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# From Data Lakes to Smart Decisions: Architecting AI/ML-Enabled Infrastructure for Future-Ready Banking

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**Abstract**
The four pillars of the banking and finance sector, i.e., risk, return, asset quality, and compliance, are enormous and diverse in nature. Traditional research techniques or methods are falling short to process and analyze such data, owing to shear volume and velocity of transactions. AI/ML methods and modeling help fulfill these criteria, and interestingly, banks globally seem to show keen interest in adopting these technologies in their research framework in a big way. In this pursuit, various models are developed with a structured study at different banks, presenting a comprehensive big-data analytics of each insight, so that banks will be ready to take the next big jump in AI/ML-enabled infrastructure.
Big data today plays a vital role in all the industries to enhance their growth in all aspects. Banking, the oldest sector across the globe, is also shifting to big data methodologies to improve governance, operation, and customer satisfaction. Shadow banking, virtual banking, and crypto banking are examples of the latest technologies applied to improve day-to-day banking requirements. Traditional banking research work involves risk, growth return, asset quality, and compliance, but banks struggle to handle big data banking research outcomes]. There are plenty of algorithms, libraries, and data cleaning techniques for intelligent data science models, but direct relevance to banking models is limited. AI and ML technologies seem to be the new set of buzzwords often used to denote the future of technology. However, for banking data, it is still a distant dream owing to huge volume fluctuations, overwhelming data cleaning requirements, and interaction with various legacy systems in multiple formats.
The failure or fraudulent transaction occurrence of any entity reveals a gap in governance and risk management documentation. Enabling the event and transaction data in AI infrastructure can enhance timely actionable knowledge-based monitoring to avoid future failure and fraud. Using testing data and building algorithms may take too much time to monitor real-time data, prompting actors to miss early signs of warning failure or fraud while planning big data handling, data journeys, and governance approaches to fill the gaps.

**Keywords :** Data Lakes,Artificial Intelligence (AI),Machine Learning (ML),Smart Decision-Making, Banking Infrastructure, Future-Ready Banking, Data-Driven Insights, Predictive Analytics, Financial Technology (FinTech),Real-Time Data Processing, Scalable Architecture,Cloud-Based Solutions, Data Governance,Intelligent Automation,Digital Transformation.

## 1. Introduction

As society increasingly develops into a digital environment, more advanced technologies have entered the scene and created a firm foundation for every sector of human life and work. Accordingly, financial technology or fintech has ushered in a new era of transformation in the financial sector. Internet financial institutions, along with the disruption, have not only brought about opportunities for development in the banking industry but also challenges. Traditional financial institutions such as banks face several pressing issues, including rapidly shrinking profit margin, increasingly fierce competition, and loss of clients who have turned to other Internet financial institutions. Driven by external competitive pressure and an internal transformation need, banks are increasingly boosting the development of intelligence-related goods and services.
Given the maturing of artificial intelligence (AI), great efforts have been made in the development of AI techniques and systems by banks. The newly announced policy in the document of "Guidance on the Development of the Banking Industry in the New Era" further states that firms are encouraged to use AI for enterprise management. Additionally, firms are encouraged to continually push computer technology to enhance the digital level in the banking industry. Deep learning (DL) technology, as a branch of AI technology, has recently achieved a breakthrough in the field of social digitalization. While AI can be generally defined as any technique or system that mimics human behavior, DL technology is a specific type of AI that imitates human neural networks with the construction of a large multi-layered model. DL technology has gained prominence in the past decade due to the creation of powerful hardware and a large amount of data. Recently, DL technology has begun to be used in various industries, such as health care, internet, and smart city, where various multimodal data exist. In the discipline of finance, DL is also believed to be a possible game changer in view of its large data-driven and man-machine integration qualities. From this perspective, commercial banks do possess a promising foundation for the application development of DL technology. In addition, given the temporal nature, high dimension, and continuity of financial data in comparison with other industries, commercial bank financial data are thought to suit the DL model more than others.
Although DL technology renders commercial banks an unprecedented opportunity for development, it is still in the infancy stage. The sophisticated nature of the DL model brings about difficulties in practitioners comprehensibility, tuning, and data storage. Also, competition with existing institutions having a significant market value poses a serious challenge to new entrants. Prior to discussing or examining the particular obstacles, local conditions must be fully considered as the financial environment

differs from one country to another. Like in many other developing countries, Chinese state-owned commercial banks also lag in talent and capital resources compared with the first-tier commercial banks. However, while some prospects can be used for AI implementation, banks ought to be cautious about the unpredictable international environment. Ultimately, specific implementation schemes must be designed as certain features of applications and local conditions have to be properly considered.

