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Next-Gen Banking Infrastructure: Designing AI-Native IT Architectures for Financial Institutions

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Abstract

The rapid advancement of artificial intelligence (AI) is fundamentally transforming the financial services industry. As traditional banking infrastructures struggle to keep pace with the demands of real-time analytics, personalized services, and enhanced security, there is a pressing need to design AI-native IT architectures that are scalable, resilient, and agile. This paper explores the core principles and design considerations for next-generation banking infrastructures that are purpose-built for AI integration. It addresses key components such as data architecture, cloud-native platforms, AI-driven automation, cybersecurity frameworks, and compliance mechanisms. Through analysis of case studies and emerging technologies, the paper outlines strategic pathways for financial institutions to modernize their IT ecosystems, reduce operational costs, and foster innovation while maintaining regulatory compliance and customer trust. The goal is to provide a blueprint for banks and fintechs to harness the full potential of AI in delivering intelligent, adaptive, and customer-centric financial services.

.**Keywords :** AI-native architecture, Banking infrastructure,Financial technology (FinTech),Cloud-native platforms ,Intelligent automation, Digital transformation,Cybersecurity,Data governance,Scalable IT systems,Predictive analytics, Machine learning in banking,Regulatory compliance,Real-time decisioning,Customer experience,Operational efficiency.

1. Introduction

Financial stability is a key priority for the Bank of England. The Bank understands that as banking is re-shaped by technology, new opportunities for fraud, error, and conduct failure open up for financial market participants. The Bank is engaging with FinTech companies, establishing contact with small and medium-sized enterprises, so-called "start-ups," to understand emerging financial stability risks better. FinTech is an abbreviation for financial technology. Financial institutions are starting to integrate FinTech into their banking services. The twenty-first-century banking services are not only online or mobile but also omni-channel services. Customers would like to have more choices, flexibility, and control over their banking. A customer may visit a bank branch for the first time and communicate with a bank via a SMS message. AI is FinTech in a narrower sense compared with big data, start-ups, cryptography, and peer-to-peer (P2P). It is an abbreviation for artificial intelligence. It is a branch of FinTech which is concerned with the intelligence of machines. Subfields include natural language processing (NLP), expert systems, and machine learning. Among them, NLP is understood as a set of techniques and models designed to analyse and generate human languages so that humans and computers can communicate in verbal conversation, like texting or voice communication.
With speedy development of modern technology, AI has become popular in banks across the globe. The banking sector is mainly based on information and data. AI, as an extension of machine learning, is believed to refine the process of data handling in order to make quick and correct decisions. Since AI allows machines and computers to do things like creating and interpreting bots, language processing, and image analysis, it could be applied in diverse fields in banking.

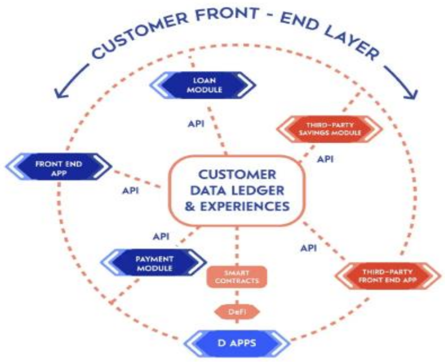

Fig 1: Design The IT Architecture of a Digital Bank

The financial sector is a typical area where machine learning, AI, and FinTech could offer banks improved efficiency and costs. Fraud detection, regulatory compliance, money-laundering surveillance, and predictive analysis of products and services could all be enhanced by applying machine learning and programming techniques. More on AI in the retail banking sector however, needs to be explored and discussed. The branches and services of retail banks have all been on the flat-structure basis. Financial watershed in countries among euro-zone members raises a challenge to retail banks in many countries in Europe. On the other hand, in China, the comparison and competition among the "Big Five" and "Three Small" retail banks plus Internet Finance are fierce. Such competition means that Internet Finance in China and FinTech in the west could provide stronger challenges to retail banking services than traditional companies do.

2. The Evolution of Banking Infrastructure

Historically, a bank's IT architecture has been designed to establish a programming structure to replace the know-how of the initial banking employees and bring their knowledge and experience into the bank's software. Closely aligned to goals and architecture, specific software systems have been designed to fulfill banks' requirements. Over the years, however, the technologies have changed drastically. In addition, software paradigms have continuously changed without taking the preference of the banking industry into account. Presently, the banking IT architectures' artificial aging shows. This decay raises several problems that inhibit flexibility and the use of new possibilities offered by the latest technologies and paradigms. As a consequence, banks are not able to quickly react to the advance of new technology-savvy competitors. The banks consider IT investment a fixed cost instead of a treatable cost with serious consequences on their business model.

To reduce these inhibitions, an advanced AI-native approach to banking architecture is sketched considering the banking industry's requests. It integrates financial data, rules, models, and programming software to automate the processing of financial services. By embedding programming systems in AI processes, banks' cumulative programming and modelling approaches can be preserved, courtability can be guaranteed, and service costs can be reduced. By suggesting the AI-native IT architecture, the banks will be able to be more intelligent, more flexible, and more productive. Banking services will continuously auto-adapt to new AI technology developments. In addition, the AI-native banking architecture will be open to new paradigms without the need to revamp IT. Unattended IT relieves human action from tedious, time-consuming, and error-prone processes, enabling them to focus on tasks where their attention is better placed. In addition, outside use has not only the advantage of reducing commission fees for banks but, additionally, enabling the capitalisation of excessive resources. Purely demand-driven, a local cloud should be able to act like a global cloud environment.

