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Chapter 9: Navigating regulatory challenges in artificial intelligence-driven finance while maintaining compliance and trust

9.1. Introduction

Financial markets have a long storied history of being some of the earliest adopters of emerging technologies, with the introduction of the telegraph allowing for faster access to trading information providing more equal participating conditions to traders and thus increasing market efficiency. The invention of the computer brought about a whole new era in algorithmic trading which has been around in some form as early as the mid-1970s. With the rise of algo-trading, and the associated efficiency gains derived from it, traders started to search for more complex market signals that computers could better decipher than the human brain, allowing for even speedier arbitraging of mis-pricings acrhaving the ability to decode and analyze them to supplement established trading strategies seemed a holy grail moment for quantitative traders (Bisht et al., 2022; Boute et al., 2022; Kim et al., 2022). Not surprisingly, the floodgates opened to a plethora of AI-driven hedge funds and trading firms attracting untold amounts of capital, with many of the corporates focused on a certain level of secrecy around their operations. However, the use of AI tools and the underlying data has since burst the bubble and democratized hedge fund trading as alternative investment products become open to institutional and retail investors alike. These developments have allowed for further scrutiny into the pitfalls of lack of regulation and oversight on these funds. Using the classical financial formulation of creating alpha through active investment management, this paper will analyze the AI-involving driving forces within the financial industry, ranging from high-frequency trading, risk management, quantitative asset management, robo-advisors, sovereign credit rating, to the credit credit sector, crowdsourcing, and AI-specific funds (Bhadra et al., 2023; Mathew et al., 2023; Singireddy et al., 2024).

9.2. Regulatory Landscape Overview

The United States has a broad regulatory framework governing financial services. This general-purpose framework covering financial institutions is complemented by a practitioner-specific and use-case specific regulatory framework governing specific financial activities that may involve fraud, deception and manipulation, or spurious claims on returns and potential resolution for the crisis of trust in firms engaging in a financial activity. Enforced by a variety of interwoven state and federal regulators with overlapping jurisdictions, the Mix concerns itself with the two critical functions of traditional financial intermediaries at the center of the financial ecosystem – payments and risk pooling.

Fig 9.1: Regulatory Challenges for AI in Finance

The Mixing Function governs activities that contribute to the smooth functioning of the payments ecosystem. Payment networks have severe constraints on the trust imposed on them. Payment network operators have to file a notice and are subject to collection of data on a confidential basis. Issues relating to balancing the safety of the payments ecosystem with competitive forces in that ecosystem are central to the oversight of the payments sector. Activities with spurious claims on issues and potential resolution for the crisis of trust in payments advertisements are governed by regulatory bodies. Payment processors by virtue of their position are subject to general industry standards as determined by the regulatory framework that influence the smooth execution of the payments process. The supervisory triggers depend on the number of transactions processed or the amount of money processed. Supervision or the threat of supervision keeps fraudsters at bay.

9.3. Key Regulatory Bodies

The rapidly growing importance of AI-based algorithms for financial markets has attracted the attention of many regulatory authorities, either through the explicit prediction of future regulatory initiatives concerning algorithmic trading in general, or through much more explicit statements exclusively concerning AI in relation to trading. In this section, we highlight the most important regulatory bodies and their respective stances on AI algorithms in finance. The introduction of digital forms of financial transactions and investments is accompanied by a demand for relevant digital regulatory strategies that require oversight on a national and global level. Depending on the degree of the distribution of algorithmic trading across national markets and regulatory domains, as well as the sensitivity about abusive 'new' trading strategies, the regulation may focus on digital trading strategies under existing rules, clarify existing ambiguities regarding the applicability of certain codes and rules, or develop specific new digital regulations.

Several financial market regulatory authorities play pivotal roles in determining global standards for market operators. Maintaining market integrity are the key regulatory focus areas addressed by the international regulatory bodies. In addition, several vertical global regulators address digital finance markets on a more micro-level, and again determine the individual strategies adopted by participating or non-participating member-states. Their respective publications highlight the areas most sensitive to abusive behavior, laid down primarily in anti-money laundering and counter-terrorist financing directives for crypto-transactions on the one hand, and market manipulation laws applicable to specific markets trading in foreign and digital currencies on the other hand.

9.3.1. Global Regulatory Frameworks

The rapid development of the AI sector has necessitated the creation of a set of regulations to govern the use of these technologies in all sectors. In 2023, we have witnessed the launch of several initiatives to create effective frameworks for the future use of the technology. We present below a selection of seminal initiatives.

