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Resilient Banking IT Infrastructure: Integrating AI/ML Models for Scalable, Secure, and Intelligent Operations

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Abstract

Banking & Financial Services are very much core to the smooth functioning of any economy and therefore need to be reliable and trustworthy. A lot of systems and processes are involved in carrying out their smooth functioning. As the volume of transactions and the interconnectedness between the systems and processes have grown, the IT Infrastructure has also been transformed. Legacy systems have been replaced by state-of-the-art technologies that have brought efficiency, resiliency, and most importantly flexibility. Banking IT Infrastructure can now be scaled up and down based on the needs using Cloud Architecture. These technologies have also created new avenues for transaction channels that offer the customer a much more easy and efficient means of conducting transactions. However, along with the above advantages, this cyber transformation has opened up the IT infrastructure to vulnerabilities. Hence with financial institutions now facing the threat/repercussions of the cyberattacks, the pressure is on banks and regulators to build more resilient systems and to offer damage mitigating strategies. AI/ML /DL-based models are now providing the means to detect anomalies and malicious attacks. These models are also being built-in B2B financial systems to detect fraudulent transactions and money laundering. In this backdrop, this research work intends to study and analyze various models that can be integrated or embedded in the Banking IT Infrastructure for secure and intelligent operations.

In the present system, though Banking includes many systems and processes but in this research study only a few core data/transaction capturing systems have been considered. These systems are very much the heart of a financial institution and therefore the compromises in them would mean heavy impact and damage to the organization. Building scalable deep learning models for these core Banking systems would mean Hacker Proofing the bank to a great extent. However, the model building on Banking IT infrastructure is very much different than traditional data models. In the present study, the dataset has been scraped/simulated from the flat file data of the database by replicating the production scenario to minimize data security concerns. Also, the study is based on Non-Security Data that doesn't compromise the customers'/bank's confidentiality. On the targeted core banking systems, a comparative study has been performed between traditional and deep learning ensemble models for data quality, security checks, and monitoring system events.

Keywords: AI-Driven Automation, Machine Learning Models, Intelligent Orchestration, Scalable Architecture, Resilient Infrastructure, Cybersecurity Integration, Self-Healing Systems, Real-Time Analytics, Predictive Maintenance, Data-Driven Insights, Cloud-Native Platforms, Zero Trust Security, Operational Continuity, Adaptive Workflows, Model Governance.

1. Introduction

In recent years, Artificial Intelligence and Machine Learning (AI/ML) models and algorithms have advanced rapidly. AI/ML solutions are increasingly used in the financial domain for tasks such as predictive and prescriptive modelling, natural language processing (NLP), generative modelling, forecasting, and credit scoring. When it comes to the banking sector, particularly in retail banking, AI/ML offers innovative opportunities for providing improved services and solutions. Consequently, deep learning, reinforcement learning, and other complex AI models are being increasingly researched and implemented, creating a need for a robust information technology (IT) infrastructure.

AI/ML processes typically involve three main stages: the design and selection of a suitable algorithm, its implementation on the chosen platform and infrastructure, and finally, operational practices to monitor the model's performance and retrain it when needed. In the given banking use case, a combination of batch, online, and ensemble learning processes can be implemented. Banking data is typically highly unbalanced and multi-dimensional, which, if not processed properly, can lead to poor predictions and questionable AI/ML models (non-transparent, bias, discrimination, etc.). This can require constant attention and manual intervention. Non-transparent and costly models will not be used by stakeholders, while costly model retraining may require significant resources.

On the platform side, a rapidly growing number of established companies and startups offer cloud-based solutions for AI/ML applications. The cloud solution is more cost-effective than the on-premise solution, providing better access to advanced technologies and resources. Nonetheless, data security remains a concern. On the infrastructure side, non-transparent and imbalanced data can rapidly lead to catastrophic consequences. Therefore, ML Operate practices are essential for testing and auditing AI/ML models.

1.1. Background and Significance

In recent years, developments in computing methods, especially in data mining and AI, have opened completely new possibilities for financial institutions to derive benefit from the massive amounts of data available to them. Since most risks can be reduced to the risk of financial loss, high exchange-traded liquidity of stocks has led to an increase in compulsive high-frequency trading activities in stock markets. Any model used for decision making comes with uncertainty, leading to incomplete understanding of its effectiveness and risks. This can lead to poor decisions if the AI models turn out to be unreliable, explainable, or fair. Furthermore, AI models can be abused by threat actors as a new attack vector or in highly disruptive attacks against financial institutions. For example, deceptive deception may mislead human traders and incorrectly trigger automatic trading orders, e.g. in an unanticipated massive dump of shares and a significant collapse in stock price.

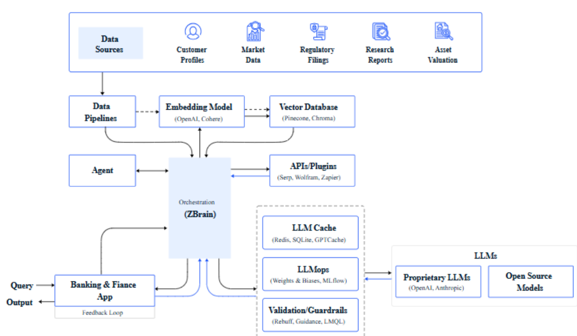

Fig 1:Resilient Banking IT Infrastructure using Integrating AI/ML.

Financial organisations are particularly vulnerable to AI-related pitfalls due to their specific task and market environments. In addition to these technologies, there are several other methodologies, like reinforcement learning and pattern-oriented discovery techniques, but their use is much more limited at the moment. Theft, loss, or accidental disclosure of data used in training data sets or AI models may lead to harmful insights on client behaviour and performance. Carefully engineered software artefacts containing models and training data can even be abused to export and reverse engineer AI models as well as training data. Attackers may be able to inject manipulated training data into the data streams in order to manipulate the AI models. Training time is highly critical when it comes to rapid reactions to new market situations. Thus, even a small disruption to a low-latency trading system may carry additional high losses, especially if the AI-based decision making subsequently fails. Traceability and auditing of model decisions are essential for a trustable audit trail of reasons contributing to decisions. When producing automated decisions, AI models must adhere to external regulatory constraints of compliance, given as shadow features. Complexity of the architecture, size of the data, and openness of the system should not preclude the ability of understanding how something works.

2. The Importance of Resilience in Banking IT

The term resilience increasingly appears in newspaper articles and scientific publications, referring to the ability to withstand shocks and disruptions, as well as to adjust, relearn, and emerge with an enhanced ability to adapt from disturbances. The importance of resilience also applies to banking IT infrastructure, systems, services, models, and algorithms. It becomes increasingly important when analyzing the impact of and mitigation strategies for the current pandemic and modeling shocks and contagions in interconnected financial networks.

For instance, due to the unprecedented and (partly) unknown nature of risks and shocks, a special lockdown policy was established during the pandemic that went beyond common holidays, weekends, or weather forecasts. Nevertheless, a banking market with many interdependent nodes was hardly taken into account, even though it constitutes the system's backbone. The failure of one key node or a sudden outside cash-shortage shock can trigger a domino effect, even for a (mostly) healthy system. The coupling dependencies between key institutions in the banking sector are emphasized here.