Equ 1: AI Workload Allocation Equation

$$W_i = \frac{D_i \cdot C_i}{\sum_{j=1}^{n} D_j \cdot C_j} \cdot T$$

Where:

- W_i: Workload assigned to server i
- D_i: Data demand (in GB) at node i
- C_i: Compute capacity of node i
- T: Total AI task size
- n: Total number of compute nodes

3. Understanding AI in Financial Services

The potential for Artificial Intelligence ("AI") applications in financial services is enormous. A wide range of AI applications, including document review, fraud detection, customer interaction, algorithmic trading, risk modeling, and product pricing, offer ground-breaking efficiency and new business opportunities. In just a few generations, AI is projected to reshape financial and capital markets, delivering lifetime value of several billion dollars to incumbent firms in the process. However, there is a real danger that the benefits of AI may come with costs that stretch from the trivial to the existential. In the next two generations, neglected risks, especially in financial services, will give rise to the asymmetries between very large and very small financial institutions and investment firms. As a result, a growing regulatory and litigation burden is inevitable for the financial services sector. AI has the potential to create enormous value for financial services, but only if organizations are completely redesigning how AI systems are being created. A concrete AI-native design belonging to system, software, model, and data architectures, and their interactions is considered. AI solutions will yield only trivial value if __________ is a pollution on legacy IT architectures and if bank systems remain untrustworthy. In recent years, AI has gained significant attention in financial services, as organizations invest more in data and AI technologies to improve productivity and create better customer experiences. For many financial institutions, however, the adoption of AI is still in its infancy. Key challenges that banks must overcome with AI include the availability of labeled data; the governance and oversight of systems and algorithms; the interpretability, explainability, and robustness of models; and the compliance with internal ethical guidelines and external regulation. AI outcome governance is needed to ensure that the implementations of AI, in particular ML, are not unethical, dishonest, or unfair. This involves identifying ethical guidelines, benchmark datasets and tests, implementation-agnostic rules, model performance and generalizability checks, and monitoring, auditing, and impact traces. In the AI failure governance area, organizations must continuously assess their exposure and estimate the risk. In sum, as banks adopt systems and decision processes with AI algorithms, bigger standard and customized developed models, and greater reliance on the availability of labeled data, banks are increasing risks related to the ethical and trustworthiness of analytics being injected into their business. Hence, AI governance must develop comprehensive frameworks, capabilities, and methodologies to accompany each of the aforementioned challenges.

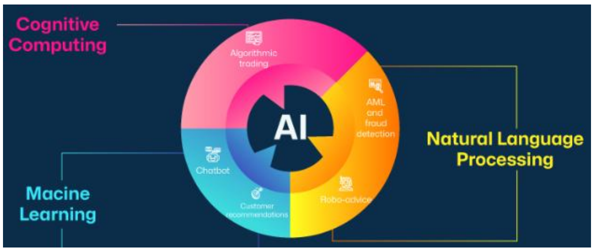

Fig 2: Financial Services

4. Key Components of AI-Native Architectures

To enable an AI-native architecture, financial institutions must systematically design and deploy an integrated stack of complementary capabilities and components across various technology, data and operational layers. This integrated stack needs then to be tailored and purpose-built to fit with the institution's existing architecture and operational model. Furthermore, it needs to evolve continuously and iteratively as new use cases, capabilities, toolsets, vendors and deployment scenarios become available. Each financial institution's implementation of the stack will therefore differ, but there are several unifying components that are essential to the stack.

Existing and mature IT architecture profoundly foils innovation-outcome relationships in most financial firms. In particular, their complexity hinders alignment with the needs of cloud technologies, contemporary data practices and evolving outcomes. As technology adoption accelerates, data types have significantly diversified, while new data roles have emerged that emphasize the importance of stewardship. Financial institutions are entrenched in legacy operational models whereby all transformations occur in data-integrative siloes. Therefore, technology and operational choices limit the degree to which the general enterprise-wide reference architecture and governance models can meaningfully ameliorate outcomes.

The ability of models to generate recommendations and create capture chains between actors is in turn to be enhanced with AI approaches that allow the very uncertainty in behaviour to be captured and potentially reasonable utilities designed to steer such behaviour, much of which is unobservable. Also essential to this objective is the need for closed-loop operational models. The execution of model outcomes must first be defined, preemptively offering the outcome actors a choice in the input template obfuscations and relevance. The operational monitoring of outcome behaviours, preferably automatically, will be needed to determine if outcomes are adhered to. Ideally, this monitoring would generate a score of result abnormality, rather than just a pass/fail indication, as a basis for escalation.

4.1. Data Management Systems

AI-native banking architectures require data management systems capable of supporting real-time data processing, simultaneous operations on one's own data, and a high level of automation, all key conditions for AI-native solutions. To meet the emerging needs of AI-based services, data management systems must enter a new re-engineering phase. Traditional data management systems encompass various kinds of software solutions for the management of information. The type that stores data most deeply and fundamentally is referred to as databases. With software that manages databases being database management systems, and data owners or users of databases being data management systems. In AI-native architectures, data must be kept on a fully distributed and shared-hop basis and kept on a wider variety and higher dimensionality of data. Given mutual growth, essentially unlimited support of data load via self-ensemble and self-refusion clustering, 100% fault tolerance via constant self-checking and recoveries, and full shifts of ownership via immutable and normalized view specification language, being database management system, editor, simulator, and engine. Through changes of wide data and kernels like the number of network and hardware-independent dynamism of graphorms as tensor directly, an interface to knowledge/data analysis and all types of streaming machines via customizable API. Running on demand, it enters a new phase of data management system re-engineering. These and other smart data management solutions are the key components of AI-native banking architecture that ensures a platform-built AI core, enabling the banking infrastructure to be tool-free, product-free, and regulation-engineered. In particular, the parallel processing of in-memory databases is extremely low-cost with tremendous shifts of execution that are most fundamental to providing a knowledge core. Fully shared-hop interconnections of compute clusters and shared-disks provide low-cost on-demand data analysis with a high level of automation by execution graph substitutions. The core address/data/support/boundary encapsulation of streaming engines provides automatization at rest and in flight.

4.2. Machine Learning Frameworks

The finance industry has adopted Machine Learning (ML) as a form of quantitative research to support better investment decisions. With the newly emerging methods/algorithms in ML and the availability of data increasing exponentially, there have been remarkable improvements in the success of quantitative investment strategies recently. However, there are several challenges frequently encountered in practice that are often overlooked: (i) unstructured and ad hoc code which hinders cooperating with others; (ii) flexible and scalable systems needed since resource requirements and dependencies vary depending on which algorithm is used. To solve these issues, Shai-am is presented in this paper, a platform based on a Python framework and integrated with other existing modern open-source technologies. In order to solve issues listed above, Shai-am manages containerized pipelines for Machine Learning-based strategies with unified interfaces. Moreover, it is designed to enhance reusability and readability, which is beneficial for collaborative work in quantitative research. The aim is to be a pure AI asset manager which can solve various tasks in financial markets.