The Organization for Economic Cooperation and Development was established in 1961 with the goal of stimulating economic progress and world trade. In May 2023, it issued the Principles on Artificial Intelligence, which are applicable to all member states. The Principles advocate ensuring that AI elements are used in a way that is safe but also respects human rights and democratic norms. The document also puts various focus areas forwards, such as ensuring human oversight of AI systems or creating trustworthy AI systems. With regards to the financial services industry, three areas are highlighted: AI for risk assessments, predictive analytics, and ML systems for algorithmic trading. AI has the potential to bring immense benefits to users, however, improper use can pose a threat to financial stability.

The International Monetary Fund has also weighed in on the impact of AI in finance. In a 2023 working paper drafted by a group of economists, it acknowledges that AI today is at a similar stage to previous technological revolutions, such as the impact of the internet or the arrival of electricity. AI's introduction brings to the fore productivity gains, boosting potential output, however, new technology can naturally also be used for illicit purposes.

9.3.2. National Regulatory Authorities

While international financial organizations engage on a high level and create guidelines, the daily supervision and monitoring of the financial markets including AI innovation takes place on a national level. At the core of the national legal systems are the financial authorities that govern the international set of standards. These include the SEC, the CFTC, ASIC, FCA, PRA, AMF, BaFin, FSA, EBA, ESMA, EIOPA, ACPR, CSSF, APF, INPC, DNB, CNB, NBB, Central Bank of Norway, and the OECD.

These authorities have the task to supervise the financial innovation and to evaluate legal violations connected with the new technologies: Global financial companies and institutions have to comply with national laws that follow the regulatory guidelines. Thereby, AI products that violate internationally accepted guidelines can be banned or restricted. The classification of the products and their respective risks ensures that the fintech innovations will be placed in the right legal boxes which enables risk-based supervision. Simple AI-driven products can be processed under existing consumer protection law or e-commerce law while their stronger counterparts that have farreaching consequences for finance have to be categorized under the financial services law and subsequently supervised.

9.4. AI Technologies in Finance

Another area of technological change is artificial intelligence (AI). AI is usually defined as a set of technologies that allows computers to solve complex tasks in a way that is perceived as "intelligent" by human users. These tasks typically involve reasoning based on empirical data and often use language. AI implementation in downstream tasks associated with human perception and understanding have two main motivations in finance. First is increasing the accuracy and speed of firm activities that depend heavily on perception and judgment. The second is performing activities that are difficult and costly for human agents. AI in finance includes the application of three key subfields of AI: machine learning, natural language processing, and robotic process automation.

Machine learning (ML) is the application of probabilistic statistical techniques that allow computers to assess the statistical implications of data using algorithms. The algorithms allow the computer to modify the function that connects input and output variables according to the data in order to explain how the output variable is affected by changes in the input. The construction of the function itself does not depend on any human agent but is solely a consequence of the ML algorithm's exposure to data. In ML, human supervision is required only in the initial design of the model and in defining the objective of the ML optimization process. This property of ML allows computers to carry out activities that would be either too costly or inefficient for human agents because the underlying task is either too simple or repetitive. Algorithms such as support vector machines, decision trees, or deep neural networks could be used to implement ML.

9.4.1. Machine Learning Applications

Artificial Intelligence, particularly in the form of machine learning, occupies an outsized role in our analysis of new processes being implemented or contemplated in the financial markets. Machine learning is the most sophisticated tool that is being made available to analyze data, to catalog, assess, and improve upon written and then human-vetted trading and analysis models, and to predict how people are likely to respond to an almost limitless array of events in the context of commercial and investment behavior. Machine learning involves computer systems that improve their performance and adapt to new circumstances without being specifically programmed to do so. They do this by processing and learning from enormous amounts of past data so that they can build a model that will be a good predictor of future events. The systems continue to learn as new data becomes available. Moreover, as systems, they can be and are augmented by human oversight and judgment. This symbiotic relationship between man and machine suggests a future that may often be better than either alone. The trading and analysis models that we discuss can be the computer generation of business insights on a massive scale, because companies are issuing a thrice-digit volume of documents. Investors are overwhelmed, and have of necessity turned to advanced technology to help them evaluate the reports. These models can also be employed by traders and analysts to augment the decisions they have to make continually throughout the day and to assist them in generating better, more informed, and ultimately more profitable decisions as quickly as possible. Machine learning has also made significant inroads into other business processes that rely heavily on data analysis and pattern recognition, such as identifying and preventing fraud and assessing and pricing risk.

9.4.2. Natural Language Processing

NLP, a domain of AI that combines linguistics and computation, studies the interaction between human language and computer systems and is primarily interested in making sense of language. RL and ML computing and algorithms have tractioned NLP applications through efficient implementation of the methods in domain-specific systems. The trend in NLP is a more holistic approach that goes beyond traditional bins of POS tagging, shallow parsing, information extraction, named entity tagging, and semantic parsing. Methods like BERT and GPT model the language use directly through the objective of predicting masked-out words in a sentence by context words. These methods are pre-trained on massive unsupervised corpora and fine-tuned on various tasks that allows them to be on current SOTA performance.

