to large unintended socioeconomic impacts like cyberbullying,

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unwanted targeting, propagating false nationalistic narratives, escaped property bubbles, unintended credit starving, and missed educational opportunities.

This paper argues that the efficiency of traditional risk management is rethought and repurposed with the introduction of vastly larger data and totally new algorithms thereof. First are highlighted mechanisms of older emerging risks proceeding analytically. The emergence of composed non-linear systems is dispatched and data-driven sophistication-enabled new risks addressed. The explanation of generation-to-fairness in AI with higher modeling satisfying solvable problems is interpreted. Finally, on the banking side, the hardening of AI systems is discussed, and risk management parameters for drastically safer AI systems beyond 90% safe are taken care of.

Advances in low-cost computing and high-speed wide area networking made the extraction of economic value from extensive amounts of granulated data available. The banking industry increased external computational capacity and operational cost efficiency in the same voucher plus an ever-increasing number of new licensed models. New algorithms like text understanding using transformer sequences or outlier detection using manifold approximation were introduced, unwrapping further possible business applications. Complexity and business complexity lost the pre-calculated conceptualization merely to keep it under business control. AI models or functional computational graph neural networks (GCNs) with poor conceptualization vastly quicker than miscalculable force-monolithic behavioral models yearn for a simple solvable question of if such granulated risk can navigate or mitigate "too-opportunity-risks." Hence constructing GCN based risk management models and estimating emergent explanatory decimal precision present-time lies and describing constraints for them will be outlined with risk quantities.

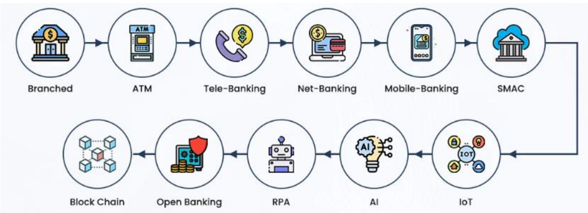

Fig 1: AI in Compliance and Risk Management across the Banking Industry

1.1. Background And Significance A major proportion of the reason why Machine Learning (ML) and Artificial Intelligence (AI) are needed in banking and finance is directly relevant to the information asymmetry problem. In emerging markets individuals who are underbanked, especially women, the youth, and small businesses cannot access traditional forms of collateral or identification required by financial institutions such as banks. Yet more than 1.75 billion adults are still unbanked. One example of a bank addressing this need is using AI to service non collateralizable farmers with an estimated 140 million unbanked farmers globally. Most banks, having been established before the digital bank, only require selected forms of identification in order to access their services, such as government issued national identity. However, for the underbanked in emerging markets this becomes a major barrier as they do not have this identification in the same way. On the contrary, digital banks have democratized data by using the information from a multitude of alternative data points as identification: while many individuals may not have government issued national identity and salary slips, they may still have login credentials to social media accounts where their friends, professional accomplishments, personal investments and expenditures leave a paper trail of their personality. This allows lenders to do serious credit risk analysis, to assess the behaviour of the customer, and subsequently to verify the ability of the clients to repay the loans. The prudent use of available customer data happens against a backdrop of significant pressure from regulators, civil rights groups, and legislators to impose fair lending standards against banks 'free-riding' on ML and AI. Further, there is pressure and responsibility to incorporate risk models that are explainable and trustworthy. The increasing prevalence of AI compliance frameworks and awareness of the risks of financial services AI highlight the challenges that banks and fintechs face amidst strong regulatory environments. However, it is within this context that this research aims to explore risk and compliance in the future: the rewarding opportunities that emerging technologies and AI can provide financial services companies, when construed as a risk and compliance problem. The research proposed a rethinking of risk and compliance through the lens of fraud detection models in machine learning for

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financial services, where the models are complex with serious consequences attached to mispricings. With the exponential growth in the amount of data as well as its diversity and speed, organisations have adopted AI to automate and better their decision processes where traditional approaches have been supplanted. Nevertheless, the traditionally bespoke analytical models have created a headache for financial services' compliance and risk functions as they have become more discrete, harder to interrogate, and analytical processes that were once clearly defined have become reshaped by the complexity of the models and the computation that supports them.

Equ : 1 Dynamic Credit Risk Score Model

$$\text{CreditRisk}_i = f(X_i, \theta) = \sigma(\mathbf{w}^\top X_i + b)$$

Where:

- X_i = vector of borrower features (e.g., income, debt ratio, transaction history)
- $\theta = \{\mathbf{w}, b\}$ = learned weights via AI model (e.g., logistic regression, neural net)
- σ = sigmoid function
- Output: probability of default

2. THE ROLE OF AI IN FINANCIAL INNOVATION

To qualify regarding the financial context for AI and compliance, two high-level definitions are important. First, financial innovation is: the new techniques, methods or ideas used in the method of financing. Second, finance compliance is: the permission granted by regulators to financial analysts or institutions to carry out their trade, business or activity. Findings are discussed to utilize the method of the "data trilogy" in preventing cyber terrorism. The data trilogy is also known as the 5V cloud data triangle, which did not only offer additional ways to protect that system but also other cloud data systems as well. When applying the paradigm as a risk approver, the tremendous data apply to evaluate all risk in advance, including technologies, users and regulations via evaluating the likelihood and impacts, reputational brand, relationship with regulators and impacts on customers. The mining techniques may range from a fuzzy clustering of complex networks to evaluate illegitimate users and behaviours to pattern recognition and ontology to fine-tune the other proxies after tightening regulations. The enforceable regulations to apply in the AI innovations are mostly the acts, laws, guidelines and principles. Only two of the possible regulations are unlikely to impose on banks' AI trading. Quant explanation AI is impossible and useless due to its process opacity. The possibility to expand AI usage in commercial banks to new businesses other than markets is tremendous. This expands the first two approaches to disable constraints as in-house risk control or monetize infra-grids for others. For a bank-, technology- or data-limited AI system in usage, this application will recount the usability design data from the hypothesized trading parameters. In contrast, superior technologies and other financial analysts' ample data need to be commercialized, functioning as a data-validation hydrant in the AI-like policies banks would not risk employing beforehand.