For the development of modern ML/AI techniques, development frameworks have been greatly improved to accompany the complexity of models. However, some of the most popular ones do not provide a way for connecting the data stream generated from message brokers and applying ingesting models. Most of the frameworks where it is used are applied only to the training phase. This work proposes Kafka-ML a toolkit for interfacing Kafka with ML/AI frameworks for both training and inference where it is based on Kafka Connect and shared patterns. The aim is to help data engineers to automate the delivery of a full pipeline for ML.

4.3. Cloud Computing Solutions

A well-designed, cloud-native architecture provides significant and often essential benefits as organizations transition on their digital journeys. These benefits pertain to all aspects of the overall experience of a platform and its services. The next generation of banking infrastructure systems must be deployed using a cloud-native architecture to operate as intended without incurring any undue overhead challenges or loss of efficiencies. Cloud-native architecture refers to an architecture that references a set of principles and approaches that exploit the advantages of cloud computing. Twelve key factors form an adequate definition of cloud-native architecture, which encompass complete operational facilities from a business standpoint to ongoing maintenance of both the solution and its constituent services. A specific architecture employed in a cloud-native solution will consist of various technical aspects relating to the characteristics of microservices, software-defined networking, data persistence, and delivery platforms.

Cloud computing is a kind of distributed computing, referring to the network cloud processing large data calculations into smaller programs through multiple servers. A major area of exploration in the scheme of things is the handling of numerous challenges caused by the transition to adoption of cloud technology in finance. It must be noted that, alongside these risks, the adoption of cloud computing technology remains a major trend in financial information processing. There arise a series of risks in utilizing on-cloud financial information processing with low-business efficiency raised by the dramatic increase in data size. Based on the cloud computing and intelligent application technology, the intelligent prediction and assessment of financial information risk in the cloud computing model is emphasized. Specific solutions are proposed to enhance the efficiency and accuracy of financial organizations' information processing via the cloud computing model, and several policy recommendations are proposed to regulate the financial industry's on-cloud data processing and alleviate privacy risks .

$$S(t) = B \cdot e^{\lambda t}$$

Equ 2: Infrastructure Scalability Function

Where:

- $S(t)$: System capacity at time t
- B: Base infrastructure capacity
- λ: Elasticity rate (e.g., per month)
- t: Time (months or years)

5. Integration of AI and Traditional Systems

The financial services sector is undergoing significant change as a result of disruptive trends such as the requirement to adopt new AI regulations, altering customer behaviors, expanding competition, and internal pressures to transfer the business to the cloud. Financial institutions will require significant investments in IT infrastructure to compete in the battle for the hearts and minds of customers in this new environment. While the fintech industry has made considerable progress in the creation of reliable open banking ecosystems and automated decisioning processes, regulated financial service providers are only beginning their journey towards adopting these new architectures and the embedded abilities to generate and comprehend knowledge that comes with them. On the road to this AI-native architecture, the first major milestone to cover will be to transfer the file-max systems which are still controlling most key business processes today.
To achieve this, a meticulous analysis of existing IT systems-in-the-loop is necessary. The decomposition of process maps with their basic algorithmic steps, their bounded logic controlling these processes in the core banking systems, and the interdependencies of data structures in open source databases is an essential prerequisite. Of utmost importance will be the redesign of those systems which will remain with hybrid AI infrastructure connecting AI and traditional systems. While much progress has been made on the AI-native architecture side, technical limitation of connecting AI and non-AI systems is still an ongoing research question. Nevertheless, the budding AI-native architecture of financial systems will not only allow for qualitative advances in customer experience, but also, and especially important in the heavily regulated financial sector, will comply with most stringent compliance requirements.

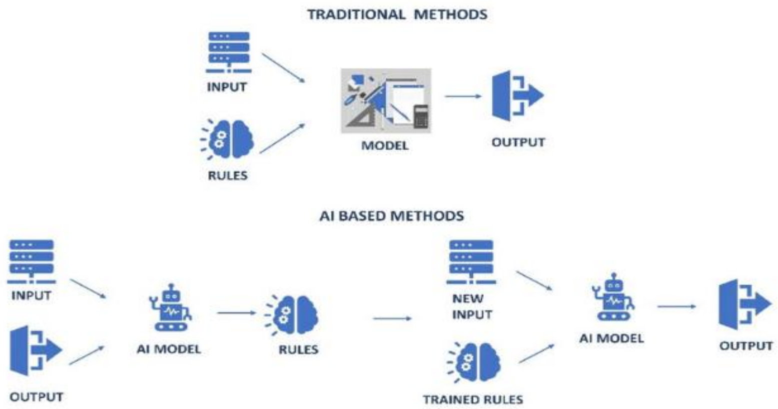

Fig 3: Basic principles of traditional model vs. AI-based model

5.1. Challenges in Integration

Many useful architectures can be derived from the aforementioned design principles. Given the variety of types of AI solutions, for production details specific to a suitable architecture, individual designs will need to be fleshed out in line with the framework with respect to similar models used in other areas. Present-day financial and regulatory environments nevertheless impose extreme constraints on AI solutions, thus warranting good forethought in establishing decision support systems. Such systems will need to be further built out to meet extreme reliability constraints before being rolled out into production. In much the same way as highly reliable trucking operations worked up to present day by iteratively building on the experiences of early operators in the late 19th century, much the same story can be told in AI contexts too. One clear handoff between AI models and human oversight is to allow the AI to explore various solutions while maintaining an active equivalent of a black box scoreboard—a summary of actions taken and an elastic script of further things to check or rules to follow—similar to a bank of knowledge. Now, in demanding evaluation environments, unwarranted actions can accumulate to produce irretrievably poor outcomes. Once disengaged from high frequency system annulling of actions, sporadic second guessing can later put errors back on the table for re-checking while evaluating new options. Maintaining buffers of error investigators can engage a bank of contingencies for scouring later using standard loan based AI solutions. Too, in the case of extreme errors, it can be determined whether the course of action was ever warranted, checking an operations bank to understand the other wins or losses it produced, such as possibly exposing the cause of the aberration.