We can classify a host of user-impacting NLP systems that are already in production into three bins based on the user interaction and implementation complexity: conversational interface, language understanding and document understanding systems. The popularization of intelligent conversational interfaces in software products has enhanced the way humans interact with their software and services. Companies have invested heavily in building complex ASR and TTS systems for attaining impeccable user experience and the intelligent assistant for the smartphone.

In practice, organizations have developed and deployed intelligent entities that converse with the user in a human-like fashion, fulfilling user needs. The technology stack is powered by ML methods for ASR, NLU, software dialog management, and TTS. Companies have invested heavily in building complex ASR and TTS systems for attaining impeccable user experience and the intelligent assistant for the smartphone.

9.4.3. Robotic Process Automation

The term RPA initially described desktop automation, often software tools that emulated user actions on desktop GUIs. However, the term RPA has expanded in popular usage to include all software tools automating business processes. This includes what we refer to here as workflow automation tools. In general, RPA tools use a combination of business rules and workflow orchestration to automate what are usually repetitive time-consuming tasks where a range of eligibility decisions need to be made on many different files requiring a number of different actions. Often RPA is described as a form of low-code automation.

RPA typically brings faster solutions than traditional automation, both in speed of deployment and speed of development as there is no requirement to develop and build out new system technology layers for solutions across the range of challenges presented by many different business processes. As a simple example consider an organization that manually completes a series of steps each week to extract spreadsheet data from multiple sources. These often only require a few human-driven steps to finalize the process, such as checking the output meets general quality standards and submitting for internal control approval. An RPA-powered solution will process the spreadsheets more quickly when it is not yet optimal to create a full tech solution but will speed things up and create extra human capacity while doing so.

9.5. Compliance Challenges in AI Implementation

The automated decision-making processes that are driving the implementation of AI technologies may be subject to various existing regulatory schemes. Financial services companies already navigate a complex regulatory environment that includes several consumer protection statutes implemented through a set of rules designed to promote lending fairness and disclosure. Similarly, credit reporting agencies must disclose certain records in response to request. This discussion provides a few highlights on these existing legal hurdles that drive compliance efforts in jurisprudence. Section 9.5.1 addresses these challenges for privacy regulators, while Section 9.5.2 discusses hurdles stemming from the fairness and bias obligations. Then, Section 9.5.3 offers compliance considerations regarding the information and notification requirements.

AI technologies optimize a regulated activity — the lending decision-making process — while also potentially harming consumers by processing their data using algorithms that are difficult to explain to third parties. Further, the fact that these technologies rely on vast datasets provides regulators with the opportunity to impose additional data security and risk measures within their respective jurisdiction. In addition to these transparency requirements, bias and fairness, as legal concepts, also depend on the religion, skin color, and ethnic makeup of the applicant. Bias and fairness violations may arise when companies process these prohibited bases in their application processes. As outlined in Section 3.2.3, although not fully achieved, AI fairness achieves great milestones through bias mitigation frameworks and techniques.

9.5.1. Data Privacy Regulations

Data privacy regulations represent a critical layer of compliance for AI models, which often leverage large amounts of data pertaining to individuals. Financial services are among the most data-heavy services and, as a result, are thoroughly encompassed by privacy laws. Although the burden of privacy regulations is often borne disproportionately by larger banks, these rules apply uniformly to entities of all sizes. The primary set of privacy standards faced by financial institutions in the U.S. are the Gramm-Leach-Bliley Act, the Fair Credit Reporting Act, and the Fair and Accurate Transaction Act. These acts are centered around the idea of maintaining confidentiality of private data; giving individuals clear notice regarding the collection and sharing of their personally identifiable information; limiting the accumulation of private data, and giving individuals access to their own data.

Fig 9.2: AI in Financial Regulatory Compliance

Because AI models often rely on privacy-protected data to transition from training to production, banks will typically strip PII to make data "anonymized," or "de-identified," in order to comply with the GLBA among other acts. Furthermore, financial services utilize a variety of data sources for model training, such as geolocation data, that may be governed by their own privacy compliance requirements. The RFPA establishes limits on how the government may conduct surveillance to gather information about individuals' financial transactions. The newly introduced California Privacy Rights Act strengthens the California Consumer Privacy Act which is already the strictest privacy regulation in place, which gives consumers greater ability to regulate businesses use of their PII, and takes effect in January 2023.

9.5.2. Bias and Fairness in AI Models

Concern over bias and fairness in AI models is not new. The concerns around algorithmic bias stem from the fact that machine learning models are trained on historical datasets and will replicate prejudice against certain demographic groups exposed in these datasets. Model outputs that favor certain groups over others would be unacceptable in traditional decision-making scenarios – for instance, a loan officer denying loans to people with similar credit ratings across demographic groups would be challenged on the basis of disparate impact theory. The Equal Credit Opportunity Act already prohibits discrimination against certain protected classes in credit decisions; in 2020, various civil rights advocacy groups expressed concern about prediction bias stemming from use of AI in credit decision-making.