The resilience of banking IT infrastructure becomes more crucial during crisis events than during standard operations. Resilience reflects the ability of banking IT to guarantee an intact operational capability по challenged by unexpected events such as brute-force attacks, malware infections, floods, fires, and pandemics. Just like people, banking IT has to cope and recover from extraordinary events by self-preserving, self-healing, and self-repairing. Extreme results and scenarios can be simulated by such a computing infrastructure. In addition, climate and geopolitical challenges have recently raised serious concerns about the stability of the global banking system. It is believed that a systematic approach is

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needed for a resilient banking IT infrastructure that integrates adaptive AI/ML models with comprehensive monitoring and testing functionalities. It would enable banks to operate safely, securely, and efficiently under changing patterns, whether gradual or sudden.

2.1. Research Design Deep learning refers to the idea of representing data in a range of levels of abstraction. Each level of abstraction represents the data using higher order concepts, which are based on lower order concepts. If features are handcrafted by experts, they fall under the title shallow learning. Neural networks can be stacked through different layers where the first layer receives the input data and the last layer outputs the processed information. The intermediate layer takes care of the signal processing. The collection of neurons and layers allows to increase the problem-solving capabilities and often leads to better accuracy in numerical experiments. Moreover, the term deep learning denotes a use of a significant number of neurons and layers.

Deep learning techniques have shown promise when data are abundant and deal with complex signals like images, audio, text, or videos. These years, so-called general applications of deep learning have spread massively, making it possible for people without any knowledge of AI/ML to create and use their own AI applications on classic hardware or even mobile devices. In addition to general applications, many sectors have begun integrating AI/ML techniques into their ecosystem. These academic innovations as well as commercialized and open-source pre-packaged success stories may generate significant potential values and successes for the sector. Nevertheless, the banking domain, a major sector that may benefit greatly from AI/ML techniques, is still lagging in AI/ML technology and applications.

Equ 1: System Capacity and Scalability

$$C(t) = \sum_{i=1}^{n} \alpha_i R_i(t) + \beta M(t)$$

- $C(t)$: total computational capacity at time t
- $R_i(t)$: resources (CPU, GPU, memory, network)
- $M(t)$: ML model inference load at time t
- α_i: scaling coefficient per infrastructure unit
- β: elasticity coefficient for AI load adaptation

3. Current Challenges in Banking IT Infrastructure

The financial services industry is leveraging AI systems to improve their capabilities and competitiveness. However, the inherent complexity of AI systems introduces challenges regarding robustness, reliability, and compliance, especially for the heavily regulated and highly risk-averse financial services industry. Hence the importance of having AI model governance practices to achieve these aspects. To date, model governance has been mostly focused on traditional algorithms and systems. However, this approach is plagued by performance, cost, complexity, agility, and scaling issues when it comes to AI models. As AI models evolve, traditional model governance approaches may not be sufficient, and financial organisations risk being stuck with far behind solutions that pose a significant systemic risk to the entire financial ecosystem. Thus, the feasibility of current governance practices in the face of the next generation of AI models is highly questionable. This paper attempts to start an initial conversation on the key challenges and solution opportunities in this area.

Fig 2: Challenges in IT Banking.

By leveraging research and expertise across the areas of Governance, Risk and Compliance, Explainability and Fairness, Robustness and Security, Monitoring, Testing and Validation, and Data/Model Management, they argue that more holistic approaches are needed that incorporate increased automation, integration and configurability into AI systems. Such approaches can tackle the following capabilities: formalize and automate the model governance process; create a governance process repository; understand the effect of governance processes on the ML pipeline; cooperatively build an appropriate governance model; increase compliance, particularly in the face of AI drift; and provide a "Single Source of Truth" regarding model governance for regulators and financial organizations. In light of one of the major AI challenges, namely AI explanation, novel approaches are needed to increase the configurability of explanation systems, in particular for bank ML models. Bank model explainers with extensibility in mind should alleviate core issues in the domain regarding complexities and hidden decision processes. Hence, the mitigation of attacker, user and bank model issues will also alleviate current concerns regarding AI.

3.1. Legacy Systems and Their Limitations
The depth of the domain knowledge leads to the belief that in Financial Services (FS) this paradigm will increasingly become maladaptative. Model degradation will reach a critical level, leading to a trigger event that will unlock innovation parameters and set in motion a boom phase defining new market opportunities. New entrants will offer innovative AI models and governance processes. The boom phase will last until the emergence of dominant designs, new business models, and industry stalemates, at which point oversaturation will bring the second innovation phase. In the Banking market, regulatory oversight will tighten. Also, internal risk management frameworks will be developed to satisfy management about investment decisions with large, multi-million budgets. The model and regulatory complexity will rise exponentially, eventually outstripping the scalability of existing governance processes. The ability to evaluate, explain, and audit a model will differ considerably depending on applicability and complexity. For instance, the AI Model framework will provide oversight over simple AI systems translating into a list of questions aiming for understanding, explainability, interpretability, and plausibility. However, more complex models will require finetuned risk framework. Credit risk models will translate into a new set of questions focusing on the quantitative aspects of such system such as estimation of the impact on the Total Capital Ratio. The Governance Framework will scale either via brownfield updates or greenfield initiatives. It will eventually evolve into a self-regulating AI System that continuously learns optimal governance policies from historical data traces of the domain knowledge and governance framework and triggers those policies depending on operational circumstances. A model may drift or deteriorate in time. This may yield several undesired events, such as new data points going outside the original scope of applicability, misspecifications via alterations of the data or model, or concept drift where the underlying environment changes. All these events are not limited to AI models but apply to any model of a complex system, be it linear regression, GLM, tree-based, or boosted tree models. All investment decisions are predicated upon exposure to risk ranging from financial risk to systemic risk such as bank run and cascading failures believed to plague the 2008 financial crisis. Such risk stems from several sources and can take many forms.

3.2. Cybersecurity Threats and Vulnerabilities
Financial services and the introduction of AI risk new vulnerabilities. These new leverage factors are closely connected to an increased attack surface and could be capitalized on by criminals and fraudsters, depriving banks of capital and future profits. Cybersecurity is an important part of risk management and overall banks' operations. It consists of a number of components, such as policies and procedures running through a bank, awareness and education, asset protection, and monitoring using the appropriate tools to detect incidents.

Detection principles used to find threats include thresholds, heuristics, and AI. Many detection systems can raise false alarms on implemented rules that may match an incident. This is significantly worse for AI systems, where explainable AI needs to explain not only which incident but also why it matched with higher or lower value. Additionally, it is important to make sure that explanations correspond not on the artificial mind of the detection rule but on the existing process that is at risk of compromise on this detected behavior. This, again, entails a complexity increase.

Having elevated threshold-value or pruned control that matches a risk without needing a constant need for explainable AI statically helps with modeling a behavior or process, given either no knowledge but simple interaction and inputs description, or sophisticated technical knowledge with metrics to log.

Behavioral detection is focused on spotting deviations from what is expected. For rapid reaction to an incident, anomalies with a decided aggressiveness must be decided, as well as what should be monitored in real time. This boils down to threshold settings for the considered set of behaviors to be quantized and detected. In this statistical modeling of an expected behavior, the most important thing is the understanding of its dynamics, or regimes, as a universal description that permits the creation of a library on how to measure it.