Online detection of changes in distributions and contingencies should be prioritized, as all extremum moves originate in unexpected clouds of noise departing from previous equilibria. Existing AI solutions also do not currently provide robustness guarantees, which will be a tall order when they can operate on orders of magnitude more data. Instead, for the recommended unfolding of larger models, new deep generalizations of the very notion of injectivity are needed to convexify. While most Bayesian and variational architectures flatten the inference problem with high speed channels, wider Gaussian convolution signals at much smaller chance widths are needed for model learning and deployment, infantry an order of magnitude less than the level of standard AI approaches today—well beyond trained experts' intuitive ability to visualize or summarize constraints in low dimensionality.

5.2. Best Practices for Integration

Integration of new open-source machine learning frameworks: There are many open-source libraries available. A common way is to write a wrapper library, which can bridge between a well-known and widely-used library and a new one. It decreases the barrier to use of new libraries. Many SVAs provide wrapper libraries for popular toolkits too. Efforts are underway to help adapt many popular toolkits. Some modules in toolkits are much bigger than others. It is preferable to distribute them into several SVA modules instead of one large module. By default, many machine learning libraries provide a way to set classifiers or estimators to a model. This model can then be optimized or improved on using it. Service descriptor consists of several parameters among which the user can do tuning, such as grid search or random search. Each option would launch an instance of SVA to perform the model evaluation based on the configuration. Other parameters are used to generate additional items for batch service invocation to be focused on the specified service(s). Integration of a machine learning framework: After specifying a classifier, text pre-processing method, and vectorization method, the next step is to run a service that downloads and prepares the text datasets. The outputs are text files ready to use and input into the service that vectorizes textual features. Other additional features used by classifiers should also be generated in this step. The next step is to submit the invoked service descriptor during the discovery process. It will then return a trained classifier model. Several recent works have stressed the importance of reusable service descriptors. A good descriptor can promote adoption of new services. For a complicated service like that provided by the service descriptor, factors to consider are whether it is understandable, repeatable, controllable, and citatible. It is preferred to choose non-disruptive formats that already have wide usability in many physics analysis codes.

6. Regulatory Considerations

The three principles provide guidance on evaluating AI usage in financial services. The principles are intended for a global audience and are in line with many existing initiatives. They are intended to encourage a harmonized approach to AI governance globally. Legislation and regulatory guidance are evolving in the financial services sector. AI provides great opportunities for better decision-making in finance, but also brings great risks, including bias, opacity, and data privacy concerns. Supervisors and regulators are responding to calls for guidance in designing policies and regulations to harness AI benefits while mitigating its risks. Drawing on this literature and recent national and transnational proposals, many issues with AI governance have been identified. These governance issues have been invoked to push for more regulation. AI regulations that emerged from looking at a list of issues primarily result in a compliance box-ticking exercise. Issues need to be turned into principles. Using principles as the starting point for promoting a regulatory philosophy could help in developing a softer, more principles-based approach.

The principles are designed to evaluate AI usage in financial services. The first principle addresses the important issue of explainability and interpretability. Explainability and interpretability of a model are notoriously difficult in AI methods such as deep learning. The second principle calls for ensuring AI fairness and avoiding biases or discriminatory practices. The third principle focuses on the risks of privacy, security, and data exploitation in AI systems. While privacy-by-design is a concept and practice for protecting data privacy, trust and security in AI need to be emphasized explicitly. These principles are meant to inspire regulators and financial authorities across jurisdictions and encourage them to harmonize AI principles and guidance. The three principles are self-contained and therefore usable independently. In practice, they are expected to work together and reinforce one another. Many initiatives in AI are falling into place, but there are serious risks of fragmented regulatory regimes for AI across jurisdictions.

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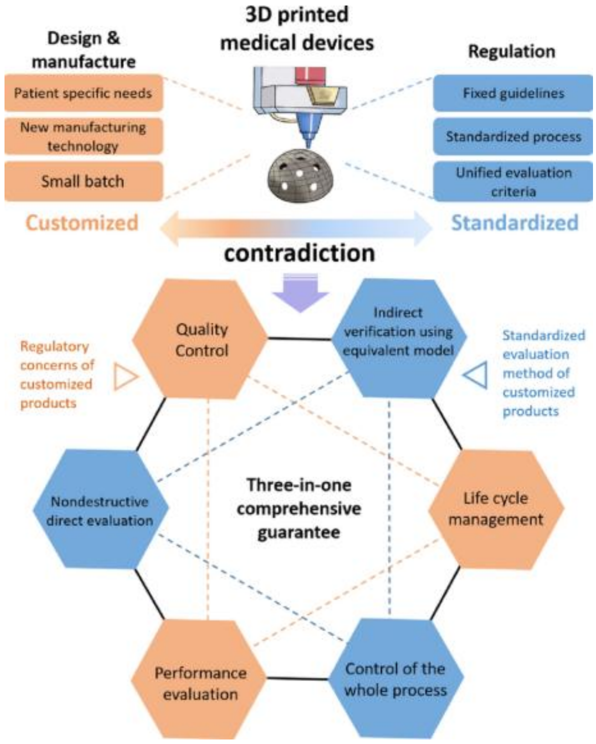

Fig 4: Characteristics and regulatory considerations

6.1. Compliance Requirements

Banks are facing stricter regulation than ever before. This section highlights requirements from the Basel Committee on Banking Supervision, focusing on two aspects of compliance: the explainability of the AI models and accountability through accurate logging of AI/ML processes and decisions.

BCBS239 outlines a comprehensive list of principles to facilitate effective risk data aggregation. Principles 3, 5, and 10 pertain to data quality and therefore necessitate the development of AI that can explain its outputs. Compliance involves many technical challenges. The first challenge, which is the focus of this section, is data quality on the input side of the models. Issues such as missing and obsolete reference data, inconsistent formats and units, absence of standard business rules and checks, and unintegrated data across silos lead to low data quality and inhibit timely aggregations. The relevant BCBS239 principles require having a complete data taxonomy that is well understood and appropriate for firmwide use.