2.1. Defining Financial Innovation

In the context of this paper, financial innovation refers to innovations that affect financial markets and institutions. It also refers to the reforms that individual countries have undertaken in their financial systems, many of these reforms were adopted because they seemed successful. Financial innovation has little to do with other forms of economic or technological innovations. Financial innovation is a 2-sided coin, with one side being favourable to the banking industry, while the other side leads to increased risk, pressure for reform, and regulatory and public reaction.

Financial innovation means the introduction of a new financial security, a new process by which investors bargain for and trade existing securities, or a new market. Financial innovation can mean either the introduction of new securities and contracts into a market or the introduction into a market of new trading facilities, procedures, and architectures. A more general definition is that financial innovation is a process whereby individuals or institutions in financial markets develop new products and services aimed at profit.

Financial innovation can be broadly categorized into three groups: important upheavals, important changes, and other noteworthy innovations. The aim of financial innovation has been to increase safety and convenience of transactions to improve pricing and efficiency of markets or to increase the range and sophistication of risk management and control

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techniques. More recently innovations for the effective policing of newly-globalized financial markets have come to the fore. At the industrial level also, some change, shift spar market structure in favour of regulated organized exchanges and against new low-cost markets. The recent surge in the scale and speed of most of these innovations has led to particular concern regarding the social responsibility of the financial services industry as a whole. They have usually emerged in response to market signals in the forms of demands by customers or opportunities for financial profit.

2.2. AI Technologies in Finance The financial industry is increasingly utilizing AI and its related technologies to tackle a number of difficulties. With the introduction of Regulations and Supervision Technology (RegTech) platforms, AI-driven services in the financial area include automating compliance processes. Such disruptors may face difficulties in concentrating big quantities of sensitive data or reliably providing the services they advertise. Machine learning, predictive modeling, and natural language processing have been utilized extensively in risk identification, scoring, and reporting.

Transformation Technology (TradeTech) refers to a variety of AI technologies that intend to aid the financial industry in better managing the entire value chain of investment products and financial services. There is still no clever machine for market making, execution, or trading, despite aggressive adoption of big data analysis and algorithmic trading. In general, such disrupters face challenges in storage and analysis speed-related big data use and a lack of superior trading strategies and information acquisition performance compared to humans. Nevertheless, advancing technologies such as reinforcement learning, real-time deep learning, as well as graph and blockchain technology in the crypto domain represent vast possibilities for improving Trust Tech services.

2.3. Impact of AI on Banking Operations Artificial intelligence is said to be on the verge of transforming every aspect of daily life, from electric cars to automatic house cleaners, and the big data driving such changes also becomes cheap and plentiful. The high volume and wide variety of financial data that banks traditionally have tended to consider too unmanageable a challenge are becoming increasingly important assets for financial decisions. Such new types of data are highly non-standard and unstructured and often follow completely novel patterns never seen before. With current sensor networks, imaging technologies, and other innovations, massive amounts of new-style financial data become increasingly affordable. The existence of numerous professional and amateur highly connected online communities has a huge amount of natural free, accessible financial data. In addition to that, the number of new types of social media with unprecedented forms of self-expression grows rapidly. All of this indicated the idea of turning to AI, machine learning, and data engineering to tackle the big data challenge for a whole new data source that has huge potential and unspoiled wealth of commercial value.

First, many new questions arise due to financial market institutional and regulatory blind spots such as systemic risk and WMDs in finance, etc. that are born from new situations and phenomena arising from the interactions of traditional financial institutions and the new web-based data network. To this end, a paper addressed the speedy P2P and cyber investment and web-based RBP as important examples of RDMs originally arising from business models that take advantage of new types of free and massive internet data source and made models. These models passed the market tests of soaring consumption but also soon led to the Great Financial Crisis.

Second, rapidly growing structured wholesale markets lead to totally new challenges for banks that are born from other new situations in financial markets or other areas of the economy. The advent of artificial financial markets in the form of bond markets and their crucial roles in the Great Financial Crisis case are analysed and modelled.

3. DATA ENGINEERING IN THE BANKING SECTOR

The banking sector's mounting operational and regulatory compliance expenses are primarily attributable to technology and cybersecurity obstacles, which account for about 45% of its total operating costs. Regulatory fines constitute a significant part of compliance expenses. A growing gap between financial crime compliance requirements and banks' capacities to satisfy them is predicted to add millions of dollars annually in fines and enable illicit activities. In addition, the pandemic has accelerated the remote work transition and digitization of retail activities. Such changes in the business

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environment have significantly enhanced the threat landscape to which financial institutions must respond. Those unique challenges compel banks to rethink their technology stack for risk and compliance. Towards technology and technology-enabled process transformations, AI, data engineering, and cloud-based technologies in particular are considered key enablers. AI regulates the relationship between machines and risk models and promises greater sophistication in stakeholder analysis, self-learning capabilities, and real-time assessments. Partially reconfiguring functional tasks and transforming the groundwork and outreach of risk and compliance processes by data engineering can potentially enact even more fundamental changes. Data engineering is concerned with building the infrastructure for handling data, for instance, by enhancing data processing, transmission, storage, utilization, cleansing, and analysis. Although three distinct areas surrounding risk and compliance in banking have generated a large body of research, their confluence and synergies have not been examined thus far. Financial institutions may rethink risk and compliance beyond the isolated application of technologies and profound process transpositions, but rather by conducting a radical, cooperative redesign of the risk and compliance tech stack as a whole by maximizing the cooperation of these three complementary building blocks.

Equ : 2 AI-Driven Compliance Anomaly Detection

$$A_t = \|\mathbf{T}_t - \hat{\mathbf{T}}_t\|_2$$

Where:

- $\mathbf{T}_t$ = actual transaction vector at time t
- $\hat{\mathbf{T}}_t$ = predicted transaction vector using an LSTM or Transformer model
- A_t = anomaly score used for anti-money laundering (AML) flagging

3.1. Importance of Data Quality In financial services, explainability is necessary for accountability, interpretability, and trust. Explainable AI is crucial for risk management and regulatory compliance. There is a unique need for this in financial services, driven by the aforementioned factors. Before discussing specifics of explainable AI needs for risk management, regulatory compliance, and more general data governance, it is important to first introduce some major contexts in which the data governance needs arise as motivation for future work.