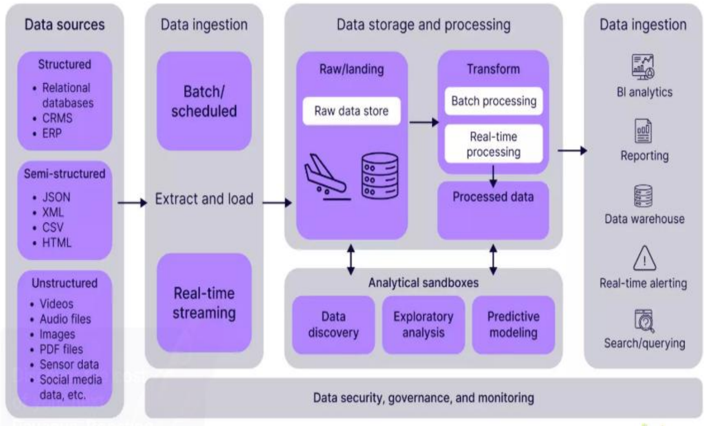


**Fig 1: Data Lake Architecture**

### 1.1. Background And Significance

Since the invention of the smart algorithm, with computers gradually becoming faster and faster, it is now the era of Artificial Intelligence (AI) and it's everywhere. AI powered applications started making an industry impact and organizations invested a big portion of their budget in it. As the literature review indicates, with AI algorithms & machine learning, systems are able to solve many of the problems traditionally deemed impossible. LinkedIn, Facebook, Amazon and Netflix are just a few examples of commercial applications of AI which have changed the way business operates. Banks have also entered this exciting area of AI step by step with the first commercial implementations so far shown in image classification for risk classifications and first predictive analysis applications. A great combination of data and deep learning algorithms provides these new AI systems a competitive advantage. But current software data administrators and intelligence level is still not enough to meet the bank's needs and challenges (metadata, handling time & analysis capacity, etc). As banks deployed storage and reporting systems these last years, the big data analysis software landscape took off and banks feel pressure to test it.
Artificial intelligence (AI) is now widely acknowledged as one of the most important digital transformation enablers across a significant number of industries. AI explore, learn and acts autonomously with little or no human involvement. AI can be applied in five broad categories: robotic process automation, computer vision, virtual agent, natural language processing and machine learning. AI powered applications are currently supporting Indian banks to upgrade their operations and processes across the board - from accounting to sales & marketing to contracts and client correspondence management to cybersecurity and risk management. Due to their intellectual (certainly differentiation) potential these applications can considerably upgrade a bank's operational efficiency. While several dozen banks worldwide already have sizable AI activities, the Indian banks are very early in banking AI. Banks & regulations across the globe are discussing the necessity of AI vigilance and how companies can responsibly develop AI systems. However, India lacks any AI risk governance at the moment. Meanwhile in a low awareness environment both banks need to build regulatory skillset, consumer protection & supervisory scheme.

**Equ 1 : Smart Decision Function**

$$D = f(A, M, Q, R)$$

Where:

- $D$ = Smart decision outcome
- $A$ = Access to quality data (from Data Lakes)
- $M$ = Machine learning model accuracy
- $Q$ = Data quality (completeness, consistency, timeliness)
- $R$ = Real-time processing capability