3.3. Scalability Issues in Banking Operations
The world has changed tremendously in the past few years for just about every industry, and the banking industry is no exception. However, banks, investment firms, and other financial institutions have a problem. For almost all of their history, they have built systems which accumulate functionality and size, and relied on a large cadre of highly trained personnel and manual intervention to keep these systems running and intact. This works reasonably well when the facts on the ground are static and consistent and the requirements and regulatory landscape don't significantly change. The result of this multifaceted growth and expansion

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is an elephantine nightmare in terms of storage, processing, and retrieval capabilities. The number of systems is continuing to grow within firms imitating a sandstorm. Integration across firms is also limited as threats and opportunities often converge unexpectedly at a dramatic and systemic level. Amid all of this turmoil, organizations face mounting pressure regarding costs, security and threats, timeliness, consistency across functions, and other assurance requirements. An AI-based risk management framework is clearly needed, but in the current operating environment, it is not enough to simply build an intelligent system. This AI framework must also be automatically retrained and patched, monitored 24/7, and as much as possible preemptively diagnosed and repaired. Starting with cognition and task automation is a good initial step, but attention must also be paid to assuring the resultant noise and finding creative ways to minimize this. AI failures must have limited impact and must not escalate catastrophically. Today's AI/ML is still in its infancy and is currently more of a dark art. The myriad of tools, libraries, models, and layers is bewildering to a casual participant. Furthermore, AI is useful, but it is not guaranteed to be either correct or consistent, and most of its output cannot be audited and must therefore be treated as black boxes. Nevertheless, necessary improvements in the AI framework for risk management are feasible and worth pursuing. There is great interest in discovering ways to automate and improve decision-making functions of firms; indeed, this is the core of any financial institution's business. This will use aspects of big data from disparate sources to derive new variables and metrics by which firms operate. The first step must tackle more mundane but immediate noise and assurance issues with today's AI/ML; these 'dirty' problems are ripe for research.

4. AI/ML Technologies in Banking

North American banking operations are facing fundamental shifts brought on by profound social change and technological innovation. The emergence of new customer groups has increased requirements and expectations regarding experience quality. This is coupled with upheaval in enterprise funding and competition brought on by the entrance of fintech companies challenging traditional players. Financial institutions are actively seeking to modify their front-end processes, with analytics and mobile apps being key priorities. The implementation of third-party analytics apps and more complex in-house solutions to recognize consumers and raise conversion rates is becoming the primary focus for most Front Office departments. Organizational adjustments and add-on solutions are also branches of such alterations, especially becoming prevalent in the shadow b2b2c channel, as more services are distributed via external third parties.

The future of the financial sector lies in intelligent financial service, building corporate memory, thereby supporting autonomous work with complex, stochastic data-driven processes, and establishing active risk-adjusted protection of enterprise models. Since first proposed in 2005, the "Internet of Animal" is still an issue that allows for new paradigms in intelligent financial service. The vision implies behavior recognition of agents acting following differential constraints and market force diffusion and detection of anomalous dominant agents creating significant oscillations and price gaps. Required techniques and solutions range from network modeling and optimized continuous-time sampling to active contractual and value-based dynamic prevention of shocks against damage controls.

Fig 3: AI & ML In Banking.

The intelligent service infrastructure leverages these technologies and tracks agent behaviors via regional information supply and agent reports, and process flow. Noisy and/or incomplete data is modeled via a synchronous, real-time knowledge model development, which is required to ensure on-the-fly processing, machine learning of behaviors, simulations, and verification. Overall, this allows the development of a national surveillance backbone, collecting, refining, analyzing, and storing self-validated transactional data on b2c sales in any sales channel or agent. Following a soundly stated national mandate and proven mathematical solutions, this enables an efficient identification of the smallest reimbursement unit and precise compensation to sellers, agents, and the state, while preventing notification and improper actions against agents.

4.1. Overview of AI/ML Applications

In the last years, banking and other financial institutions have seen a dramatic growth in the volumes of data available for analysis and the demand in decision-support systems used to manage risk, compliance, and customer interaction. At the same time, the sophistication of cyber-crimes and offensive security measures has been increasing drastically. All this has led to the adoption of AI/ML systems as the technology of choice for safety-critical applications and the flourishing of adversarial attacks w.r.t. to AI/ML developments. To mitigate risks, AI/ML-based solutions (models and/or applications) have to be monitored and governed throughout their entire life cycle addressing drift (in data, models, or both), performance decay, and attacks (psychological, adversarial, and environmental).

Detection, mitigation, and explanation of drift and attacks are key requirements to monitoring and governance frameworks. They need to facilitate a modular design that allows for the integration of the best algorithms available. Governance of AI/ML applications also requires the management of technical, operational, and technological risks throughout their life cycle. With a system level approach, this research has investigated what are the main challenges and opportunities for financial institutions of integrating new AI/ML models, including both in-house and peer solutions, into the existing IT-infrastructure that was designed to accommodate only classical rules-based systems. This encapsulates the development of technical and operation risks as well as the identification of mitigating opportunities focusing on the integration of robustness and governability requirements into model design using a library of test and governance module templates.

AI/ML based applications constitute a comprehensive set of monitoring and governance solutions for financial institutions able to effectively manage the risk of introducing new ML models and applications into their IT ecosystems which has been considered one of the key challenges in the further development of the technology. Although AI/ML models promise increased performance and configurability, integrating them into the existing high-stake and security-conscious environments that are typical in finance is non-trivial. Some of the reasons for this, which also represent key challenges around the world for financial institutions and regulatory bodies, are also detailed.

4.2. Data Management and Analytics

To reduce usage costs while maintaining security and scalability, multiple data storage engines offer a smart storage solution. Therefore, not-centralized storage solutions with monitoring tools for each data engine will be designed and developed. The second problem is that heterogeneous data sources and types are difficult to manage, making it impossible for clients to analyze data without specific implementation customizations. To quickly and easily configure the pipelines of transformation tasks, ETL and ELT tools for every database engine will be studied and compared. As a result, smart tools with preset data mappings that can be activated by clicking on specific buttons will be provided. These tools significantly reduce the need for middleware programming within data analytics tasks. Data lakes in an organization need to interpret and analyze multi-type data from various systems. Clients must invest in cleaning data from different sources and types, as badly written databases produce badly formatted data and produce low-quality analysis results.

Several software tools assist in the analysis process. However, to analyze the data from various kinds of data sources, clients must implement a customized software programming layer to gather logs, convert formats, and link various types of data. To increase the overall quality of predicted outcomes and analysis results, the data analysis layer (data cleaning and transformation, machine learning model training, checking model weights and accuracy) will be monitored through the visualization front-end on top of the analysis programming back-end. Therefore, machine learning models quickly learn to identify which variables can significantly affect forecast quality. Additionally, using trained model visualizations, it is possible to learn what features of raw data affect classification decisions. Then, pre-analysis tasks, such as filtering high-impact data or losing species, will be completed. Customizable analytical tools only require the input of names for data sources.

In financial forecasting analysis, adding effective log returns is a common method to linearize the exponential time series of prices, and a strong series is reduced to effects close to white noise. To produce predictions, FinTech refers to changes in log returns and gets blurred values with data intervals per minute and transactions per second. These tools will visualize the performance of existing machine learning models, enabling users to find knowledge about the model's outputs. Building dashboards and combining tools with state-of-the-art data prediction and interpretation algorithms will further reduce the burden of knowledge engineering upon data scientists or quantitative analysts, enabling business decision-makers to understand model predictions and gain insights from existing robust and successful machine learning operations and models.

4.3. Risk Assessment and Management

As AI technologies have increasingly permeated financial services, financial institutions have reaped the competitive advantages stemming from enhanced predictive power, behavioral targeting, and process automation. Nevertheless, the AI models, owing to their complexity, may also pose risks to the credit policies and reputation of financial services companies, potentially leading to substantial financial loss and noncompliance issues. In light of the rapid proliferation of AI models, financial institutions have identified a clear need for AI model governance practices to mitigate the various risks stemming from their development and deployment.

A comprehensive overview of the challenges and opportunities for AI model governance in financial services is

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formulated, along with a novel AI model governance framework that merges the traditional and novel paradigms of model governance. The AI model governance challenges in financial services are first introduced. Current financial model governance practices are then analyzed across the first- and second-line model risk management.