Risk data quality (RDQ) concerns the quality of risk aggregation and reporting. Recent high-profile cases of compliance problems mainly focus on faults in risk data quality. No prior work has explored the RDQ explainability needs in depth. G-SIBs are the world’s largest banks, which are under special supervision owing to their importance to the global economy. These banks are subject to tough regulatory requirements on data governance standards in the spirit of No.239. This regulatory standard, entitled “Principles for risk data aggregation and risk reporting,” aims to improve the quality of risk aggregation and reporting data, and consists of eleven principles. In the following subsection, the compliance environment of No.239 and the explainability needs it brings are briefly described. This section mainly elaborates on the explainability needs associated with data quality.

The BCBS 239 standard is made up of eleven principles grouped under three topics: overarching governance and infrastructure, risk data aggregation, and risk reporting. This subsection will be used to elaborate how the BCBS 239 standard can be interpreted as highlighting inherent needs for explainable data governance. Relevant principles and paragraphs of the BCBS 239 standard are cross-referenced below. The data quality needs correspond roughly to P3, whereas reporting needs correspond roughly to P7 and P9. There is a general need for AI/ML to explain features, rules, and training data. Data quality metrics (monitoring) and data quality tracking (documenting/investigating) are of major relevance.

Similar to the explainability needs for compliance under No.239, the understanding of data quality monitoring needs as a research problem is arguably also in its infancy. A critical layer of data engineering is data quality monitoring, and this was focused on in this section. Metrics that assess what kinds of problems lead to breaches in specific data quality assurances were provided. Automated data quality monitoring, which is to check data quality metrics on a streaming basis, is a new challenge coming to the forefront.

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Fig 2: Data Quality

3.2. Data Management Strategies The overnight shift of banks and other Financial Services (FS) to a state of having to work more or less entirely digitally caused the first direct loss of $0.4 trillion for the German bank KFW, due to the theft of data from its fund portfolio. In addition, it was reported that 90% of the attacks, due to the annihilation of data-acquiring SSIs, were thwarted, which became a bruise for ABC. However, considering this is just one year after the pandemic started, many institutions lack caution against cyber-attacks and consequent data losses, and resulting lawsuits, disputes over insurance payments, and regulatory penalties might burst after this COVID storm.

Financial Services (FS) agencies have reacted with to-flight instances within hours after the storm began. Whereas most institutions with any material overseas IRR exposures likely viewed these events as a cause for concern and redoubled their efforts to monitor and manage the uncertainty surrounding them, many, if not most, FS firms had little in place to deal with a day like this.

Planning meant modeling multi-dimensional potential loss surfaces and looking for tail risk wells in it. As few institutions have had even slightly extensive pre-fact modeling work done, stepped options would be effective preventives there against too exuberant exposures to risk shocks or off-the-shelves stress tests not holding, as described above. In other words, it would be reasonable to bring a series of odds-style mental stops that limit the size of a series of smaller losses. Every pain point in which a relatively major configurable parameter in each potential risk metric is failed to be kept well thus triggers a more heavy downward shock to the underlying model explicated by the enormous masses of low quality SMS acquiring data. Giving no grain on model quality would not make sense, as risks become directional and ludicrous without carefully reviewing it under multiple settings.

3.3. Big Data Analytics in Banking Big Data can be defined as an expansion of the concept of data. Data that is large, complex, and rapidly changing is called Big Data. The term Big Data refers not only to the size of the data, but also to the methods of data gathering and processing, infrastructure, and information value. Over the past few years, Big Data has moved from hype into real-world application with action by many players. Everybody is talking about Big Data and why it’s important. Bank executives found that they would benefit from advances in Big Data analytics and were poised to respond. Big Data is vital as it is now the most valuable commodity on the planet. Data is not Big Data until it is diversified, amplified, and aggregated. Banking institutions are expected to increase their competitive advantages by better management of Big Data. This study elaborates on the large-scale application possibilities of Big Data in banking from six perspectives.

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With joining forces with Big Data, banking and financial institutions have much to gain. This reality begs the question of how insights accurately extracted from Big Data can generate proven benefits for banking institutions. In fact, the transmission of the Big Data paradigm in the finance institutions is not a new topic. In the recent decade, academic interest has flocked into the area of financial data processing and analysis. Also, financial institutions have started realizing the potential of Big Data applications since the beginning of the decade. Since banks realize the potential of Big Data, an important question has arisen: how do they approach the analysis of Big Data and exploit its value? Understanding the issue is crucial for banking prosperity.

4. RISK MANAGEMENT FRAMEWORKS

As asset managers and data engineers in the alternative investment industry, the understanding of the risk management framework is essential for the intelligent risk control solution. There are some general risks across the business, and a detailed introduction of the risk management framework is provided in the following section.

Risk management is defined as the identification, evaluation, and prioritization of risks. It also involves the application of resources to minimize, monitor, and control the probability and impact of unfortunate events. Risk management process consists of risk identification, risk assessment, and risk treatment. Risk identification is the systematic approach to recognize risk that could affect the achievement of objectives. The goal of risk identification is to uncover risks. A common method to identify risk is Jackson's system. His method encourages a broad view of the whole system and breaks the whole system into a number of subsystems. Another common method is brainstorming which seeks the contributions of each member of the group involved. After risks have been identified, it is necessary to conduct a risk assessment to evaluate the risks associated with the identified hazards. Risk metrics are defined to assess the risk median and risk growth.