## 2. Understanding Data Lakes

Just as data warehouses have reshaped the traditional approach to data storage and analytics in the mid-1990s, the emergence of data lakes impacted big data. What is a data lake? In its simplest form, a data lake handles raw data from diverse and heterogeneous sources. Data lakes keep the data in original format and do not require the expensive preprocessing of the data, for example, schema creation needed in data warehouses. A large variety of tools are available to ingest data onto a data lake and many are open-source. While originally proposed to store big data, data lakes are now actively used in small and medium size companies, where they are more than able to store the amount of data that is wealthy for analytics.
In 2013, AWS published its architecture for a business data lake. The architecture ingests data sources in three abstract tiers: Landing zone, Business entity zone and DataMine (where data are mined). The architecture highlights that data lakes do not

provide a premise that all data lakes are fitted for analytics. Instead of being usable and friendly, data lakes may evolve into 'data swamps' if there is no proper governance and no management of the metadata. Data lakes tend to grow exponentially as more sources and datasets are ingested. Consequently, users face increasing challenges to interact with the data lake. Missing information of the data hinders user interaction. This missing information may cover the origin, quantity, distribution and quality of the data. Dixon stresses that a data lake must also include the metadata and a governance to enable the ad-hoc analytics that were expected from the outset. Other research proposals have highlighted new possibilities with respect to AI and Crowdsourcing for the integration and quality of the data.

ML and AI may capture the relevant content for extraction of features and for modeling data without intensive manual effort. Some other research proposals target the generation of metadata for linking to social networking data, recommending data to users or detecting redundancy in the dataset to avoid needless computing. Since 2016, there has been a hasty growth of the realization of data lakes, a large variety of architectures and components have been proposed. Numerous commercial tools for building data lakes are now provided by the biggest IT companies. Domain specific tools for data lake exploration are also proposed. There are several research challenges that are still pending. These comprise the specification of metadata and management of the metadata.

**2.1. Definition and Importance**

According to, Artificial Intelligence (AI) refers to the ability of machines to imitate intelligent human behavior. AI is increasingly being adopted as an important digital transformation enabler across a wide range of industries, including agriculture, automobile, education, financial services, healthcare, aerospace, and manufacturing. AI applications assist enterprises in enhancing their operations across the board – accounting, sales, contracts, and security. Deep learning, machine-to-machine communication, data mining, natural language processing (NLP), neural networks, and robotics are some of the components that make up the AI solution stack. It was decided to focus on the use of AI in banking services and its impact on the business model of banks. Banks are the backbone of economic development, playing a vital role in forming a financial system, giving effect to planned expansion, providing assistance for imports and exports, implementing economic measures; and financing investments needed for growth and development. The banking industry operates in a unique regulatory environment. The banking user, whether the government, corporate sector or individual, is a representative of either the depositor or investor, to whom the bank owes a fiduciary duty.

According to, many banks are now considering integrating FinTech into their services because customers want more choices, flexibility and control over how they bank: who they bank with, when and how they bank, and what tasks they want to perform. These customer preferences spur innovative competition from a growing number of new design banks, cloud-based banks and 'cool' banks. By designing their own systems and bypassing a bank middleman, customers save on banking. However, income is a primary concern for banks; they need to remain profitable amid declining margins on traditional fees and interest. Banks can address these risks by distributing tasks to other regulated financial entities, including those that currently remain unregulated or sit outside the UK. Conversely, banks might build an in-house 'plugin' to be integrated behind the current establishment. On the one hand, this prevents further dispersion of value-generating tasks; on the other, the task of controlling it all becomes substantially more difficult.

**2.2. Data Lake Architecture**

The foundation of the banking industry is a data lake. While social accounting, digital currency, and payment networks are all influences of AI/ML and will support the banking industry, AI/ML cannot be implemented without a data lake. A data lake is where all of the data from an organization is captured and stored in its native format. The data is kept unordered and unstructured, just like a water lake. The data lake has become crucial and vital infrastructure as customer and employee information flows in various formats into banks. These data come from various external social networks, internal accounting platforms, and executive and salesperson conversations during internal meetings. All of these datasets must be kept, and a data lake allows for subsequent analytics by utilizing AI/ML techniques.

The organization in question will be used as a case study. Recently, natural language processing (NLP)-enabled products that automatically transcribe meeting recordings and follow up on action items from written minutes have emerged. These companies would require access to conversational (text) data for training purposes, which an in-house data lake cannot provide. Therefore, the banking industry must be prepared to integrate external data into the data lake, in contrast to traditional industry data lakes that only contain internal data. Banks must carefully consider data loss due to safety concerns, but they should also acknowledge that this is a crucial need for the financing industry as other industries advance. Due to stringent security requirements for customer and transaction data, a data lake for banking must be well-defined. A well-implemented data lake provides opportunities to build safe data analytics products while avoiding inadvertent data loss or exposure.