Any intelligent algorithm with the ability to self-adjust its own modeling parameters falls into the description of AI models, including but not limited to machine learning models, natural language processing models, and deep learning models. AI model governance in financial services focuses on how these advanced intelligent algorithms are governed. Decisions based on banking, credit, insurance, investment, and capital market applications could expose financial institutions to risks, including credit, fraud, AML, compliance, conduct, reputation, and model risk. AI models may further intensify these risks due to the potential presence of model bias, model robustness, and model explainability issues. As a consequence, financial institutions need to ensure that AI models are developed and deployed in a fair and compliant manner, adhering to applicable regulations, public ethics, and the code of ethics defined by industry associations. AI model governance is also required to ensure that these models are accurate, reliable, and stable throughout their lifecycle to avoid substantial financial losses and reputational damage.

5. Integrating AI/ML into Banking IT Infrastructure

AI-based applications in the banking sector can include voice and chat-bots for customer service and account information inquiries, smart password systems for better security, customer acceptance solutions like digital onboarding and credit score prediction, process optimization models such as automated expense reports, and compliance applications like banking integrity (AML/KYC), e-Discovery, and sanction list screening. However, integrating and deploying AI-based services face several barriers. Firstly, some innovations will require more clear regulations in various areas such as self-explainability and fairness. Secondly, integrating some of these advanced ML/AI technologies into existing legacy systems will be a challenge, since most of them were not designed to be flooded with data and operated on complex models. Thirdly, outside academics, there is a talent gap in ML/AI and automation.

Due largely to the latter two barriers, many banks currently try to build a specialized Center of Excellence to focus on small-scale proof-of-concept projects, instead of adopting technologies via large system-level transformations. It's paramount that banks invest in technology stacks and tools to make sure massive deployment is assisted by automations. The responsibility cannot simply be on engineers of model risk management teams, they will need better development and verification tools with easier ways of user interactions for both engineers and risk professionals. A technology stack for AI applications would provide unprecedented opportunities for firms to robustly develop, verify, and monitor their models. It's designed to flatten the Migration from Lab to Live barriers and would make AI models as compliant as today's pricing models. Banks currently face very low model coverage and much higher compliance risks in AI applications compared with pricing ones.

The pace of AI development inside banks could take a wider jump if comprehensive stacks are built. This system-level approach is mostly focused on own-built models in either banks or vendors. Each piece of these tools is also explainable and interpretable on their own. However, integrating these tools into a full suite would provide a self-looped procedure for iteratively developing, monitoring, and improving the libraries and tools, keeping themselves current and ensuring they are robust. Model documentation is required across the whole lifecycle of the models and tools, with specific emphasis prior to production deployment and redevelopment.

Fig 3:Integrating AI/ML into Banking IT Infrastructure.

5.1. Framework for Integration

This section presents a framework for the integration of AI/ML models into the IT infrastructure of large-scale banks, as an output of the concepts and best practices discussed in Sections 3-5. While the process is expected to vary from bank to bank, the design of the framework remains applicable.

Artificial intelligence (AI) excludes the simulation of human characteristics by computer programs, such as perception, reasoning, learning, and decision-making. Machine learning (ML) refers to the specific group of in-depth learning techniques that learn to complete tasks without programming through the processing of vast amounts of data. The AI/ML paradigm has attracted considerable attention from many industries because of its success in solving tasks that are infeasible for conventional computing systems.

For example, it has been adopted by health care for applications such as image analysis for diagnosis and prognosis, genomics, and drug development. Finance and banking have also adopted this paradigm for a wide variety of applications such as general anti-money laundering and fraud detection, credit scoring, algorithmic/quantitative trading, foreign exchange trading, and the self-automated identification of industry news. However, the extension to large-scale, mission-critical, high-stake applications faces several challenges, such as a lack of availability of data and models, model transparency and interpretability, and a lack of a governance framework, including model building, testing, curating, deployment, and use.

The hybrid financial system, consisting of banks, broker-dealers, other financial institutions, financial market infrastructures, and central banks, is segmented into a highly organized multi-stage structure. Each stage has a long history and has developed its own culture. Financial regulators and financial system infrastructures, considering national boundaries and their narrow mandates, are still not unified and overlapping in many ways. The overall governance of the hybrid system is fragmented, outdated, and insufficient, raising concerns of systemic risks.

5.2. Best Practices and Guidelines

Identifying the governance requirements for Financial Services AI frameworks is arguably the most important and challenging task. These requirements are grounded in what rules need to be followed for post-driven decisions and ethics, and what do-or-don't need-have-behaviors the systems must exhibit. It is based on a mapping of the FRTB-IMM. This is, concerning behavior, exposing information that could be requested by regulators. Concerning compliance, logging behavior is necessary, the concise translation of which into human-readable text for the close-eyes-explanation. On the data side, there should exist sources that can resolve the identified governance needs.

The initial intellectual endeavor translates the requirements into solid yet revisable governance needs, either broad or fine-grained. The next step studies this mapping reversely, to suggest a conceptual class of AI behavior monitoring tools to assure compliance with the governance needs. The team attempts to formalize IT/ERM/FRM/BI tools that are also applicable to certain AI systems, including document-tracking-rule-based-derivative-claiming needs that borrow ideas from existing model-attribution explanations, and idea-based multiplayer games. This effort diagnoses the kind of governance need designs and those tools to be developed.

Extending out-of-the-box tools is often insufficient, as specialized situations warrant custom-built solutions, particularly in a swift-moving environment as invoked systems refine continuously. Instead of enforcing pre-defined rules on such systems upfront, compliance should be actively curated flexibly by IT and risk teams. A co-regulatory design will involve compromises of what decisions must be trusted on the one hand, and the efficient performance of AI systems on the other hand. This trade-off needs a more agile toolset, better assisting stakeholders to elaborate implementations of requirements together, iteratively searching for a workable balance.

It is advisable to involve business players deeply, gathering their feedback on various tooling designs as well as a trial-and-error enactment of requirements across different stakeholders, to ensure ownership as well as consensus of suggested co-regulatory practices. To this end, it is vital to provide agile low-code tooling infrastructures as well as freely adjustable request languages. Essential output thereof might be unleashing direct compliance monitoring by subject matter experts, often a priori violation detecting service.

Equ 2: System Resilience

$$S_r(t) = \eta_1 R(t) + \eta_2 A_v(t) + \eta_3 F_r(t)$$

- $S_r(t)$: resilience score at time t
- $R(t)$: redundancy (replication of critical components)
- $A_v(t)$: availability (uptime percentage)
- $F_r(t)$: failure recovery speed
- η_i: importance weights

6. Enhancing Security with AI/ML

In the banking sector, AI and ML models are playing an increasingly prominent role to improve decision-making processes, including fraud detection, credit scoring, fair lending, and more. Questions of security, fairness, explainability, and governance are of utmost importance since the consequences of faulty decision-making can be disastrous, especially in areas involving bias, discrimination, or explainability. In light of those challenges, it is equally important to ensure the resilience of the ML models used in these processes due to the pressure from various threat actors. Threat models for certain classes of threats to AI/ML systems have been proposed, and various attacks have been demonstrated to successfully leverage such vulnerabilities in real-world systems. Existing defenses either informally consider ML-related aspects or are predominantly empirical, focusing on robustness against performance degradation as the first success criterion to verify against such attacks. They

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often lack a formal model that is able to describe the second threat model aspect, i.e., the attack surface containing feasible attack options against ML components.