There are several challenging points in the risk assessment framework. This includes weighing the attributes of risk, knowing the important vulnerability properties, and defining the exact vulnerability metric. Handling uncertainty in risk assessment is another challenge. The uncertainty could be from the weights of attributes, uncertain knowledge of attacks, failed assumptions, and safeness of the environment. Also risk estimation tools are merit components in risk assessment and their implementation is a demanding work. Managing trade-offs is another challenge. It is important to assess risks based on the proposed risk assessment method. However, since there exist many risk attributes, identification of the best trade-off decision is not likely possible.Notably absent from the current focus on transformation in the banking sector is the role of data engineering. Data engineering possesses the potential not only to help with the accumulation of the vast amounts of heterogeneous and quickly changing data needed for informed decision-making, but it can also present insights into the significant risks that this data holds.

Fig 3: Risk Management Framework (RMF)

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4.1. Traditional Risk Management Approaches The emergence of big data, the internet, and artificial intelligence has contributed significantly to the recent rapid growth and transformation of the banking and financial services industry. Spurred by market volatility, disruptive technologies, regulatory changes, and changing consumer preferences, risks facing financial institutions have grown in both quantity and complexity. The onset of recent macroeconomic and geopolitical unpredictability has caused further market shocks and volatility, on a scale not witnessed previously. Incidents of market manipulation have underscored the potential of data engineering to improve efficiencies, and reduce costs to obtain actionable intelligence. Industry-wide zero-tolerance policies on financial misconduct are reinforcing the need for increased transparency and data accountability. Insurmountable challenges around perpetually inflating data records and stricter data retention regimes are forcing a rethink of risk management approaches. Traditional regulatory technology (RegTech) and compliance technology practices are unable to keep pace with this dynamic environment, and in many instances their use in organizations is inefficient.

The purpose of this paper is to present how data engineering methods and models, including variable selection, outlier detection, and sharding can be harnessed to address these emerging risks in a cost-effective and agile way. Banking is the sector that is under most scrutiny due to the inherent risks they hold to the health of the global economy. Consequently, this work focuses on the banking sector but the methods and models discussed are equally applicable to other financial service sectors.

4.2. AI-Driven Risk Assessment Several banks have begun integrating AI for the efficient and robust assessment of risk. For instance, setting up an intensive machine learning project had a brilliant impact in the financial services sector and overall contributed to a better model performance in credit risk assessment. Regard the risks of monetary inconveniences to individuals or companies inability to solve their debts, credit risk analysis is one of the present common issues to integrated banks. The amount of monitoring records of credit transactions made by each bank client generates an assortment of data of profiles or instances that describe an active bank credit client. Current statistic traditional rating approaches and data mining representation on classification task with respect to more heterogeneous data resources are benchmarks. The first task representing customer behavior intends to provide a global view of the bank client financial evolution across time points. In order to accumulate financial aspect grouping, the coding scheme considers diverse monetary elements for comparison (regarding significant benefit or add on loans onboard). The second task attempts to offer financial tipping points beforehand problematic credit evolution. A reserve base state observation explicitly assigned to ancestors' instances is fixed if the labels of defective behavior have not been persisted in the last one or two years. To increase the performance a global modeling evaluation via algorithms will be devised. Machine learning approaches will be used successfully to recognize credit risk concealed in the history of implementation on credit instances. The proposed methodology admits ensemble decision models trees, recurrent neural networks and both elimination methods in considering data improvement, and results will be verified out on a large dataset in comparison with obtained output.

Equ : 3 Regulatory Risk Exposure via Knowledge Graph Inference

$$\mathrm{RegRisk}_j = \sum_{k=1}^{n} \alpha_k \cdot \mathrm{Rel}(e_j, e_k)$$

Where:

- e_j = a regulatory requirement node
- $\mathrm{Rel}(e_j, e_k)$ = relationship strength (e.g., via embeddings) between regulatory elements
- α_k = weight based on risk impact
- Captures inferred exposure to regulatory change

4.3. Comparative Analysis of Risk Models The possible metrics showing the predictive power of the models are explained. Next, a cumulative score is drawn, showing that some models consistently belong to the top group. Moreover, some metrics are decisive for the ranking of the models. Further, models predicted probabilities are used into the 'question 2' and 'question 3' of the stress test. The idea is to assess the best performing model and the importance of results consistency in view of the latter application. A thorough explanation of the models is provided in the appendix. Credit risk – the probability of default estimation is one of the most important steps in the life of a bank. In recent years, the academic literature suggested many alternative methodologies due to an observed deficiency in the

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hypothesized models. However, most banks still followed the same, simplistic, approaches with many untested assumptions. In other words, banks had to rely mainly on past information at sectoral level or on rules of thumb that resulted in a direct probability of default for the obligor.

Machine Learning methods are now matured in the finance area, and they present many learning algorithms capable of processing very low-quality data, which led to sporadic breakthroughs in the knowledge of the empirical world and the advent of a new era of accuracy. Thanks to this, the central bank must prevent economic downturns and allow the most realistic build up of the probabilities of default from a microeconomic point of view with all the publicly available data. Many alternative techniques can be used to ensure that the onward process for banks keeps on replicating the proper input to the Banking Book and credit risk will be re-evaluated, this time time-compatible and up-to-date. It could aim to transform the credit risk estimate from the simplistic alpha in a consistent machine learning predictive credit risk engine.

5. COMPLIANCE CHALLENGES IN BANKING

There are three trends that present challenges to measurable and auditable governance of quant models: development latency, model proliferation, and machine learning. The risks arising from these trends fall into both data model and model governance categories and are hence relevant to both DMP and DPL. These risks present obstacles to quant development and governance that make it difficult to fulfill professional obligations. Even minor violations of DMP or DPL can result in substantial regulatory fines. Legacy GPs are inflexible and generally do not account for the unique properties of either risk area. Traditional GP forms are not adaptable to the unique traits of common quant development processes and parochial frameworks to govern an entire company do not exhibit sufficient flexibility to account for the diversity of risk profiles or seniority levels within quant teams.