Such AI bias concerns have spread to other areas besides credit decisions as AI use has expanded into areas such as employment, housing, health care, and criminal justice. At the financial institution level, such biases are concerning for at least two reasons. First, financial institution headquarters and their business unit strategy heads not only enjoy significant discretion in designing their companies' risk models – they also have considerable leeway in selecting the vendors and algorithm providers for offering models for loan-tracking, model validation, recommended changes, and model performance benchmarking. From this starting point, it is essential to understand the importance of stringent validation procedures to mitigate the possibility of faulty, biased, or non-optimized models that could be used to identify mispriced risks, especially with respect to lower-income groups.

9.5.3. Transparency and Explainability

Another important concept in ethical AI is that of transparency or explainability. The financial service industry has long been obliged to provide explanations for its actions. Mortgage lenders, for example, must provide explanations for its rejections of applicant requests as required by relevant regulations, as well as for any adverse action taken during the life of the loan. Traditional models, such as regressions and credit scoring models, are very simple in nature and easily explored. They can be interpreted as a series of weighted should/should-not statements, meaning a lender can simply look to an applicant's score to see the reasons leading to the model's decision. More advanced, supervised AI models, such as deep learning techniques, support vector machines, and gradient boosting are often dubbed black boxes because the relationship between inputs and outputs is so complicated that they may provide predictions without any supporting rationale. Attempts to explain black box models often yield unpalatable conclusions. For example, recent research found that black box visual models can easily be confused into associating certain groups with negative scenarios even though they did not initially present any such conclusions.

The black box feature of advanced AI models is especially problematic when they are used for tasks that can strongly affect people’s income, wealth, and credit quality, such as approving applicants for credit cards or loans. As models become more powerful, however, the understanding of their operations and outputs becomes more complex due to the increased number of variables and the intricate nature of their relationships. Model outputs are declared sometimes without proper understanding of the reasons behind them. So far, there are no established laws and regulations that are specific to the transparency or explainability requirement of AI models. Some new regulation bills related to AIs have been proposed in some countries.

9.6. Building Trust in AI-Driven Finance

A critical component for ensuring that AI is used safely is that all involved stakeholders – from designers to users – buy into the motivations for its development and use and feel comfortable about how AI will work to achieve that motivation. While there seems to be a lot of excitement about AI systems located in the tech space, there is also a lot of distrust towards these same systems, and more generally towards much of tech in the user space. This distrust stems, at least in part, from some of the awful implementations of AI that have occurred and have led to harmful effects for users, and the very fact that these have become widely publicized. Addressing these concerns starts with the realization that talking about AI is not talking about one thing but instead talking about a bunch of technologies that can behave very differently.

Elements of how the development and use of AI are communicated to members of the user community can be critical for cultivating this buy-in and trust. Such elements should seek to present details such as what exactly is meant by AI, about an AI system at a higher level what general task will the AI system address, who would be involved in the decision-making process, and how would AI be assisting the decision-making process, what policies are in place to make sure that the technology works as intended, and how those policies are governed, including the input that the user community has in the implementation and monitoring of such policies.

9.6.1. Stakeholder Engagement

Active engagement with stakeholders and communities impacted by AI systems is critical to silently navigate the unfamiliar landscape of AI in finance and establish societal trust. This kind of investment in stakeholder relationships is critical to gain accurate insights into the problems and risks that AI can bring. This decision intelligence is mandatory for the ethical design of AI solutions as well as to identify some unintended consequences that AI use can spark. Periodic consultations should be laid out not only to collect feedback but also to share experiences about the journeys with the design, development, deployment, use, and monitoring of AI-driven systems. To this extent, it is important to educate stakeholders and the community on how explainable the AI-driven solutions becomes over time considering the numerous interactions amongst stakeholders and the AI system. Trust in the design and development of AI solutions does change over time with the interplay of feedback and communication between stakeholders. This opens up the door to a radically different design, development and deployment of solutions in comparison to rule-based systems, especially in situations of personal and financial crisis. Information asymmetries disclosing the unknown unknowns about the behavior of AI systems are most pronounced in high-stake situations like the acceptance by victims of Natural Disasters of Automated Systems recommending the type of initial relief actions triggering the allocation of billions of dollars in public funds.