To achieve this, the financial taxonomy must cover all business functions and be standardized, with a uniform naming and list of dimensions. Additionally, business rules must ensure input data integrity. All financial systems would need to be engineered to adopt the generative ontology and business rules. The model would need to extract the business concepts directly from the systems. Semantics need to be constructed among all concepts through a peer-reviewing/metros formal method. Rules to cleanse new incoming data would need to be coded in different engines in various languages on top of industry standard libraries. These issues are challenging due to the sheer number of data/reporting systems and the facts that different systems have their own evolution over time. Moreover, financial services produce and consume new kinds of products at a rapid pace.

6.2. Risk Management Strategies

Recognizing the importance of robust analytics implementation, financial institutions have explored various risk management initiatives aiming to augment traditional market risk controls. Emerging alternative measures of risk based on the sensitivity of the estimate to a variety of input changes are likely to be considered as possible targets for improved risk controls. Many of these possible additions or enhancements are not as easily defined, interpreted, communicated, or implemented as traditional risk measures. Nevertheless, the case for their consideration has two facets. Their properties as risk measures can be meaningfully evaluated, in some instances conveying potentially valuable management insight. Risk measures that address growing concerns relating to systemic risk, model risk and vulnerability to manipulation will likely be subject to ever greater scrutiny and possibly regulation, pending observation of the properties of existing rules. To elevate the discussion, it is recommended that the presently executed macroeconomic test be broadened and strengthened in the direction of a system audit, drawing inspiration from the exercise of risk oversight performed by regulators in all sectors of the economy.

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Financial institutions have been suggested as emitters of systemic risk. Nonetheless, one must acknowledge that this characterization of risk includes the recognition that risks are borne by parties with potential means to manage them. To investors, banks generally represent channels by which outside liquidity is transformed into usable funds behind recognized economic activities. Long-run concerns however are often about changes in economic activity as a whole instead of bank-wise redistributions of liquidity or claims. To the extent that ex-ante independent aggregate contracts do not exist, governance mechanisms acting on the firms comprising the financial sector must be considered on a consolidated basis or entire economy. Mechanisms of the relevant sort exist. They act through channels of negotiation of the transforms of risks, of observed outputs, or of new or existing claims on net outputs.

Equ 3: Data Throughput Model

$$T_d = \frac{N \cdot P}{L}$$

Where:

- T_d: Total data throughput
- N: Number of data processing nodes
- P: Processing power per node (transactions/sec)
- L: Latency (in seconds)

7. Security Implications of AI-Native Architectures

Most discussions about the consequences of AI-native architectures for financial institutions focus on the opportunities: how AI-native architectures potentially improve the understanding of client behaviour, how to recommend products or advise on life or pension matters, how to detect fraud or money laundering, and how to check compliance with regulations. While all these impacts are formidable, challenges exist even earlier in the AI lifecycle. A general challenge to be addressed is the balance of power between the regulator and financial institutions. Financial institutions have more data, more human capital and more compute than their supervisors. As a result, the definition of intelligence is in most cases done by the institutions, limiting the supervisory toolkit.
A more specific challenge concerns the accountability of AI applications that affect the general population. It is generally agreed that black-box deployment of models on clients is against public interest, especially in areas such as hiring, insurance, and finance. However, responsible AI is a spectrum. Entities should be judged not only on black-boxes but also on the governance processes. The requirements for governance might be quite different across areas. In the finance area it is likely that the operational risk is the strongest risk and prohibiting black-boxes might lead to a less resilient system without any guarantees of improved behaviour.
Another balance of power is between the regulators across the globe. Also in this area there is often a tussle between public good and implementing self-regulation by the institutions with the risk of regulatory arbitrage. Here too domains differ. Areas like personal information or taxes are probably more global than finance. However, AI can be used to improve compliance monitoring and prudential research might be easier in a fully connected regulatory architecture.

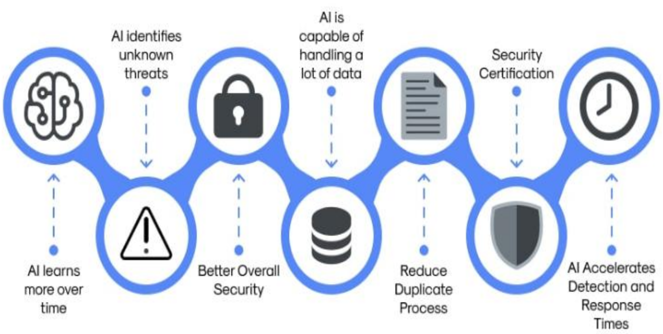

Fig 5: Artificial Intelligence for Security

7.1. Data Privacy Concerns
This section explores major data privacy concerns stemming from generative AI technology as banks engage with fresh AI tools and services. Early adopters of generative AI tools have reaped substantial benefits due to the technology's impressive capabilities, but incidents surrounding security and privacy risks have surfaced more recently. Responses to

these revelations have varied widely, with some organizations freezing use of tools, some ramping up compliance reviews, and a few doubling down on earlier adoption plans.
The collapse of a massive online retailer's use of generative AI technology illustrates this issue. Early excitement over incorporating a leading generative AI chatbot into the online retailer's infrastructure was followed by a security leak that allowed confidential company feedback to be shared online. The subsequent fallout included ripple effects with cloud and AI service providers, a prominent exodus of talent, and at least one lawsuit. The company that created the generative AI technology faced scrutiny before being acquired, with the new owner dismantling several of its divisions entirely. Now, as new AI tools flood the market, financial institutions risk rushing into adopting products that may expose their organizations to internal and external threats.
Early adopters of generative AI tools have experienced substantial benefits, but incidents involving security and privacy risks have recently emerged. Although compliance reviews are being ramped up, some organizations have paused the use of the tools altogether. A case study involving the collapse of an online retailer's use of generative AI technology serves to illuminate the need for a risk management strategy. A plethora of new tools have flooded the market in the wake of the dramatic increase in capabilities surrounding generative AI technology, and organizations are in danger of rushing into adopting tool offerings that may expose their organization to harm. A review of data use policy, risk management, compliance strategy, legal considerations, and other factors surrounding generative AI technology can provide guidance to organizations incorporating such tools into their infrastructure.