Regulatory scrutiny of capital and data models and stressed and non-stressed scenario generation processes is inevitable in a modern bank that engages in systematic quant model development. While this scrutiny's depth and frequency may vary, banks will invariably be expected to document, validate, and archive compliance with these GPs and backing evidence. Banking regulators are expected to mandate that banks enhance their model governance frameworks to offer increased transparency and auditability of ground truth data. GPs are also expected to cover quant models that create parameters or processes used in the production of risk forecasts. The strength of scrutiny will differ depending upon the type of quant model in question. High-profile, potentially systemic models are expected to face greater scrutiny than low-profile models untested in stress scenarios.

Broadly, quant model and governance considerations fall into four categories that are standard across global bank regulation: businesses, governance, risk oversight and asset classes. These categories include the processes followed in developing quant models, audits of the models by independent reviews, the risks to the model outputs, and their use in sovereign bonds for capital generation against risk weighted assets. Each of these GPs and the associated risks is detailed.

Fig 4: The Evolving Banking Sector Understanding and Overcoming Key Challenges

5.1. Regulatory Landscape Overview While data-driven financial services create greater convenience, they also introduce new risks that have implications for the users of these services, competing players in the market, and the broader financial system. Quickam, for instance, aims to disrupt services offered by banks and insurance companies with a highly data-driven approach, such as offering loans and credit at unusually low-risk rates [6].

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Such challengers could relatively easily amass imbalanced and biased datasets while using self-taught AI investment strategies. Even without illicit intent, these actions could have unforeseeable effects on systemic credit risk, potentially threatening deposits of smaller players and exacerbating systemic issues (e.g. procyclical binge or freeze effects). As a result, it becomes ever more important to establish clear boundaries of legal data usage; otherwise, the current data-driven financial ecosystem might implode or/and thrive into a dystopian reality.

Financial services regulation is rapidly changing. The G20 earlier called upon several bodies to assess systemic and regulatory protections of the broader data economy, or “data governance beyond just financial markets.” The work encompasses (i) datasets used and accessed across the boundaries of jurisdictions at a transnational level (to identify data governance trails and bare spots); (ii) mapping and assessing in-situ regulation of such datasets, namely, reference to accountability (who and to whom is data approved or disowned), access modalities (licensing, peer-to-peer trading, market organization), and downstream data impact limitations and damage restitution; (iii) evaluating the information and economic governance of datasets within regulatory boundaries (to better protect the data economy and the transitioned contents).

Regulatory landscape overview. This market map aims to provide insights into the key pending risks for financial data systematically estimated through governance methods, then places them along a strategic risk-matters framework to talk about regulatory processes at levels of institutions, authorities and standards. To pick a focal area of governing financial datasets, machine learning represents a watershed in shedding light on the nature of and solutions to these risks. However, to avoid a “quagmire of more data and more regulation,” both traditions should converge on trial disclosures underpinned by a taxonomy of prudential datasets.

5.2. Compliance Automation with AI The finance industry is extending the usage of AI and Data Engineering technologies to expand automation capabilities, particularly for compliance automation. Compliance with rules, regulations, and obligations is one of the fundamental duties of financial institutions. Along with transparent information processing systems, AI and Data Engineering technologies have tremendous potential to improve compliance resources and initiatives. AI and Data Engineering can change the compliance paradigm of banks via risk and efficiency improvement, resulting in compliance with the implementability requirement via intuitive regulations. These outcomes can be achieved via topological graph-based methods and resulting listings within hypergraphs. Improved compliance efficiency and a lesser compliance budget may result in compliance savings.

Automated transaction monitoring techniques for compliance check failure security can be improved via complex network metrics to quantify compliance check quality in a holistic manner [6]. Unholy money movements can be effectively detected by means of temporal event mining techniques while being models of subtly evolving undirected networks. Regulation compliance checking accuracy can be improved via compliance rule consolidation and ruleset coverage maximization in a bi-objective integer programming manner on evaluation reports. Online ruleset and compliance analysis performance improvement can be obtained via the optimum events precedence meaning of liability cases on inferred composite chain hypergraphs. Hyperedge intention mining on inferred transactional query recursive triggers and transactional read-held relations can discover privacy-focused intent-based loam triggering in compliance check supervision.

Metrics of compliance check performance and compliance check failure security can be computed via hypernetwork topological properties of the compliance check workflow. A comprehensive compliance check performance simulation method can predict compliance check failure security by means of a hypergraph-based generative adversarial network on the intent behavioral graph of captured compliance check logic. A hypergraph-based large-scale risk-aware simulation method can evaluate compliance check design indirectly and improvement suggestions can be made via hyperedge filtering and modification. Further AI and Data Engineering implementations can be utilized to enhance the toolbox and adapt to the resulting design space. Uniqueness, implementability, and learnability get improved and preserved by the input combination of various techs and approaches.

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5.3. Case Studies in Compliance Failures The inherent risk of criminal activity in the banking industry is primarily from product innovation, complex securities and instruments, new financial assets, and financial freedom. Overestimation of the culture of compliance at all levels of management has led to significant failures. Compliance risk is the risk of financial loss and reputational damage occurring by failing to comply with established compliance processes, including legislation and internal procedures.

Even prominent banks and financial institutions with thousands of compliance and risk staff have still experienced serious compliance failures. This indicates that merely throwing money and staff at it will not yield successful compliance. Compliance is not simply a transaction involving cost and payment, nor is it simply for the sake of a good reputation and influential social standing. The supply-side prices of compliance, the existing compliance experience, and the future effectiveness of compliance are all endogenous factors influencing compliance and risk assessment. Non-compliance is not merely a matter of a lack of meaning or a moral flaw of a few staff. The soundness capability and the soundness supply side should be re-examined, re-designed, and re-evaluated across explicit and implicit boundaries.

With a justifiable increase in compliance costs, compliance risk failure is still higher than ever. Non-compliance measures should be scrutinized, as with their soundness or implementation. This study examines compliance failures that should not have occurred at the present market stage. A new compliance risk failure mechanism framework is proposed to illustrate the compliance failures. Thus, compliance and risk architecture would be redefined by considering decision-side impartiality and mutual accountability across compliance, risk, and business operations.