9.6.2. Consumer Education

Consumer education is key to building trust in AI-driven finance. The vast majority of consumers lack a strong understanding of how AI is utilized and what its limitations are in the finance industry and elsewhere. As a result, misconceptions can result. For instance, some consumers may not understand how functions such as credit scoring work and the role that AI plays in optimizing and improving these processes. Without holding a strong understanding of credit scoring, a consumer may be less likely to trust their score and the monetary risk associated with that score. Engagement between relevant stakeholders can also facilitate the promotion of consumer education initiatives. Moreover, at present, there is immense financial and market power concentrated among several large technology firms involved in the development of generative AI solutions. The trust that consumers have in these developers, or lack thereof, will directly affect the degree to which enterprises, organizations and regulatory authorities can adopt such technology in accordance with their directives.

Additionally, stakeholders could bring together academically-grounded and applied practitioners in joint actions at informal education conferences. At these events, attendees could explore how to illustrate the pros, cons, bullseyes and pitfalls of AI for Financial Services and how to actualize the benefits and de-risk any distorted expectations around AI deployment. More formal hands-on programming workshops could also involve a few firms leading bilateral programs as a dry run for educating their user base, as well as partnerships with college professors and students from local colleges to create coursework for non-companies, potentially together with the user-desired outcome.

9.6.3. Ethical AI Practices

A suitable compliment to stakeholder engagement and consumer education is the ethical development of AI systems and deployment of AI services. Transparency helps to boost trust. Trust in the quality of AI technology must also apply to the development of all AI technology, whether that is in the form of third-party AI models or internally built models. In many areas of finance, there remain relatively few third-party models available. This is a consequence of previous challenges in obtaining sufficient training data in standardized form and in controlled conditions so that every party's models would be trained in comparable ways. Advances in large language models are beginning to change this. Today, many large language models built by specialized companies provide APIs that can be used by financial services firms to build new applications that will lead to data sharing and model training on standardized outputs.

First-party model development has to be accompanied by a rationale for the data selections and model training and validation processes that demonstrate that bias and unfairness have been appropriately addressed. Firms should consider being open-source with their model designs, parameter choices, and datasets as much as possible. As fieldwork research in sociolinguistics has long shown, having lists of common examples is actually not enough for detecting and addressing potential bias and fairness problems. Transparency on the datasets used, and the rationale for continued internal scrutiny of the potential for bias to have a negative impact on the services delivered through AI models are critical to building stakeholder trust.

Engineering steps must be taken. These include quality control functions to check for critical outputs. Static prompts that have generated bias issues in the past must be stored and reviewed regularly to see how monitored and automatically assessed performance has changed over time. Investigate any new prompts that generate outlier model performance and report process changes that have increased risks associated with the change.

9.7. Case Studies of Regulatory Compliance

The burgeoning landscape of AI-driven finance is not without pitfalls; thus, it is incumbent upon firms engaging in machine-learning-driven trading in the finance space to fully consider the ramifications of engaging in such activity. These considerations include how to address various regulatory and compliance obligations once trading begins. There are existing historical examples both of successful implementations and of failures, the latter of which lead to severe consequences for regulators and affected investors alike. The lessons learned can provide a roadmap of sorts for younger companies developing new architectures or scalable frameworks to meet the risk-associated goals of regulators.

A research firm developed a natural language processing algorithm designed to send trading signals to clients engaged in high-frequency trading in securities markets. The algorithm was better able to detect changes in earnings per share projections than analysts' recommendation revisions. The company found that these proposals earned them backtesting revenues every month and were prepared to commercialize the algorithm. As a result, they turned to a consulting firm for assistance in addressing regulatory compliance obligations and control considerations. The algorithm was subject to risk-compliance, suggesting that the actuarial control model could contain both qualitative and quantitative risk features. Subsequently, each client was assigned individual risk ratings, which factored in the potential risk of regulatory scrutiny and the loss of potentially valuable advertisers.

9.7.1. Successful Implementations

Regulatory compliance places a significant burden on financial institutions, which generally lack the know-how and resources to implement state-of-the-art technologies. Smart regulators can jump the boundary and reshape more efficient relations with their banks. An increasing number of successful implementations suggest a roadmap to other regulatory agencies. One regulatory body has teamed with another organization to use semantic AI to find ideology-based fraud in electronic trading, filing, and chat-room data. Another agency has developed an electronic filing and business process analyzing

API to streamline the fee identification page, incorporate new fee types, reduce the data tagging burden on issuers, improve processing efficiency, and analyze the fee portion business process using a standard model. A state department has worked with an international authority to use blockchain to facilitate the real-time collection of unclaimed property. An international task force has explored the use of natural language generation to favorably affect the speed and quality of text-heavy reporting and related processes for supervised and regulated businesses.

Attempts by a government department to use artificial intelligence to identify employers who fail to meet labor standards during investigations illustrate the barriers that continue to stand in the way of using AI in agency efforts to improve compliance assistance. Nevertheless, another department is using machine learning to process incoming discovery material faster. A company claims to use a type of AI to automate the handling of clearing and settlement processes, but there is little public verification.