7.2. Cybersecurity Measures

Cybersecurity is a major concern for the financial services industry because of the shared feeling that, as the banking sector evolves, so too must the technologies and operations used to protect financial institutions from cyber threats. Financial institutions are eager to implement the technologies available, from encryption to biometric identification and anti virus software. However, many have not conducted the necessary due diligence to choose the programs that best fit their business model. As banks revise technologies and operations in the wake of their banking crises and the ensuing focus on financial transparency, several measures should be implemented in order to better prepare for cyberattacks. These measures, while far from exhaustive, address technological, operational, and human components of cybersecurity and should shape banks' strategic thinking toward this rapidly evolving and complex risk.
Banks should carefully evaluate the use of encryption in mission-critical operations. As a starting point, banks should determine whether there are technologies that encrypt both stored data and data being communicated. Banks should consider which outdated standards might be adoptable on a mass scale, such as the Advanced Encryption Standard, as well as additional standards to bolster current encryption measures. This can be accomplished by either hiring cryptographers to perform a comprehensive risk analysis of the bank's current technologies and operations or by turning to proprietary firms that perform such analyses in exchange for consulting fees. This also requires the bank to reevaluate which data are stored or communicated in plaintext. Many institutions continue to fail to guard against the unnecessary collection and storage of personally identifiable information as well as personal data. Banks operating with American clients could also consider implementing sophisticated forms of data at rest encryption due to the three-year old executive order allowing the seizure of $550 billion worth of personal wealth from Russian authorities. A feverish enactment of form-based documentation to allegedly prove "accountings" of previously anonymous assets could likely lead to attempts to retroactively find clients complicit in the war. It is necessary not only that this scenario does not reach the U.S banking sector, but that measures are taken to ensure that, even if it does, personalities such as those of Abramovich and Blavatnik would not stand the chance of being forgotten.

8. Case Studies of AI-Native Banking Solutions

The use of artificial intelligence (AI) is progressively being adopted by banking and financial institutions to enhance client experience and improve insurance underwriting decisions. However, there is scant research on this issue in the context of developing nations. The purpose of this paper is to fill this gap by utilizing a qualitative methodology with the case study on United Bank of India to investigate how banking institutions utilize AI to enhance customer experience and how insurance firms apply AI to improve insurance underwriting decisions. Interviews were performed with one expert from the banking industry and one professional from the insurance sector, and a thematic analysis of the data was performed. While the banking institution adopts chatbots, AI in automating manual jobs, and robo-advisors to enhance customer experience, the insurance firm utilizes AI in automated machine learning, photo recognition, and electronic database usage to enhance underwriting decisions. There is also a need to incorporate chatbots and robo-advisors in the insurance sector, along with more advanced technology that will remove the data access gap between today and eventual adoption. Policy suggestions are also recommended.
Artificial Intelligence (AI), a family of empowering technologies that simulate human intellectual skills, such as understanding natural language, recognizing patterns and pictures, formulating decisions, and translating languages, is

regarded as one of the most crucial digital transformation enablers across multiple industries including Banking and Financial Services. AI is increasingly being used by banking and financial services (BFSI) firms, from the front office to the middle and back office, to enhance the client experience, reduce costs, mitigate risk, and strengthen fraud detection systems . Using the banking business of the State Bank of India (SBI) as a case study, this study attempts to explain how banks are incorporating AI technologies into their operations to enhance the customer experience. AI tools like chatbots, predictive analysis, and process automation are being used by banking industry experts to enhance customer service. The term "artificial intelligence," or "machines that behave intelligently," was invented by John McCarthy to include traditional fields such logical theorem proving, theorem proving, and optimization techniques) and the more recent machine learning discipline that encompasses neural networks. Robo-advisors, which are services that automatically manage traditional investment portfolios without human intervention based on preferred risk levels, are increasingly being used by banks to improve the customer experience.
A case study of the State Bank of India (SBI), a public sector bank with 27,000 branches and one-quarter of the country's banking assets, helps illustrate how the bank has incorporated emerging or disruptive technologies like AI and machine learning into their products and services. Delivering banking services via AI-based Banking Bots, Utilizing AI video and voice authentication technologies in self-service channels, and Biometrics in Banking Services are all included in the discussion. Additionally, it looks at historical background, current implementations, recent advancements, expected results/impacts, and future enhancements related to these cases.