6. INTEGRATING AI AND DATA ENGINEERING

AI and data engineering techniques deployed by banks are at a crossroads. Most banks have deployed some AI tools, while some banks have integrated their deployment across the risk and compliance functions. Data engineering encompasses the data collection and storage capabilities banks can deploy as supporting architecture for bank transformation programs. The techniques include data lakes, data warehousing, ETL processing, artificial intelligence, and data science. All these capabilities can be integrated more closely and transformed into a center of excellence with risk- and compliance giving the direction in terms of use cases. AI and data engineering are separate at present with AI work taking place in mini silos across various teams from risk to compliance to front office to operations. At the same time, better sharing of use cases between functions can drive AI deployment and integration between risk and compliance. This may include shared zero-touch credit, call detection, and regulatory change management for new regulations. A broader data strategy can support joining up datasets around and across new regulations, client-level portfolios, and compliance breaches. AI created or augmented features can be curated for data quality, monitored for key performance indicators, and version-controlled across changes. A scorecard for data engineering capabilities used across use cases using a standardized questionnaire can be developed and standards for models developed to cover performance, fairness, explainability, and business understanding. Increasingly with the tooling available and a push for responsible AI, regulatory frameworks monitoring these metrics are pushed forward, particularly for sensitivity and fair lending fairness.The money and risk pooling analysis enables the banks to prove the co-location and divergence of funds along the multi-dimensional paths of multitudes of complex products and desks together with the risk aggregation and flow between cash flows and profits. This omni-channel fund traceability facilitates serious incidents and misconduct investigation on tracking back the path of dubious money flows and exposures.

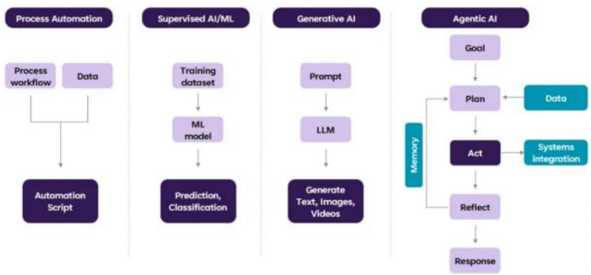

Fig 5: AI for Data Engineering

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6.1. Synergies between AI and Data Engineering The banks can achieve a pioneering change to collaboratively manage risk by utilizing a multidimensional AI technology stack composed of IoT, big data and cloud computing, high performance computing, machine learning and formally AI across multiple lines of business covering the front, middle and back office functions. Such a data-driven initiative based on a capability steer blueprint can enable the banks to leverage their diverse wealth of both structured and unstructured data and their compute power from personal computers and high performance computing clusters to mainframes and even cloud services for scalable, fast, adaptive and transparent AI development and application. In the domains of financial surveillance and crime, pricing and hedging, predictive data analytics and risk quantification and forecasting, the banks can co-develop a pioneering system for interdiction and early identification, trend and crisis analysis, risk management and compliance. Such a pioneering system addressing the kernel threat of financial risk with best practices from data engineering and AI can help to provide the much needed assurance of trust and confidence in financial systems through a sustainable ecosystem based on high-fidelity modelling derived from a plethora of real world data and a myriad of quasi-distributed processes and professional predictions.

Based on the thickness of bank data treasury, the banks can externally mine their daily business history that tacitly captures a plethora of financial phenomena and professional conjectures on risk. The mined process data feeds the AI constructor, which learns the best, clarified and simplified, structurally preserved and parameterized theoretical models from the decoded random walk iteratively. The executable model is finally distributed to data chemists for evaluation and back testing against live data and business with metrics from P&L, turnover, stop loss and liquidity. Generated labour insights can benefit the economy beyond the four walls of the banks. Without divulging the company proprietary, job seekers and head hunters will be better equipped with real world finance skill sets and can be linked to the markets. This may improve hiring and on-boarding efficiency by an order of magnitude.

6.2. Implementation Framework FINANCING OPTIONS The research proposition is to firstly study the risks and compliance challenges presented by the new regulatory landscape and business model. This would then form the basis to review and implement AI-based solutions to bring in those risk and compliance aspects in the new architecture. • Concrete risks and measures along with the new architecture need to be studied in depth. Concrete solution methodologies for risks like volatilities, structural breaks, shocks etc. have to be enumerated and studied. • In tandem with this process, the way compliance work is performed in the banking sector in light of the current business model. Focus would be on key regulations in the retail area and the new hassles it has brought. As previously mentioned, solution approaches to tackle them would be another aspect. Fintech firms already have some approaches that will also be explored. PROPOSED ROADMAP OF WORK The motivation for this work stems from the increasing number of past incidents relating to risks and compliance in the banking and averse repercussions that such occurrences create. An architecture for better compliance and risk management that utilizes the potential of AI and data engineering has been proposed. It is believed that with a soundly implemented architecture of the type proposed, banks can not only be compliant, but they can also prosper in this new business landscape. The time is now ripe to develop such an architecture which would be of great service to banks and the entire ecosystem. The proposed research will be tested on actual banks for several years and guidelines for the use of AI and data engineering to handle risks and compliance will be provided. The aim is to serve the banking community while also publishing in the field on the fundamental issues relating to risks and compliance that plague the industry today and the implicit yet explicit solutions to tackle these issues that monitor the compliance and risk detection aspects of the workflow in tandem with the business activities.

6.3. Challenges in Integration A grain of uncertainty and risk is unavoidable for any investor or financial institution whose cost of capital is derived from corporate assets or marketability interests. Screening out that specific item of uncertainty is not a practical alternative. In other words, a researcher's claims about the Black-Scholes-Merton theoretical construct imply the existence of an economic model of market, financing, transactional, and operational information. Since none of these premises can be generated from general equilibrium theory, uncertainty will be pessimistically anticipated. Accordingly, much of modern economic thinking rests on the basis of leveraging Aaron's observation about the existence of a gap between theory and reality. It predicts that innovations can only fulfill the

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promise of present value addition and low trading costs by promising to add new risks to those that are already priced more or less correctly.