**2.3. Data Governance in Data Lakes**

Data governance is regarded as a major enabler in order for organizations to prepare their data for the coming word of AI. Data Lakes have raised institutions' ability to store and share vast amounts of data from heterogeneous sources. The need for data governance in such architectures is substantial, however. Recent guidelines on a data governance framework and the accompanying processes based on an established data lake architecture are discussed. Additionally, feedback on how to operationalize data governance from currently available products is discussed. An academic data governance framework is compared to enterprise-ready open-source and commercial products. Needed components and services to build a prototype platform for data governance in data lakes is suggested.

Structured and unstructured metadata are crucial to allow users to discover and understand what the organization has in terms of data, and to know how to consume it. Physical metadata must include information about the data physical storage, needed in order to access and manipulate these data. This aspect enables data consumption and the analysis within the organization. At this stage, additionally to the generation and storage of metadata, tools are needed to allow users to access and explore such metadata. A data governance tool should be provided that allows business users to create and modify both the business and the physical metadata of technical assets, and automatically generate metadata rules, which are indicators that define the data range and cross-dimensional validity. Additionally, pre-generated metadata would allow the discovery of data assets that are not easy to find by the users.

## 3. AI and Machine Learning Fundamentals

Machine Learning (ML) is a scientific discipline that represents one of the most important advances in Information Technology (IT) in the past decades. It describes the capacity of systems with analytical capacity to learn, using problem-specific training data, to automate the process of model building and to solve associated tasks. For many applications, the resulting ML models, widely referred to as "intelligent systems", outperform – in terms of prediction quality, scalability and maintenance efforts – traditional data analysis approaches, statistical models or simplified rules-based automation. For a broad understanding of the methodical underpinning of current intelligent systems, this entry summarizes the fundamentals of ML. It provides a conceptual distinction between relevant terms and concepts, explains the process of automated model building through ML, discusses the process of data-driven ML as well as the transfer of domain know-how, critically reviews the challenges that arise when implementing such intelligent systems, and highlights the relevance of an improved understanding of ML to benefit from current IT developments.

Machine Learning (ML) describes the capacity of systems to learn, using problem-specific training data, to automate the process of analytical model building and to solve associated tasks. For many applications, the resulting systems, widely referred to as "intelligent systems", outperform traditional analysis approaches. Initial approaches were knowledge-based systems using hard-coded, human design rules. The inability of manual knowledge acquisition and representation to keep pace with the increasing complexity of analyzed data, is complemented by a shift to pattern-based systems. Intelligent systems based on either statistical analysis models and/or ML algorithms are increasingly used on technical systems (predictive maintenance) or in business (risk detection, fraud detection, marketing score modeling), and trained on sensor data or non-tabular data stored in unstructured formats. These systems represent a black box of intelligent complexity, originating in vast ML methodology and fertile data environments.