A more formal approach is needed to help practitioners assess the robustness of their systems against threats able to exploit vulnerabilities in the ML components. Such an approach should take into account both performance degradation and misuse of the ML component during the overall security and privacy assessment of a target deployment. Recently proposed more formal fuzzing-based approaches that, unlike prior work, are capable of fuzzing both traffic and the ML component have good potential for further exploration of practical usability. However, since the appreciably relevant search space for ensuring a sufficiently thorough coverage of the possibilities for feasible attacks against ML components grows exponentially with the size of the components involved, adequate search and pruning strategies are also needed to support the intaking of operationalized fuzzing techniques. It is also important to evaluate the efficacy of attacks leveraging ambiguities and non-robustness in the representations learned by the ML component, e.g., by mining a false model for a scalar explanatory in the shadow of a classifier with multiplicate class representations. So far, such attacks have been informally analyzed, making it difficult to ascertain their potential impact vis-à-vis prospective defenses. Therefore, it must be systematically studied how significantly latent vulnerabilities can jeopardize security properties, so as to inform the development of better defenses targeting this class of attack at a higher level of abstraction.

6.1. Anomaly Detection Systems

To prevent IT incidents before they become issues, Paradigm Projects help untangle the complex ecosystem of production systems. Alerts on individual service, impact, and notification can flood engineers' dashboards and end up getting ignored. Engineers then miss relevant alerts, leading to late detection of issues and increased business impact. Since it is humanly impossible to keep track of the waves of data generated by hundreds of app, infrastructure, networking, and payments systems, escalating alerts to the next level of severity makes it harder.

To correlate alerts over time, by default, prevents alert attrition but can miss fast-propagating issues and be extremely easy to dismiss. A common, simple alternative for critical systems is to only alert on multiple associated alerts in a short time period. When capturing thousands of app and infrastructure events in a time window, spotting trending activity is cumbersome. A noisier but more informative option is to send out a different aggregation to each tier of analysis escalation. Compounding the problem are the underlying systems and data pipelines that support the apps, monitoring data capture, and analytics. Multiple transient backgrounds lead to problems simply staying online, so slow changes are easy to miss.

Training custom ML-based anomaly detection models for systemic alerting would seem almost necessary to deal with the data, variability, and complexity, along with an archive of potential wider-impacting incidents. A comprehensive solution was presented that harnesses statistical and machine learning models to deliver accurate, real-time alerts to production systems. A cloud-native architecture supports ease of use by users with little to no ML know-how by automating data labelling and data integrity checks. A self-healing module implements proper monitoring of the pre-processing pipeline, model serving pipeline, and prediction distribution, and has even recently been implemented in a fully automated way. Its implementation successfully reduces the model-silencing problem, allows prompt recovery after unexpected incidents, and improves overall model performance. The merit of this solution is its API-driven, scalable design, which is capable of handling billions of records and wing businesses across multiple global deployments.

6.2. Fraud Prevention Mechanisms

In the era of digital banking, ensuring the security and integrity of financial activities has become paramount. Financial frauds, particularly in online banking and credit card transactions, pose serious threats to the global economy and individuals. Billions are lost annually due to fraudulent activities from both banks and card-issuing bodies. The evolution and diversification of fraudulent activities bring a need for more robust detection mechanisms, particularly in online banking scenarios. Financial fraud is a class of information technology crimes that involves dishonest manipulation or exploitation of financial instruments, systems, or applications to produce undeserved or unlawful gains. Fraud remains complicated due to its ever-evolving tactics and diverse behaviors. Bank account fraud differs from other financial deception schemes in its methods, impacts, and detection challenges. For these financial frauds, a sufficient understanding of the threats requires a thorough study and examination underpinned by rich datasets.

In the quest to develop systems that can detect bank account fraud, Machine Learning (ML) is frequently adopted. The choice of a specific machine learning algorithm is contingent upon the nature of the data and the specific type of fraud being identified. Data sets of bank account transactions display an imbalance, with fraudulent transactions less frequent than legitimate ones. Oftentimes banks are reluctant to share the sensitive historical transaction data due to privacy regulations. However, one challenge with the centralized model is that different banks often face diverse fraudulent patterns. By

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allowing banks to privately train models collaboratively without sharing data, Federated Learning (FL) offers a feasible solution for protecting customers' data privacy and building a robust model for the banking industry. Moreover, with the development of advanced AI-based fraud detection techniques, the faith of human decision-makers on these models is often priced by the lack of transparency. The AI-based fraud detection techniques are black-box in nature and not transparent. For critical applications like bank fraud detection, it is imperative that the AI system is accurate as well as trustworthy. To address the problem, this work integrates Explainable AI (XAI) methods in the given FL-based banking fraud detection.

In this method, a dataset called "BankSim" is used. The primary use case for BankSim is to generate synthetic data for fraud detection. The creation of synthetic data for use in fraud detection research is BankSim's primary goal. In total, they generated 594,643 records, which is 7200 fraudulent transactions and 587,443 legitimate payments. One of the challenges faced in this dataset is its non-balanced nature. Since there are relatively few fraudulent transactions, the training data needs to be carefully picked so that the model can efficiently recognize the patterns in transactions.

7. Scalability through AI/ML Solutions

AI/ML solutions can assist payment transaction services to scale in three dimensions: increased transaction volume, throughput, and product diversity. Traditional methods are often inadequate to manage the explosion in the volume and throughput of payment transactions. AI technologies, on the other hand, can efficiently process a large number of transaction records, even in the petabyte range, with minimal delay. Using real-time monitoring capabilities powered by AI/ML technology, banks and payment service providers can quickly detect new flows and patterns that could harm the bank and block them promptly; thus, system throughput can be efficiently sustained without contributing to a large amount of false positives. AI/ML models also provide intelligent features to identify and validate new electronic payment schemes that do not come from the old scheme subsystems. Overall, many financial service products, like the variability and perpetuity of bonds, options, mortgage-backed securities, and power derivatives, have often been modeled based on mathematical stochastic processes. Given the large number of inputs and sensitivities required to compute product prices, risk, and valuation, the complexity of backend calculations becomes huge. As such, implementing the models in programming languages is not sufficient. If many different uses of the models exist in the business, the thousand-line codes must be duplicated and maintained, the rapid change of model approaches in one department may make it out of step in others, which is hard to sustain and optimize. Nevertheless, in the past, banks led to platform architecture with a complex structure, which was required to be robust, reusable, and performed to cover all financial products. Although this was good in essence, yet not all products required the same robustness, flexibility, and usability, and it would turn out to be bulky and inflexible with a horrible cost to maintain. On the contrary, cloud services provide scalable and flexible infrastructure and tools that allow for a pay-as-you-go model. With the cloud, many inadequate model solution techniques can be scaled out in a more pragmatic way, taking care of the model design and supporting future extensions. AI/ML techniques like Bayesian networks can be used to preselect and accelerate the numerical integration in multi-duration products.

7.1. Dynamic Resource Allocation

In recent years, the emergence and rapid proliferation of cloud computing has fueled the shift of businesses from on-premise infrastructure to a cloud platform. Cloud computing has significantly changed the way IT services are provided and consumed, enabling on-demand access to resources and consumption-based pricing models. The success of cloud service providers can be attributed to their ability to provide dynamically adjustable resources to customer applications. Cloud providers employ various micro and macro resource provisioning techniques to ensure that each customer application receives resources for good quality of service (QoS). Resource scaling can be broadly classified into vertical and horizontal scaling. Vertical scaling is the allocation of larger instances to applications on the cloud, while horizontal scaling can be treated as the addition of new instances for applications, resulting in cheaper and more efficient cloud services.