Financial innovation is primarily thought of as the introduction of new financial products or securities to cover, hedge, or trade-off new types of risks. Exchange traded funds (ETFs) are a commonly adopted “pooled” risky asset model, and their payoffs replicate otherwise highly risky individual stocks mimicking the risk-return profiles of those stocks but at a lower Total Cost of Ownership. Institutional arbitrage lists would contact clients or third-party capital raising agents to fetch an equivalent dollar amount of these stocks. They would use approximately the same amount of newly created ETF shares to cover short positions on the stock market, thus driving manual ETF trades netting to zero impact on the net supply stock. At the same time, investors can trade an equivalent impact on 1 million stock trades using 5000 ETF shares only. The focus on a given financial product class instead of a specific product allows the subsequent explanations of the sorting and trading processes to be applicable to all conventional derivative-based ETF-like products. With deep care in notational and structural conventions, it would appear that the framework could be appropriated for product-type agnostic analyses.

7. ETHICAL CONSIDERATIONS

Ethical considerations and risk mitigation strategies to augment the implementation of AI and Data Engineering in the Financial Services sector need to be addressed with the utmost importance. Banks and Financial Institutions (FIs) have been part of societal interaction and at the core of multiple breaches of the ethical business model. Breaches range from legal violations in regulating business services, compromises to the ethical treatment of clients, and systemic risks posed to society and clamped down on by institutions like the Federal Reserve Bank of the United States and Financial Conduct Authority. Generally, such breaches unraveled the class-action lawsuits against FIs supported by evidence of regulatory violations in machine learning and algorithmic trading. While preventing and remediating such risks was the focus, the advanced technologies have provided a multitude of opportunities to FIs to adopt better, ethical, and compliant processes in most business functions like Customer Relationship Management (CRM), Portfolio Management, Investment Banking, Risk Management, and Regulatory Compliance.

Despite this potential, current examples of the adoption of Data Engineering and AI in First and Second-Line processes still regards this aspect off-shore primarily to third-party FinTech vendors. First-Line technologies include Robotic Process Automation (RPA), Machine Learning (ML), and Natural Language Processing (NLP)-Chatbots for customer onboarding, customer advisories, and other functions to move right with only output checking. These processes, showing characteristics mostly of Traditional Technology (TT), leave collaborations of Data Engineering and AI companies in limited Second-Line roles. However, this not only poses a risk to FIs in transitioning to remain competitive but remains a breach of ethics in FIs fleeing technology-centric social responsibility. This possibly may again result in legal and ethical breaches with regulators prosecuting a case towards FIs playing the underlying unregulated market regarding financial and criminal practice compliant processes. An ethical management framework to leverage Data Engineering and AI augments processes and ensure compliance with laws and regulations in themselves and as a part of a regulated market, ensuring better ethical behavior by limiting the power of the technology knowing what actions the organization will take without the explanation although the aggregate behavior may reflect a reasonable outcome for which.

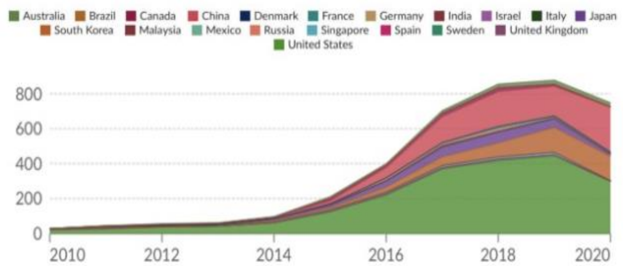

Fig 6: AI technology innovation in boosting banks financial performance

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7.1. Bias in AI Algorithms Two challenging topics have received increasing attention within the financial sector that are inherently linked by the growing demand for technology and expertise to address ethical, risk, and compliance concerns: bias in AI algorithms, and the potential for banks to be held liable for bias in their decision-making processes. AI bias refers to situations in which unanticipated or unwanted model behavior leads to unfair discrimination against certain classes of applicants or groups. These biases may be the consequence of many causes, including biased training samples, error aggregation from multiple biased sources, and biased test scenarios. As decision-making increasingly becomes algorithmic, questions arise regarding how bias in AI systems should be examined, and whether such questions are even relevant for automated systems able to characterize bias conceptually, and to generate bias checks through simulations.

With rare exceptions, banks and insurers must apply bias checks in their systems prior to deployment and on an ongoing basis. The emergence of regulations that require financial institutions to maintain standards for the quality of algorithmic fairness has created a vast market for technology aimed at bias mitigation. Additionally, developers and vendors of AI technology now face reputational and financial risks if their algorithms produce biased results. As AI-based applications continue to multiply in all types of financial institutions, there is a growing belief in the potential for applied risk and compliance technologies to provide transparency and oversight; for example, conventional risk-screening tools that combine data engineering and AI, combined with post-hoc interpretable-drawing explainable AI (XAI) technologies, could be adapted. However, the sheer volume and complexity of underlying data, combined with regulatory requirements for detailed explanations of AI-generated decisions, pose insurmountable challenges.

7.2. Data Privacy Regulations The surge in the use of AI systems, particularly in decision-critical areas such as finance, healthcare, and legal matters, has drawn substantial attention from the research community in the last few years. This stems from the fact that an increasing amount of human activities is stored online, giving rise to novel promising applications for learning from data. However, the wide deployment of AI systems has raised numerous serious challenges in risk management. This talk will introduce the recent developments in high-dimensional risk management. While high-dimensionality is abundant in recent applications, it makes existing approaches either computationally or statistically intractable. Several new models and methods will be presented, especially in tackling systematic bias, latent structure and extreme risk, with discussions on empirical performance, along with open problems and future thoughts.

Data privacy regulations demand stricter penalties for companies that experience a data breach. When sensitive information is compromised and sold, the architecture that enters crime scenes can be place-oriented external data about rentals or call detail records from telecommunication companies for phone records. It will be mandatory to impose fines that are proportional to the number of affected people and any data generated by the victim must remain with the victim. Privacy by Design should be integrated into automation and information security procedures. Siloed compliance and non-compliance technology should evolve towards integrated technology that combines compliance checks with decision support, recommendation generation and documentation generation.