9.7.2. Failures and Lessons Learned

Regulatory compliance can also be a complicated issue and a factor of concern for AI in Finance, and some cases reveal different risks. A case reported is the failure of the automated mortgage origination system of a company. The system was easy-to-use both for the applicant and for the lender, and the company was highly rated by the industry. The high level of automation of the origination system did a great job in providing its users with cheap mortgage loans. However, a major weakness of the system was that it did not address the risk of the applicant falsifying the provided information. As a result, the company started facing delays in payment and other bankruptcies among its mortgage clients. Audits conducted into the matter revealed that people were providing fraudulent income tax returns. After a while, the company went out of business. This case raises concerns about the need for continuous verification of the information being offered by clients as most of the new AI and MB technology implementing companies become more and more reliant on automated systems for achieving efficiency.

The lack of supervision, monitoring, and ongoing audits diminishes the effectiveness of the system. However, new and more secure verification systems have been developed and are currently in use. There have been many financial disasters and failures that stemmed from the bad use of AI. For example, there was an event when a company was hired to verify the eligibility of Medicaid applicants. Due to the myriad references from administrative records that were mismatched and incorrect, at least 186 individuals were wrongfully offered the Medicaid plan, which did not help the people in need. These incidents reveal the significant risk of AI not performing any live or real audits and verifications.

9.8. Future Trends in AI Regulation

The need for ethical and accountable AI in finance will become more pressing as generative AI continues to be adopted. More organizations will have both ethical objectives and actual regulatory obligations to prioritize consumer welfare and societal interests. From a regulatory perspective, it is likely that hybrid models will be used to enforce oversight. While outcome-based regulation is primarily used to account for innovative financial technology, such as AI, machine learning, and blockchain, a real-time, dynamic, principles-based vs rules-based hybrid approach will be used to ensure compliance during the product and service design phase, but also during the usage and application of these products and services by consumers. It would not be enough to only review the design of the technology and create a disclosure framework and a testing protocol to minimize risks. As products and services that relied on generative AI deployment continue to evolve, policies will need to be in place to ensure that consumer harms are actively monitored and accounted for so as to not create a pro-cyclicality dynamic where there are gaps in active monitoring of consumer impact.

While creative regulatory oversight is essential, it does not necessarily mean that there will be an expansion in the number of government regulators or regulatory agencies. What increasing use of generative AI means is a chance for more innovative synergies to exist to permit streamlined oversight. Partnerships between finance regulators and both international and cross-field governments will need to occur for outcome-driven regulatory frameworks to be defined and implemented accordingly. Along with this enhanced cooperation, the application of advanced technology for regulation-driven purposes will be needed to offset the potential issue of increased workloads associated with widespread use of generative AI, and how to create more effective solutions for automating detection and addressing standard issues that can arise from the more rapid turnover of consumer-facing products and services. Considerable investment into technology applications from financial regulators, but also from the banking sector, will be needed to both develop and implement AI solutions.

9.8.1. Evolving Regulatory Frameworks

The realm of financial services has never presented as many novel and diverse opportunities for the adoption of AI technologies, nor as many consequential risks to consumers, investors, and the economy from harmful uses or the unintended consequences of AI systems. In light of these forces, the regulatory framework governing the use of AI technologies in finance will inevitably evolve, both in shape and content, across regulatory organizations, jurisdictions, and the verticals that comprise finance. We expect such evolution will be additive; in other words, AI regulations will not replace existing financial services requirements, such as error-reduction and disclosure obligations; rather, AI regulations will layer obligations that are AI-specific on top of the existing travelings and safety requirements. These new obligations may be inspired by other regimes that have already been implemented, perhaps most notably a model on which certain regulations are modeled. But we also expect future models to chart new territory, filling gaps in provisions related to trustworthy, transparent, or explainable AI in the context of financial products or services. These provisions may require explainability and transparency to regulators, such as functional testing.

It may not be sufficient for a party to declare that an AI system is "trustworthy" or "explainable" or that the party has a good-faith belief that the system is not producing biased results. The regulatory resources to test for safety and fairness, however, are limited, and AI systems are highly context-sensitive, adaptive, and capable of generating results that require expert validation. A lot of the foreseeable inconsistency across AI regulatory regimes derives from several interrelated factors from the general approach taken, which varies between a hands-on, case-by-case intervention compared to a hands-off, stricter compliance-based approach. These factors include but are not limited to which government body regulates AI. Such bodies and initiatives have, in effect, already begun to evolve the regulatory framework outside the ambit of the legislated statutes on which each of these bodies relies.