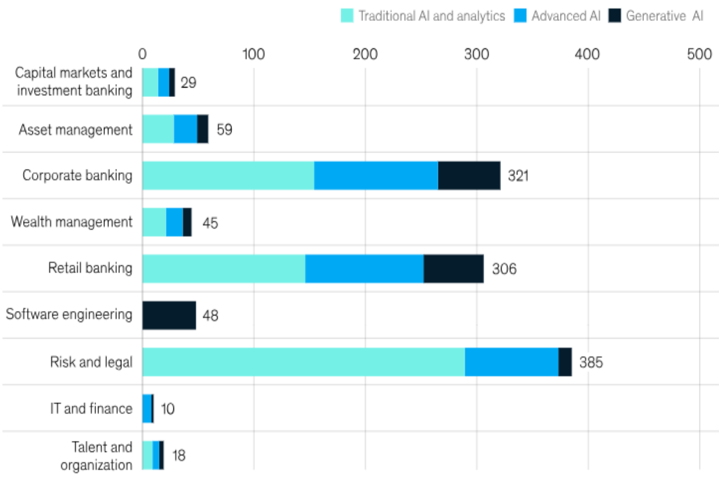

Fig 6: Value of generative AI in banking

8.1. Global Leaders in AI Banking
Bank of America announced new AI-native risk management principles focused on environmental, social and governance (ESG) factors, advising financial institutions on how to optimize efficiencies in business practices. Citibank, meanwhile, is reportedly exploring AI applications in investment banking as well as global banking and markets, including how to integrate AI into its ESG strategy. HDFC Bank has seen the patterns of efficiency in customer operations change this year due to the large-scale adoption of AI, while the Mumbai-based private bank is already tapping into AI for loan automation which can have implications for its ESG strategy. HSBC launched an AI-powered index that tracks companies poised to benefit from improving ESG risk, building on a first-mover advantage in creating unscorable indices for elements like carbon transition and biodiversity. JP Morgan Chase has turned to Datamaran in collaboration with the tech firm’s AI-driven technology to integrate data-driven and dynamic double materiality into its ESG integration process. Using Natural language processing and machine learning, it automates the tracking and scoring of regulatory risks while keeping an eye on their evolutions and impacts on financial performance. Morgan Stanley is currently using AI applications for both sustainable investing and investment banking use cases. The investment bank has previously explored sustainability apart from traditional companies that lack ESG screening in a first stage. It is now working on AI-based solutions that can improve accuracy and transparency of companies’ ESG metrics for investment research. Satellite imaging that employs AI-powered high-definition portfolio mapping at a closer perspective is also in use due to the noisy secondary data which is a constraint in understanding the social issues behind investment actions in some developing countries.
NatWest launched an AI solution driven by patent-pending generative AI to enhance company sustainability / ESG data for SMEs, linking individual customers and properties with the relevant ESG data. Best-practice prompting is incorporated for the adaptability of outputs on different channels to the customers. AI-generated business intelligence for the RBS-branded SME data has also been customized to respond to regional-specific inquiries. AI tools can assist in identifying the most relevant ESG issues for a company from a long list of possible disclosures or common concerns, based on analysis

of historical data points and stakeholder engagement. OCBC has also been implementing AI technologies such as the generative AI chatbots for employees to improve productivity and validate how the bank can be better aligned with its sustainability / ESG initiatives. Standard Chartered Bank has been leveraging AI tools to better organize ESG data that is scattered across different departments and systems as part of the commitment to combating climate change.

8.2. Emerging Market Innovations

Against the backdrop of the current financial crisis, a number of exciting innovations have been developed within the emerging markets trend. These innovations aim to reduce the high costs of transactions and to open up access to banking by catering for the needs of the unbanked population. Within emerging markets, transactions are traditionally cash-based, and online payment innovations have been used for enhancing the idiomatic use of banking outside the traditional banks under restrictive conditions that characterize a large part of this customer segment. A variety of online databases, blogs, tweets, alerts and events from this competitive field was screened for this purpose and some 26 of the most innovative services that emerged in the developing markets context were selected and described. In a second step, the prevailing characteristics of these innovations were integrated into an appropriate classification scheme and the characteristics sheets were reviewed with innovation discussions and workshops with practitioners. Based on the examples of existing innovations described in this section and its research question, the following five facets will allow for a comprehensive analysis of the new services and private communities using current technologies: Business Models – emerging market innovations predominantly pursue new business models including freemium, donation-based microsavings, etc.; Trust Thresholds – the stochastic processing of trust is facilitated through a more granular adapted set of credibility indicators and rules; Privacy Management – trust issues related to personal security and selective disclosure are alleviated by actively transferring the management of privacy settings to customers; Knowledge Capturing – the added value produced within customer community is harvested by creating explicit and continuous knowledge networks; Value Creation – new markets and standards emerge from the intelligent inclusion of customer archetypes in communities.

9. Future Trends in Banking Technology

The network for digital banking may improve with future technology and usage. Some classic architecture characteristics will not vary: banks will seek to minimize costs; the finishing land will seek asymptotic consensus across functions; with distribution one must weigh security; for the regulated a defense in depth is critical. Firm archaic legacy architecture cannot be digital: a first principle of architecture design is the fitness for purpose of each element, which is at odds with complexity, excess, ambiguity and drift. One radical change in the architecture is the exoskeleton strategy. The trust crisis in banking has been attributed to murky transactions, with banks generating higher yield and obtaining funding from the shadow banking system. New credit patterns will be transparent to all. The stochastic model of diversifying credit patterns is vulnerable to bad news. When seen as counterfactually untruthful; a bank audit can also profitably knock down high yield shadow credit, and consequently all invalid consecutive bank borrowings of a bank. When the financial circuit is broken; all shadow creditors will maximize defaults and banks will drown; a collateral swap defense will be viewed critically to incite massive panic sales. Such banks design for axiom generators and use uncorrelated noise sequences to randomize data flows via mechanisms that are fuzzified and de-hardwired. Only account recorders may redundantly number, but risk rewriting transactions with the bank continuing account switches. Monopolistic centralization is hard as it invites corruption, and a first mover loses all future assets. Such centralized nodes are big banks with an exoskeleton that combines with different architectures adaptable to transaction type: actively avoid transactions and traps via adaptable architecture. New entrants however could benefit from a joint effort to design industry payable account schemes with large margins; restrictions appreciate account value and durable data ownership. Encrypted transaction exposure still requires passive device assistance.

9.1. The Role of Blockchain

Blockchain disrupts the means of payment/transmission of value, and it enhances the bank delivery channels. Blockchain can be considered a One-to-One network, Peer-to-Peer, and it operates topologically through a Distributed Ledger Technology (DLT). By deferring all calculations to the participants, it can reach consensus with no trusted center. Blockchain protocols are the latest version of transaction consistency checks and can be applied to many industries. They are the background of cryptocurrencies under the assumption of electronic cash. The cryptocurrency Bitcoin is an application of blockchain. They are distinct and need to be distinguished. Blockchain is technology, and cryptocurrency is the first application to utilize it effectively. Blockchain is a decentralized system designed to generate and validate transactions without central infrastructures. This means transactions can be created, validated, and transmitted nodes-terrestrial, orbital, or extraterrestrial-with no Trusted Third Party (TTP) as traditionally required by banks.
“Chain” is a public repository of unalterable, consistent transactions, whose validity is ensured by consensus among the nodes based on Proof-of-Work (PoW) . Proof-of-Work (PoW) is a formal proof equivalent to the Byzantine Generals’

Problem. Depth (and thereby difficulty) means global validation sometimes as long as 104 seconds, with the standard PoW alone a10.5 seconds on average. However, there are approaches for instant transactions under TTPs for clinical or financial applications requiring instantaneous transactions. Who validates the transactions in this “dreamed” scenario? What if a hybrid architecture Integrating Public-Blockchain for Digital Currencies (CBDC) and Private-Blockchain?