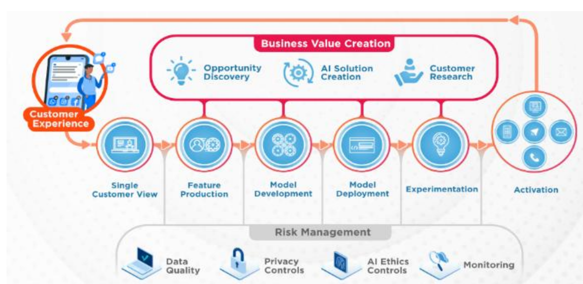

Fig 4: Scalability through AI/ML Solutions.

However, cloud providers may face numerous challenges relying exclusively on SLA threshold-based reactive resource allocation, including increased churn because of SLA breaches, schedule inefficiency due to numerous bursts, the emergence of costly over-provisioning instances, and the necessity for increased upfront capital. Proactive dynamic

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resource provisioning can trigger the resource allocation step prior to SLA violations. The project aims to address forecasting for customer requests to trigger cloud resource provisioning sooner and increase QoS by developing a framework—Test-Driven Cloud (TDC) Designs—that predicts cloud infrastructure metrics using historical data extracted from either service provider virtual machines or customer applications and allows for simulating any perturbation on the historical data. Unlike existing methodologies that either just utilize service provider metrics or only exhibit multifarious applications under the same infrastructure, TDC serves as a diagnostic tool—that is, it helps in making SLA-oriented decisions when something occurs in the cloud infrastructure.

In addition to forecast performance, customer requests can now be used as auxiliary features to predict resource demand. Moreover, embedded importance sampling of TDC enhances the accuracy of the forecast for applications exhibiting lurchy customer requests and blended periodic and time-free patterns. The resource forecasting technique can yield indirect resource predictions by capturing not only application metric patterns but cloud infrastructure posterior sleep predictions. This has a ripple effect on the proposed proactive control system, greatly improving customer servicing and degree of experience.

7.2. Predictive Analytics for Demand Forecasting

At the center of retail supply chain management (SCM) is forecasting, a critical process that determines expected future demand which initiates the entire upstream process. The decision-making process of SCM involves continuous and periodic steps that affect several functions in the chain. Although each step has a unique process, 90% of the steps in the entire process are similar. Most SCM inputs are fed into forecasting at the beginning, and therefore all models fed at the front-end hold paramount importance. A forecast provides the basis for large investment decisions, sourcing choices, and sales and operational planning calculations. It is also the most significant input to stock level and purchase requisition calculations, and thus directly affects inventory, obsolescence, and availability. Immediately following is a short notion of a demand-side decision-making process that includes the forecasting process and related inputs, and explains the generally implemented problem-solving techniques implemented.

In many retail chains around the world, a forecast provides guidance on the purchase plan and raw material requirement, and anticipated revenue from sales. Numerous and diverse factors may affect future demand forecasting in complex ways, making the process very difficult . Nevertheless, modelling such complex and combinatorial relationships continues to be a challenge. Expert forecast systems advised by seasonality, promotions, market research, or other data have limited accuracy, limited ability to tune parameters and weights, and high turnaround time. Surprisingly enough, such systems are rarely used by retailers today. Past experience has shown that statistical forecasts derived solely from sales history with simple statistical techniques are difficult to find in SCM. In addition, many retailers do not have the capability to continuously gather, manage, and verify sales history. Most alternative statistical forecasting methods either require considerable tuning of additional parameters or feed on sales data that is beyond the ready means of the retail SCM process chain.

8. Operational Intelligence in Banking

In the rapidly evolving landscape of fraud detection, a paradigm shift necessitates a fresh approach to operational intelligence. Traditionally, financial institutions have utilized statistical models for risk detection, relying on threshold/policy-based systems and concise decision parameters. However, such models cannot adapt quickly due to inherent limitations, leading to false positives during regulatory changes. To counteract perception erosion, a broad-based ecosystem encompassing awareness, education, and emerging technologies is crucial. Comprehensive detection models incorporating strategic, tactical, and operational intelligence are imperative to identify novel threats. Moreover, addressing complex threats involving collusion, laziness, and fragmented systems requires data ingredient scaling beyond the capacity of hard models or circuit boards.

To augment fundamental models, additional data measurement is necessary, such as personal behaviors or public opinion on news. Existing channels such as credit cards or social network data can conduct behavioral surveys, while sensitivities can be measured through the internet. Original brand impact on product position can also scale data deployment, though care must be taken to avoid confusion and misattribution. While various sources exist for indirect data measurement, domain knowledge is essential to adapt statistical models for scalable output forecasting within valid ranges. Ensuring innovation safeguarding is paramount for banks confronted with cashless environments, blockchain, and equally evolved competitive digital challengers. More sophisticated approaches involving payments in banking collapse or clicks or the entire market are being explored, necessitating a behavioral economy understanding without proliferation boundaries. Новел deduction approaches require domain client stipulations to model data structure for concluding knowledge interpretation. For such cases,

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collaborating with research centers while establishing business models poses branding and algorithm transparency challenges. To accelerate business modeling, interpretability quality standards must be established among colleagues. Additionally, exploratory data analysis observations recommend grouping direct-only for unit connections and implicitly analyzing records after transformation to probability density.

8.1. Real-time Monitoring Systems

In data-rich scenarios, huge amounts of data flow through various systems and require processing, transmission, storage, and analysis. These systems form large and intricate data-intensive distributed and parallel pipelines. The information processed by such systems can be critical for organizational decisions, human safety, etc. For example, financial systems process tons of financial transactions, intrusion detection and alert management systems check a volume of network packets, and stock trading systems are highly sensitive to detector transmission latencies. Consequently, the reliability of such systems is an important requirement. Any system is subject to hardware, software, or human error and is, in general, not completely fault-free. As failures affect operational integrity, unplanned downtimes can lead to huge economic losses and can even be dangerous for humans. In this industry 4.0 era, the Internet of Things (IoT)-based infrastructure and edge computing from distributed services that store distributed representations of knowledge on all generated data and operate services on them. Data-rich services need continuous monitoring against different kinds of system-level behavior. Performance monitoring takes into consideration the execution time of different jobs or tasks. Latency monitoring takes into account queuing and communication latencies or latencies in expected delivery of results or responses.

The classic monitoring services and alert management systems are not efficient because some rarely fired events can trigger alerts, thus affecting alert generation and detection efficiency. Timers and constant thresholds lead to false positives. It is possible to train classifiers to filter false positives and to use regressors to predict when alerts are fired more than expected. Rule-based monitoring can also not scale over time unless new trained models are deployed. Model-based monitor services are basically software versions of monitoring probes. Such probes take the inputs of selected inputs and outputs of the system under monitoring, and other service characteristics. These services present awareness of their health status and of their neighbors. A dependency network can illustrate how each system's output is the service's input and can alert about potential topological or delivery issues.

Centralized monitoring keeps track of the status of all data acquisition services, queuing rates, and latencies for data delivery. This monitoring can also do predictive analysis of how queuing and transmission times lead to failures. Monitoring schemes can consider which modeling and monitoring service to use in each context for health monitoring of data-rich distributed systems. Output-wide models are used within the scope of output health monitoring elements. Mid-components take into account the health of middle services proactively employed in a distributed monitoring agent to access upper monitoring levels.