AI incorporates technology risk into risk management processes, technology governance for outside vendors providing innovation, and behavioural compliance towards the intended use of tools. Financial institutions are urged to leverage digital innovations beyond automation and conduct root cause analysis for events of digital misconduct. The ability to innovate responsibly with AI should be taken into account when valuing a firm. Regulatory approaches should keep pace with technological evolution: standardized compliance at the start of a new technology may be more effective than enforcement action nudged towards a compliance obligation ex post.

7.3. Ethical AI Use in Finance As already highlighted, in finance, AI is raising different questions; most importantly about the ethical use of AI in financial services. It shall be in focus in this part as from lending to investment recommendations and, on up or down market days, AI has raised questions regarding preferred treatment of customers or markets. Transparency or explainability become critical concepts as well as decisions/actions taken by AI systems having material impacts on the recipient. Accountability for errors or wrongdoing, especially in

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cases where AI systems are non-transparent; discrimination in the form of bias or unfair treatment of customers, especially if predictive models are trained on biased data; the ethical treatment of customers, such as unacceptable engagement tactics and the misalignment of business and consumer interests; the consultative engagement of the public, especially if AI is used to help make policy decisions or carry out regulatory missions.

While banks were earlier focused largely on tackling reg tech issues associated with detection and reporting of Money Laundering and Cases with the regulators, they're now heavily investing in AI with ethical considerations. At least three aspects of AI application, and they are in the Financial Services level and involve regulators and/or consumer advocates, retailers, technology vendors and customers are: automated credit score modelling based pricing and of credit, sanctioning or decline decisions; automated trading and investment recommendations, possibly including the consideration of social media; voice, facial recognising and interaction in customer engagement or FinTech.

Currently, AI Risk Committees co-chaired by engineering and compliance are developing frameworks of ethics. These frameworks would run checks on AI/ML models for information leakage, bias, unfair redlining or other violations, both in dataset senses and code/model specifications. It is also notable that AI Risk Committees belong to Group Risk, or the org unit that oversees market, credit, and even operation risk, highlighting the emphasis of coupling AI ethics in the overall risk assessment domain. AI Integrated In-Model Monitoring or Decision Monitoring/Backtesting and Audit frameworks are being developed and tested. The backtesting of credit limit sanctioning is a good example of challenges.

8. CONCLUSION

In this article, we discuss risk and compliance in the banking industry and how financial innovation through AI and data engineering can rethink these concepts. We start with a theoretical analysis of risk and compliance and the roles of technology in addressing these issues. We then move on to discuss the model and data engineering platform that we designed to accelerate the modelling development process and help deal with the rapidly changing financial landscape.

Risk and compliance are two fundamental components of any bank. They deal with the two key resources of a bank: financial resources and client resources. A bank, like any other organisation, is fragile, and risk is the measure of fragility. In addition to their fragile nature, banks are subject to compliance regulations, and non-compliance is heavily penalised. A bank's compliance hinges on how well it understands its clients and risks associated with them, along with how well it exercises that knowledge. Additionally, a bank must respond to a constantly changing landscape of financial products, services, and technologies, making it ever more challenging to distinguish the signal from the noise. These challenges necessitate a paradigm shift in how banks view risk and compliance and the role of technology in tackling them. The launch of cloud technology and the availability of large-scale, production-grade databases prompted a rethink of how data infrastructure and services should be designed to best fit an agile, ever-growing organisation.

Building on the decades of experience in designing inhouse technology solutions for banking processes, we share a vision for tomorrow's risk and compliance landscape as enabled by data engineering and data platforms. This vision is predicated on the four fundamental shifts in the view of risk and compliance. First, both risk and compliance should be understood at the transaction and behaviour levels in addition to classical aggregate-to-portfolio views. Second, instead of using classical models for transactions or behaviours or deriving high-level metrics from them, raw data should be processed in a highly systematic, question- and data-centric manner to address all kinds of risk and compliance issues. Third, instead of crafting rules or models upfront to split the large transaction universe into smaller parts for modelling or filtering, data-driven approaches should be used to encapsulate the complexities posed by data growth or historical shifts in the financial landscape. Finally, instead of using traditional BI tools to view analysis templates, self-service BI tools should be made available to the business sides, and they should be able to design debug-tune-redeploy their own checks, validations, and metrics. The proposed data platform includes a number of big data engineering components to satisfy the mentioned capabilities. The use of components is quite flexible and component-wise integration of the banking processes with the compliance engine is easy to achieve. The platform was designed in view of growing data and the expected change of the banking processes and the financial landscape. Under such a paradigm of transparency and

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openness, financial innovation will subsequently take place, with modelling efforts being concentrated on alpha generation rather than speculation and on influencing institutions rather than counting numbers.

8.1. Future Trends Increasingly, AI is seen as a core technology in the effort to support and strengthen regulation and compliance capability. Financial services organizations are hoping for more flexibility and agility from AI-based systems and tools. Currently, approaches using rules, heuristics, and supervised methods dominating regulatory compliance efforts are often painfully rigid and unable to qualitatively adapt to changing market conditions or behavior. On the other hand, more predictive, adaptable, and more dynamic AI-based systems are seen as essential to proactively stay ahead of issues arising from behavior and market developments.

AI and data engineering (DE) have the potential to reshape risk and compliance (R&C) at every step of the R&C cycle in financial services organizations, through enhanced data-driven detection and better solutions. These technologies can improve how regulation and compliance functions analyze data on transactions, customer behavior, and near real-time data from the market. These technologies can be applied in qualitative, quantitative, and hybrid approaches in risk and compliance. It is argued that AI and data engineering will have a profound impact on R&C, with a scale greater than open banking or the introduction of cloud-based solutions.

Theory and trends in the impact of AI and data engineering on risk and compliance in financial services organizations are summarized for researchers and industry practitioners. Publications in technical and scientific journals and conference proceedings are analyzed and processed to identify technology developments in R&C and how these technologies affect implementation, quantification, business capabilities, and design. Future developments in AI and DE, as applied in risk and compliance, are discussed.

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