9.8.2. Technological Advancements

The financial services industry is prone to tech-engineered innovation and disruption, in the wake of which lies a market flooded with new cash generators. In recent years, the technological frontier has been moving in exponential overdrive, at the tip of which lies artificial intelligence. Till two decades ago, Financial Technology was an area of niche service providers, helping financial institutions operationalize tech in order to optimize back-office processing tasks. This used to be the world of niche players who developed infrastructure tools for clearing, payments, reconciliation automation, etc., and these were essential services needed by the giants in order to do what they're doing better than others. Today, all of that has almost been completely digitized and automated by technology over the last decade or so through the work of both banks and their FinTech partners; hence the thinking is to jump the queue and do it quickly through either buying the Non-Bank Financial Company or the Bank which is channelling funds into these NBFCs.

Simultaneously, the financial services sector is transforming rapidly, through challenging the space with solutions which use smartphones and biometric identification to open bank accounts, offer lending terms that are diametrically opposed to those being offered by banks, virtual currency usage, lowering the cost and the sheer volume of cross-border remittances, investing with no advisory fees, eroding services banks pay client for, and creating a new ecosystem of digital banks and services operating outside the regulatory reach of state central banks and finance ministries. In addition, these financial services are leveraging the effect of network that every new user is adding, and some of the players are heading towards monopoly to create their own walled gardens. All of this also leads to asset creation on the technology backbone, which fundamentally really ought to be the monopoly, and the battle now is to create the moat around the physical asset.

9.9. Strategies for Compliance and Trust

The discussion of ethical compliance and trust as it relates to AI applications in the finance sector is not just about addressing regulatory constraints. Financial services must be able to demonstrate and owe trust in AI-embedded systems to customers and society on a wider scale. A major trust factor is the solid design of a compliance function. Compliance teams should in a very early stage work proactively with their business partners in the setup of an AI-driven financial service. Risk assessments should not just be limited to the systematic but should include additional non-systemic factors. Collaboration, training, and the trust factor explaining unfair decision-making should be crucial elements in shaping an effective compliance function. Technology design and product development should become a team sport where compliance is present from the very first idea of services generation. The compliance infrastructure has to be accompanied by data and ethical excellence. Data control and sufficient explanatory power around the model's design are essential to support a smooth supervisory evaluation phase. Explanations can be a valuable support to compliance officers to support business partners in their communication with customers.

Besides internal collaboration, the compliance reports represent a good milestone in establishing cooperation with the regulator. These were proposed to be implemented during the setup period in parallel with the supervisory framework testing. From a trust perspective, it is essential that the supervisory period does not just end after one supervisory cycle. The establishment of a committed supervisory process is key for the use of complex technologies during new product development. The trust would support the industry innovation cycle and create security for long-term investments. Companies would be encouraged to build highly competitive, complex AI-based services that can be entrusted with considering new behavioral patterns, dealing with vast amounts of data, and using determinants that cannot be structured into fixed decision trees.

9.9.1. Proactive Compliance Measures

As financial services firms continue to adopt AI-enabled tools, many within the industry are looking for answers about appropriate compliance and risk mitigation for their models. Even within the bounds of current financial services, regulations may require a variety of proactive compliance measures. At the outset, it is likely many models will fall with the focus thresholds of existing fair-lending laws, including certain race and ethnicity groups. However, many industry experts expect increased scrutiny from regulators and the public. Recent news and social media reports on the customer experiences of particular businesses can create reputational risk that cuts across the industry. In anticipation of concerns from regulators or the public, it is prudent for firms to conduct objective audits on the impacts of their models prior to deployment and build in safeguards during development.