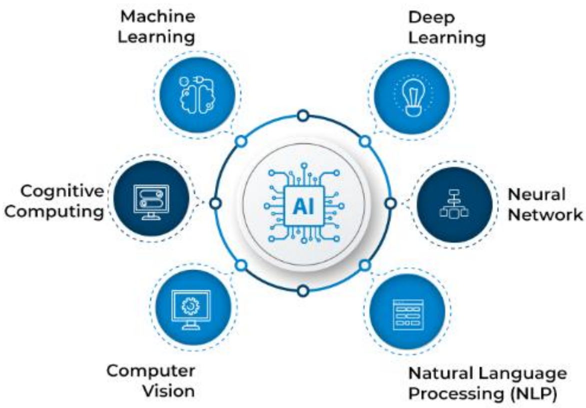


**Fig 2: Machine Learning Understanding the Fundamentals of AI Technology**

### 3.1. Key Concepts of AI

AI denotes a wide variety of algorithms, methods, tools, and processes for analyzing data and facts, designing digital models, inferring input information from existing models, and enhancing learned models with new data and facts in the context of banking. The main aim of such analyses is either to support decision-making and optimize business processes or to fully automate work steps as 'autonomous agents'/systems that act and adapt by themselves. AI technologies may be classified into 3 broad categories: AI technologies based on surrogate models, AI technologies based on deep-learning technologies, and AI technologies based on streamlined processes using heuristic rules. The first technology class includes, for example, regression, time series analysis, Kalman filters, Copula models, path-dependent models. AGGREGATOR is a hybrid risk model that fits both a parametric proxy-with-threshold and a non-parametric à-la-carte pricing via two types of surrogate models. The second technology class includes, e.g, feedforward networks, recurrent/memory networks, convolutional networks. Digital tools may be employed to recursively enhance pricing reliability via screening massive historical and synthetic data with self-learning surrogate models. The third technology class includes, for example, expert systems of rule-based systems. Such knowledge may recycle non-linear and categorical inputs into continuous fair-provision loss queries using a numerical question structure. Companies devoted to models and AI applications are integrated into this AI definition in two aspects: Algorithm companies mostly license algorithms for technical implementation. Systematic process companies implement analytical AI tools in the banking ecosystem with established digital infrastructure in compliance with regulatory and security requirements. Newly available tools and technologies like ontologies, natural language processing, machine learning, blockchain, and graphics processing units empower the further development of AI in banking. In contrast, data continuity and access to heterogeneous data sources is the most challenging AI implementation of all. Data volume in raw form may equal 100 petabytes and require around one petabyte for yearly processing. In addition to an outline of compulsory work steps and show how AI is attached along the banking value chain, all tools and technologies advertised are pivotally turned against unconventional data sources and use cases.

### 3.2. Machine Learning Techniques

This section first discusses supervised learning algorithms in detail (artificial neural networks, decision trees, random forests, support vector machines, and gradient boosting). Then, k-means clustering, which is applied to a dataset of bank transactions to identify segment customers, is discussed.

Artificial Neural Networks (ANN) were initially modeled after biological neurons and utilized a relatively simple way of looking at the world. They consist of interconnected neurons (artificial neurons) that work together to solve a problem. Each neuron has its own weight and threshold. The input data is generally stored in a matrix, and each specific input output calculation is assigned to an input weight and node (input weight * edge weight) + bias(i). At the end of the first layer, the result of the last input node calculation is fed to the next layer of hidden neurons as input. These nodes calculate their outputs in a similar manner, and the feed-forward process continues until an output is produced. A neuron generates an output based on an activation function and threshold (typically expressed as a segment function) that produces a binary signal when outputted. The error from the outputs is calculated and transmitted back through the ANN using the back-propagation algorithm. Each weight and bias is updated according to the following algorithm: weight = weight – learning rate * error.

Numerous approaches are used to prepare the data for a trained classifier, including Binning, One-Hot Encoding, Feature Scaling, Normalization, Data Imputation, and Deduplication. After pre-processing, the dataset of 8 million bank transactions was divided into training, testing, and validation datasets. The prepared dataset consisted of 8,298,864 transactions in total (sum of the training, testing, and validation datasets). The imbalanced dataset and target variable were further discussed by class?แรก. The descriptive statistics (mean) and counts across each target variable as a percentage of the total number of data points were also shown in the 8 million transactions.

### 3.3. Deep Learning in Banking

Knowledge graph models like Graph Neural Networks have recently gained increasing prominence in a variety of domains, including recommender systems and biologicine. General GNN paradigms have been mainly recognized and standardized, notwithstanding the fact that many critical banking-related algorithms exist, such as credit rating, loan identification, and anomaly score. Despite covering several real-world scenarios, current advanced banking approaches rely heavily on limited node-level labeling features. This survey provides a sample of GNNs and focuses its attention on banking applications. GNNs-based algorithms and tools exist to understand the structure of these applications while further improving its banking-related approaches. A recent attention-based recurrent graph attention network model is explored and detailed to emphasize GNNs' application for credit rating tasks. Meanwhile, software is implemented based on three state-of-the-art GNN frameworks to demonstrate the GNN capabilities for bank-related applications. Bank institutions are crucial for a stable economy by executing financial transactions as a middle agent and boosting the development of corporate investment and national economic growth. To this end, banks aim at creating demand by gaining deposits from individuals and financing loans toward fruitful investments. Today, the flourishing network-based companies also occupy the bank market through engagement with mutual funds, cryptocurrency stayaboard and exploration of communities where divergence occurrence reports have been proliferated. Nonetheless, bank systems do not escape from anomalous activities, and anomalies expose money laundering, violent fraudulence, others' property abuse, etc.