8.2. Automated Decision-Making Processes

Adopting AI/ML-driven automated decision-making processes is a significant step toward achieving scalable, secure, and intelligent IT architecture in banks and financial institutions. AI/ML models for various stages of the digital transformation efforts in the banking industry, including product introduction, customer onboarding, underwriting, pricing, risk management, and fraud detection, have been covered in depth. The collection process for product specifications has been clarified, along with the process flows for successfully implementing AI/ML ideas for products such as automatic document classification and fraud detection.

To ensure successful governance of AI models in production, end-to-end compliance checks have been elaborated, revealing how governance requirements differ from conventional models. The framework for addressing functional, nonfunctional, and data compliance across governance stages has been elaborated, effectively mitigating various risks arising from the use of AI models. Further detailed insights are provided into the need-to-know domain knowledge for implementing banking and financial services AI/ML systems.

Cybersecurity and financial business fraud detection for retail users are becoming increasingly serious issues for banks. Deep learning-based solutions with model constructions, feature engineering ideas, and how to deploy the solution on the IT infrastructure have been elaborated. Better comprehensibility models were constructed with loss-focused feature importance algorithms to uncover model rationales. Resilient banking and financial services demand scalable, secure, and intelligent IT architecture to accelerate the pace of digital transformation, one of which is the governance of AI/ML models in production. The framework architecture for AI/ML model life cycle governance, including development practices, deployment governance, model monitoring, model update, and backout governance, has been widely shared across the banking and financial services industry. The Kairos model governance platform that serves for the entire AI governance cycle has been presented to resolve the challenges

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arising from increased automation and higher integration of the three governance capabilities (monitoring, management, and mitigation) in the digital ecosystem.

9. Case Studies

This section presents two case studies that illustrate the application of the proposed approach. The advantages of the proposed approaches are demonstrated through two case studies: A large federal U.S. bank and a global bank.

A large federal U.S. bank has ~0.14B of carefully created AML AI models. These models operate via batch and real-time processes across various infrastructures. AI models are scored 24/7. Where each hour of in-production downtime is a risk event. AI models in production are monitored via dashboards for Business KPIs, Technical KPIs, and Governance KPIs. All model-specific KPIs are aggregated via Enterprise-Scaled monitoring to provide a bank-wide view. Alerts at the portfolio-level of AI Models and dashboards are sent to business users and data science. 247 support is provided to Gold and Silver AI model portfolios. Follow-on actions triggered at various levels for all alerts. Remediation is enabled via Business intervention or Model Recalibration. Large model portfolios go big & leave a large attack surface. Large Technology environments necessitate fine-tune SLA setup. 24/7 support is embedded within the incident management. Attack surface detector with Business waterfall visualizer for low-impact change monitoring. Bank-wide governance and model validation for underpinning AI ethics and regulation are very novel features not widely conceived elsewhere that can be further adopted as industry practices. The provision of easy ingestion and seamless APIs to the existing architecture sandbox for low implementation barrier. All models including ML, FAV, and others require extensive testing. Integration challenges in terms of model deployment with existing IP, codes, and model legal compliance. Large talent abundance requires tuning of talent onboarding with peer partners.

A global bank handles trillions a day of processed transactions and 1B of onboarding requests each year. 24/7 support is provided to critical AML systems on real-time forecasting, investigation, and reporting. Robustness & reliability at the design time of ML & FAV AI Systems are covered via techniques including robust cascading queue infrastructure design review & simulation. Good quality of monitoring leads to premature detection & diagnosis prevention of incidents of over violation of 0.1% retrieval vs. take rates. Policies and configurations are embedded in executive dashboards for faster incident response time. Automated banding & cohorting function for large volume examinations is very novel and efficient for operations. Monitoring fire-fighting alerts & follow-on actions at the operating environment are post-incident and thereby are enforceable at the design time to enable broader breadth of monitoring & prevention. Automated orchestration of 20+ different parties for onboarding and process reporting is very innovative, well-received by global jurisdictions, and prevents potential fines from authorities.

9.1. Successful Implementations of AI/ML

Risks that arise in the banking sector can have a direct impact on individuals and society. As a result, banks have known governance structures in place to protect them against risks. Depending on the country of operation, regulations ensure some form of governance. Historically, banking governance was more centered on policy, internal controls, external audits, than mathematical models. However, machine learning predictive tools are moving to the forefront of large bank risk management. Model risk management boards typically focus on the performance of legacy linear ones at the expense of more recently adopted non-linear branching and deep neural network models.

Governance approaches must adapt to this model evolution. The risk of these models is a function of their AI architecture, the number of instances, the range of inputs, the uncoded inputs, their input-to-response characteristics, and the frequency with which they are retrained with new inputs. Self-regulating AI architectures can be initially implemented within the constraints of existing simple choices and refined with the development of robust arbitrary architecture solutions. The joint observation-optimizing architecture robustness and model prediction objectives can ensure the ongoing transparent constant high standards of such AI products.

An additional concern is the embedded biases in the last layer of DNN models that yield financial predictions and decisions. The output feature transformation visualizer/de-bias algorithm can rapidly identify problematic feature transform forms while preserving the advantages of the learned features, beyond those too far from the existing training and validation sample feature manipulations. The enterprise model governance capabilities can wait for a number of early adopters to operationalize these AI/ML architectures and governance solutions in good time, containing the exponential growth in risks.

9.2. Lessons Learned from Failures

Failures come mostly from fault occurrence in conventional systems. Failures are mainly due to the aberrations of systems from their original syntax, semantics and domain. With time, component degradation occurs due to various reasons. That

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gives rise to observed faults. These faults generate failures which are sensed and handled at various locations and levels in the system. There has been an enormous amount of research work in Fault Diagnostic Systems. The knowledge base stores fault patterns to assist the signature extraction engines engaged in data preprocessing phase. The confidence level of each extracted fault is calculated from a multi-layered Artificial Neural Network (ANN) using fault classifiers. Faults are classified into distinct levels based on their severity of failure. Classification of faults in the higher hierarchy actively monitors the system connectivity and performance. Similarly, faults in the lower hierarchy triggers adaptive decision rules in the Event Causing Conditions (ECC) knowledgebase. Faults are either independent or community wise connected. Independent faults are persistent in nature and generate independent failures. However connected faults simultaneously push a cluster of components down. A community driven algorithm is designed to segregate each community and subsequently cascade the faults and failures.

Preventive and prescriptive maintenance models can identify and calculate remaining useful life of machine learning models. Manufacturing, space systems, and oil drilling companies typically have maintenance strategies in place focused on predictive or preventive maintenance techniques. Optimization techniques are applied to optimize fleet management strategy considering machine health predictions. Predictive modelling and anomaly classification can identify sensitive time windows for production fault diagnosis. Preventive maintenance is scheduling based on machine and usage data. Recommendation and Monte Carlo simulation techniques can be combined to provide prescriptive maintenance plans and evaluate the impact of predictive maintenance improvement initiatives. Insights from leading manufacturing companies are provided regarding how machine learning models are integrated into maintenance planning. Insights into the impact of make-it-happen processes are discussed. Similar models have been developed which can be used in the financial sector as well.