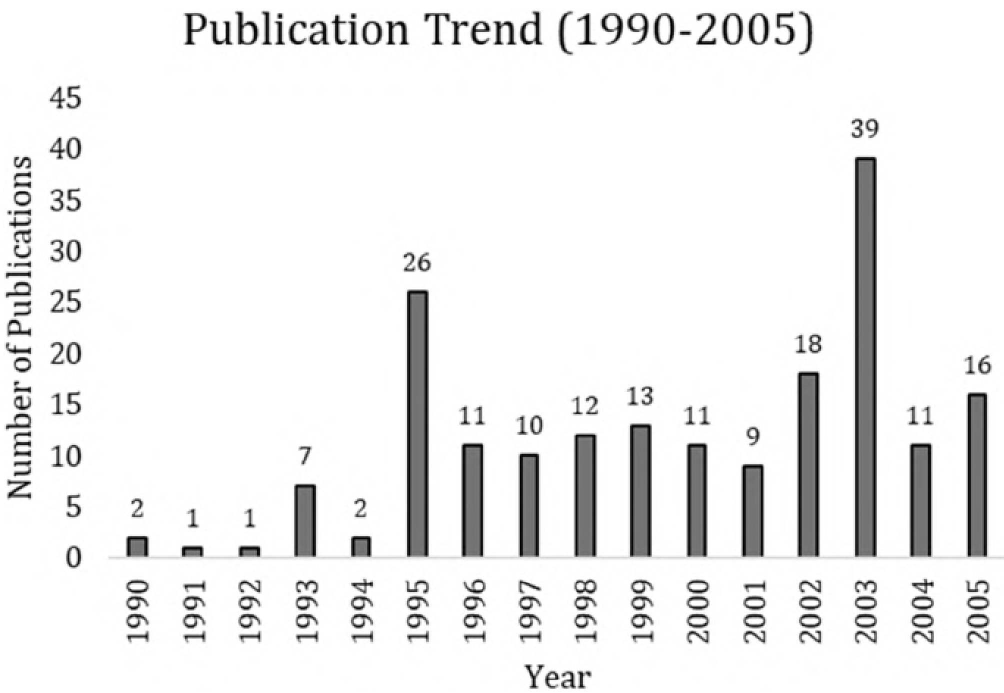

Fig : AI integration in financial services

Various stakeholders have called for greater pooling of data on model impacts by protected class among lending institutions, which would serve to bolster both industry and individual compliance. Across the financial services regulatory landscape, there is a growing recognition of model risk management among critical stakeholders and a bottom-up prompting effect of stakeholders calling for additional review of AI models to increase transparency and prevent discrimination by modelers. To that end, a variety of cross-industry efforts have been undertaken to create common impact metrics.

9.9.2. Collaboration with Regulators

A final strategy for coping with the complexities of regulatory challenges in AI technology is not to view regulators as adversaries. Regulatory requirements are formulated by statute or regulation, and require compliance. Dialogue and trust go both ways. Just as the regulators must work hard to understand the technology in order to effectively regulate it, the institutions also have a responsibility to inform and educate the regulators. Transparency and sharing information that is critical to understanding the manner and impact of the technology, and how that affects the institution's operations is an imperative. Institutions developing algorithmic technology ought to consider proactively providing a window into their algorithmic systems. The more confidence that regulators have in a bank's internal risk management and compliance systems and practices, the less reliance they may have to place on their examination and supervisory process. A proactive and well-considered strategy to gain and retain the confidence of regulators should be an important component of any institution's business strategy. Institutions developing algorithmic technology should also make it a priority to hire employees, and develop cooperative relationships with partners, who have regulatory experience and deep knowledge of regulatory guidelines and concerns. Industries that develop deep interaction with their regulators appear to do better during periods of change. The insurance industry has succeeded in establishing a workable process with their regulators. While the world of insurance has experienced dramatic change, the insurance industry has moved from a world governed by extensive regulation and oversight of the product, price, and market component of insurance, to a more relaxed world, where insurers are able to manage their own internal risk management processes – provided that they meet qualification parameters specified by regulators. The healthcare and pharmaceutical industry has done the same to a certain extent, although the pace of change there has produced some backlash from regulators. The constructive outcome in both of these industries was created with careful dialogues with regulators who were willing to listen and employers willing to keep the regulatory issues at the top of their lists, even when they were not in compliance at the time.

9.10. Conclusion

The rise of AI in finance promises drastic technological shifts in enhancing and transforming almost every aspect of the financial services ecosystem. AI is being deployed to automate and improve efficiency, achieve better risk management, boost consumer protection and enhance tailored product and services offerings of financial institutions, and detect, investigate and prevent financial crimes more efficiently. Against this background, the deployment of AI-driven technologies poses major challenges for policymakers and regulatory authorities. Widespread adoption of AI technology by financial institutions in the absence of clear regulations and measures could lead to unlevelled playing fields and loss of investor and customer confidence, as well as increasing risks of consumer harm and financial instability. Regulatory frameworks, therefore, need to be established and AI governance examined. At the same time, however, stringent regulations and prescriptive compliance measures could slow down the innovation pace of highly tech-driven industries such as finance, hurt the competitive landscape of the financial services ecosystem, and hinder the positive use cases of AI. Thus, researchers and regulatory authorities are left with the difficult task of balancing the need to invest in innovation and the need to outline rules of the game that safeguard against its associated risks. As AI and financial technology are topics riding high in the policy agenda of the majority of countries, suggested regulatory frameworks need to keep track of rapid innovation, jurisdictional spillovers, and the global dimension AI adoption. Policy makers also need to discuss how AI-sensitive functions of each financial institution and the wider financial services ecosystem can be steered towards safe and responsible innovation fostering positive use cases while reducing the associated risks, and how these guidelines can be translated into AI strategies of regulatory authoritiesoss the markets. AI research centers sprung up in the last few decades, allowing the integrative merger of AI with algorithmic trading, completion of the trading loop, and automation of the automated trader with little human intervention across the board. Adding on top of this the exponential data expansion brought on by the dawn of the information age has allowed AI models to be trained at a quantum leap larger dataset sizes than was possible before. With social media, news, and other data information sources present online at staggering volumes, .

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