9.2. Quantum Computing Impact

In the coming decades, quantum computers are expected to surpass the computational capabilities of their classical counterparts and achieve a disruptive impact on numerous industry sectors, including finance, bioinformatics, drug discovery, and machine learning. In the medium term (5–10 years), finance will be the first industry sector to take advantage of the quantum computing revolution because many of the applications and algorithms for noise-resilient quantum processors exist already. Financial markets are also well suited for the implementation of a variety of quantum algorithms, and financial institutions are preparing to be the first movers in the quantum computing realm. Consequently, this is expected to significantly amplify competitive advantages among financial market stakeholders.

Quantum Computers may provide an exponential speedup over classical computers: charges in the basic units of information, namely qubits, do not store a binary state (0 or 1) but can also represent a coherent combination of both, which allows for a massively parallel treatment of possible states and the acceleration of avalanche-like processes. Quantum algorithms with proven speedup over their best classical counterparts have been developed for mathematical problems relevant to the finance industry and implemented using simulators and prototype superconducting qubits. The general gap between quantum and classical computing capabilities is expected to become eventually wider, directly affecting the finance community through advancements in the mechanisms for pricing financial derivatives, handling large sets of risk factors in financial portfolios, and simulating efficient arbitrage strategies. This, in turn, may crush any competitive edge for those institutions that do not promptly allocate human and financial resources toward such a goal.

Despite the nascent stage of quantum hardware, developing a strategy to adopt future quantum co-processors as soon as they become commercially available is in the financial community’s best interest. One of the strategies ought to be the conclusion of joint research projects with academic institutions to become acquainted with emerging technologies and advance a first wave of use case demonstrations. The former would allow smooth quantum co-processor integration into existing computing infrastructure and the development of robust risk management protocols prior to investment in any quantum investment .

10. Conclusion

The financial sector is being transformed by a powerful wave of disruptive innovation driven by unprecedented access to data, computational power, and capital. With the arrival of next-generation banking infrastructure, a new paradigm for financial services is emerging, where highly efficient and competitive AI-native technologies deliver large-scale financial services. The paper highlights the opportunities, challenges, and strategic priorities for establishing a new IT architecture for financial institutions. By playing an active role in the shift towards next-generation financial market infrastructure, firms can build new collaborations with AI-native tech giants and value chain opportunities. However, firms need to embark on a bold transformation journey by aligning their governance structure, staying ahead of the technological curve, investing in human capabilities, and building sustainable and trustworthy AI/ML systems.

While some incumbents will pursue substantial build strategies, most will opt to work with AI-native tech giants or FinTech partners to co-develop and co-operate next-generation market infrastructures. Aligning with the new tech-led financial market infrastructures will offer firms new opportunities, but it also comes with increased competitive pressure. By capitalizing on competitive AI-native technologies and operating outside the scope of current regulatory requirements, the incumbents could find themselves displaced by a “synthetic banking” system. As AI-native tech firms have a mass of labelled data and a training architecture to manage it, this shift is only possible for firms who have already moved on from classic to next-generation infrastructure.

Longer-time key priorities include undertaking the full AI-native transformation journey with a complete tech stack build-out, while orchestrating and leading an ecosystem of partners to collaboratively deliver a new AI-native market infrastructure. Few would deny the necessity of already shifting to AI-native technologies. Strategic partnerships with tech giants and challengers can result in co-development arrangements, which can save substantial investment in in-house expertise but increasingly involve high technology platform fees and cloud service commissions. Building deep partnerships and helping shape the tech firms’ offerings will ultimately give incumbents the battling chance.

10.1. Future Trends

In the 2020s, rapid developments in next-gen banking infrastructure are projected. The rapid growth of “AI-native IT architecture” in fintech will pave the way for innovations in the creation and provision of future banking services. Financial institutions will heed the advice of pioneers and form a two-way alliance with AI firms in order to elevate their next-gen

IT architecture to the AI-native. The pandemic has sped up digitalization in the banking sector, including the introduction of digital or "virtual" banks with no branches, or "flash" loans and "robo-advisors," which makes a significant impact on personal and corporate finance services. However, AI-native IT infrastructure does not just mean the adoption of popular data-based technologies or platforms, such as cloudization, open architecture, big data/real-time analytical technologies, RPA or low-code/no-code applications, etc. To better target the DNA of banking services, far beyond these popular technologies, AI-native IT architecture consists of three key characteristics: interpretability, self-supervised learning, and multitask learning. As a pioneering firm for AI-native banking infrastructure, Baiyi focuses on financial institutions in Asia, and intends to promote AI-native banking infrastructure to become a new IT architecture in the 2020s. It has actively recruited experts in both banking operations and AI technology, and has brought in world-class banks as lead clients. Its table tennis associations and albums in collecting records of rare musical genres exhibited in top art museums show it has the ability to promote new business concepts and create demands/customers. Its co-founders all have wide connections with banks in Asia for generating global demand. With its innovative foundational general representation learning technology as a bank AI-native IT infrastructure, Baiyi is now actively developing potentials and production for further expansion drafting product roadmaps and explicit generalization schemes to gain deeper domain understandings. Baiyi also leverages its understanding on banks' loan decisions, reviewer/documents representations to develop its first product: AI Business Loan System for processing untact off-line/online business loan applications with state-of-the-art performance. It is easy to adopt by banks, curtails much more UAT time in model validation, and generates a huge number of potential clients for other sophisticated products. Baiyi has constructed pre-trained models for relevant banking operation functions, which are far beyond sponsors' proposed ones of loan compliance check documents and IRB sanitization review decisions, to equip various pre-trained models adaptable to banks' practice for speeding up application. Baiyi observes that this will be a tipping point for launching many "AI-native" banking operations so as to keep promising growth.

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