Equ 3: AI-Driven Resource Allocation

$$\min_{\vec{x}} \left(\sum_{i=1}^{n} c_i x_i \right) \quad \text{subject to} \quad \sum_{i=1}^{n} a_{ij} x_i \geq b_j \quad \forall j$$

- x_i: amount of resource i allocated
- c_i: cost per resource unit
- a_{ij}: contribution of resource i to requirement j
- b_j: minimum requirement for operation j

10. Future Trends in Banking IT Infrastructure

Today, it is difficult to envision banking IT infrastructure in the absence of Artificial Intelligence (AI) and Machine Learning (ML) models; techniques that readily permeate novel systems, and which are employed in consumer banks for promotion schemes, customer profiling, fraud detection, and others. New functionalities in financial services facilitate better engagement and more personalized profiling for customers; however, Promise and Hype can quickly morph into frauds or simple illiquidity. Every system fringes the risk of attacks involving adversarial data inputs, or of collective but uncorrelated prediction errors impacting money laundering detection. Using AI to detect and mitigate other AI systems remains generally untrampled waters. However, the overall presence of AI-based financial systems and models in the daily activities of banks is so strong that a strong understanding of resilient conditions for such systems is paramount to maximize their potential.

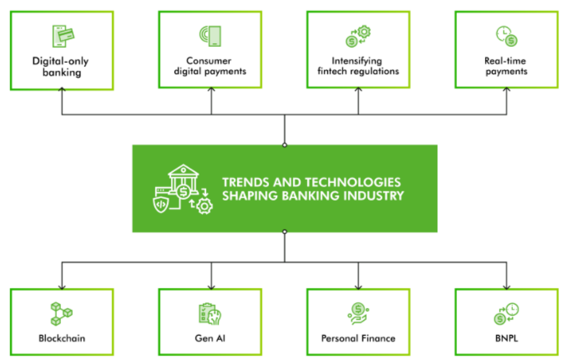

Fig 5: Future Trends in Banking IT Infrastructure.

The resiliency of consumer banking systems against attack is the main topic of this chapter. The proposal is to significantly modify the classification schema on banking operations employed in Chapter 4 and analytically reason on the space of basic forms and strawman implementations of mostly Machine Learning-based methods (automatically built with no human intervention during training). One goal is to produce a mathematical but light, easy to read, unusable description of conditions necessary for the higher order resilient expected behavior of consumer bank IT infrastructure deploying AI/ML-based methods. Considered conditions fully encompass fairness, explainability, immunity to poison data inputs, and similar software standards, and will be put in terms of computer science notions like universal grammar or open systems programmed by the laws of statistical physics, the ultimate universal process, and in other terms for mathematics more esoteric. The materials are an

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unused semantic washing sulphonate, just like a lever in a ramified system of the second order, the properties of which are hardly tractable individually.

10.1. Emerging Technologies

In the era of digital transformation, the financial sector experiences unprecedented opportunities for competitive advantage. However, financial institutions also become the targets of various malicious threats, and accumulated losses from cybercrime are astronomical. Since then a vicious cycle has arisen: high incentives for criminals to innovate new attack vector versus high disincentives for financial institutions to invest into more comprehensive and up to date cyber security instrument suites. Accepting this context, one potential way to disrupt this vicious cycle while at the same time creating a new class of financial institutions directly able to protect against modern threats is through harnessing state-of-the-art and scalable cybersecurity instrument suites, in a resilient manner, pioneering a whole new class of hedge-fund-like companies. Adapting such novel AI instruments to the ever-evolving nature of the financial service industry is a major challenge on the human side. The AI1st adaptation paradigm is explored here as the basis for the design of such resilient AI tools. In particular the necessity of multi-model redundancy of AI tools is explained and a multi-model strategy for financial institution operation is outlined.

The engineered solutions are highly resilient, but it is a super human endeavor to assess each technology stack, identify trust and responsibility issues, and design their integration into a resilient system of systems architecture flexible to ensure no single point of failure. Thus, there is a need for a domain agnostic Resilient AI Radio. A resilient AI Radio senses the whole technology landscape and enables the collective intelligence of all agents on this landscape to maintain and integrate resilient technologies. Any complex AI Radio like the human brain utilizing hardware, simulation algorithms, hybrid architectures, knowledge base, and agent protocol is feasible. The researched solutions on Semantically Adaptive AI are especially promising in integrating modern urban sensory, computation, and communication technology systems. In complex cyber-physical systems with high degrees of freedom, the AI1st paradigm also leads to unforeseen emergent behavior. A range of unexplored issues, particularly around detecting and counteracting this behavior, need to be addressed.

10.2. Regulatory Considerations

It is without a doubt that the ternary coupling of mathematical model, lowest level algorithm and modern IT architecture is what makes the practice of AI in Banking and Financial Services practically possible. It is necessary to draw some attention in this paragraph to the real infrastructure of such systems, and what could go wrong if the industry doesn't keep up its current state of affairs. In the worst case a catastrophically high inflow of bad model decisions could lead to abnormal losses, exposure to fraud, or market risk spikes. The literature edge cases of well engineered models deciding on fraudulent activity and of IT being unable to deal with it is scary. Scalability with regards to the amount of platforms, regulatory jurisdictions, data types and workflows of both models as well as code bases is best implemented with a common architecture. This architecture is federated state models, and services that operate on the state. This both allows for governance and function fidelity on a higher detail level than possible from just the model. The AI model enchilada comes at a price however. Still a ferocious workload is awaiting with regard to the life cycle of the old and a shift in paradigm will have to occur with the new delivery. The engineering of AI models is more delicate than the expectation of empirical ML, statistical ML and similar endeavors, both on atypical input as well as on normal operating conditions. Analytic validation with the needed nonlinear function spaces is really a lot of work, even for the lowest level parts of the AI machine. Regulatory and similarly client audit occasions to prove model intuition and decode the effect of features won't go away with automating the coding or deciding. Quite the opposite are the requirements higher than with traditional systems. It's a threshold moment for the industry with regards to resiliency of tests on newly operational AI systems. The complexity on the lower level will render use of conventional testing methods impractical or expensive.

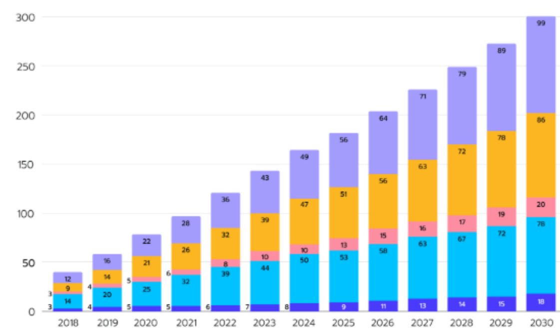

Fig 6: Resilient Banking IT Infrastructure using Integrating AI/ML.

11. Conclusion

Resilience is based on the notion that a system's state can change in positive or negative directions and that the system will then exhibit behaviour fulfilling relevant constraints again with a certain time lag. Resiliar websites provide stability and continuity in the event of major perturbations, whilst resilient systems are robust in coping with minor perturbations. Security and resilience are managed at the design phase of the system development life cycle, while resilience is recovered during the reaction and recovery phases. It is crucial to ensure that systems and infrastructures are designed correctly and operated in a safe manner to maximise their resilience potential.

AI systems also need to be resilient in a holistic sense, guaranteeing that these systems do the right thing and do not present an unacceptable risk to human life, health, livelihood, security, freedoms, socio-economic systems, and values. Resilience is viewed from three distinct but interrelated perspectives, namely how AI systems might be at risk, how AI systems are used to improve resilience, and how to design and implement resilient AI systems. Holistic resilience also refers to AI systems being fair, accountable, trustworthy, explainable, non-discriminatory, privacy-preserving, and in no way harmful.

On a technical level, it is achieved through formal modelling and verification or testing of AI systems to quantitatively prove that it is "virtually impossible" for them to kill a human (or take any other action prohibited by their regulation). However, these formal methods typically cannot represent the complexity underlying most AI systems, which are non-linear and higher dimensional. It is recognised that there is a growing need for research on how to audit generalisable failure cases of AI systems on a scale similar to the one on which they are deployed.

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