Consequently, modern banking institutions give priority to seeking efficient, explainable and credible methodologies and techniques to sustain a healthy market and banking systems. Several efforts have been made toward graph wise anomaly systems in which an anomaly score is generated and summarized for each graph/client. Generally, there are two categories of conventional architectures: graph-centric supervision paradigms and node-centric supervision ones. Thus far, only limited methods are directly reporting on graph-centric anomaly tasks.

**Equ 2 : Predictive Value of Banking Model**

$$V_p = \sum_{i=1}^{n} (w_i \cdot F_i)$$

Where:

- $V_p$ = Predictive value of model
- $F_i$ = Feature importance score
- $w_i$ = Feature weighting (learned by model)
- $n$ = Number of key features

## 4. Infrastructure Requirements for AI/ML

Equipped with extraordinary technology frameworks and infrastructures, the commercial banks should, however, act fast and seriously in terms of improvements on higher levels in terms of providing AI/ML-embedded services to the client institutions and end customers. Aware of the risk occurrence measures and their mitigation procedures, the core departments dealing with market risk, credit risk, trade error reports, compliance, options & derivatives valuations, and post-trade opacity monitoring may try to evolve an internal proposal on various AI/ML-supported tools for operational management purposes within the aforementioned departments. Apart from these provisions, other product departments like treasury, operations, product management, settlements, and guarantees may think of evaluating their areas for the development of AI/ML-based tools for feasibility, productivity, and accuracy improvements.

Level-wise digital innovations can be taken on the process line as well as the product line. In terms of process-wise innovations, the commercial bank can think of various means to enhance productivity and accuracy in the follow-up of loan disbursement, ISDA preparation, and CRD reporting processes. To this end, the roles of the existing data management systems and the enhancement of these systems are to be understood properly. After being knowledgeable about the data landscape of existing systems, business cases involving the use of AI/ML-based tools should be thought about. Here, it may be prudent to look for internal and external experts who can advise as well as train the related employees on how existing systems may be engaged in business cases of AI/ML models development.

Process-wise errors can be thought of in the loan processing followed by deviation report preparation, ISDA preparation for large buy/sell deals, existing CRD reporting process followed by capital adequacy computation, option contract submission & rollback process, profit & loss identification and profit sensitivity report preparation in the cash market. In terms of product-wise innovations, the Bank is to evaluate existing products and see which models can be constructed for their enhancement using AI/ML-based models. Payments mechanism-wise product/account base enhancements can be thought of in existing AI-based tools. Analyses on internal/external forces, influencers, product rationalization, and user acceptance module assessments are a few of the lenses to be adopted for product innovation evaluations.

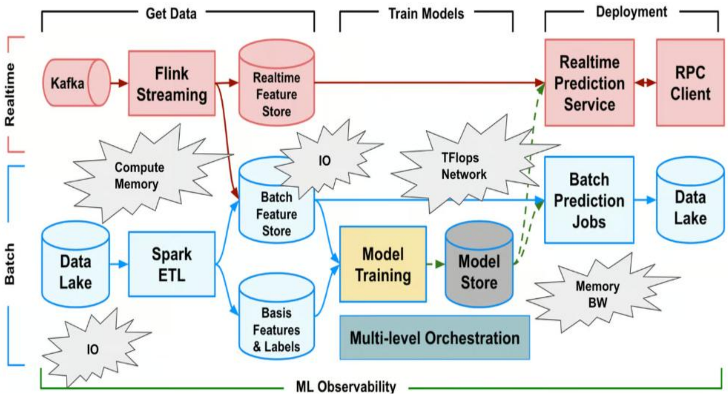

**Fig 3: AI/ML Infrastructure**

### 4.1. Cloud vs On-Premises Solutions

Cost is typically the biggest determining factor for choosing between a Cloud solution vs an On-Premises solution. The question of how much a Financial Institution, FI, is willing to spend on a new AI/ML solution (platform, tool, service or product) will steer all decision making. On-Premises solutions generally require heavier upfront costs due to the need to purchase the solution outright, or to make significant investments in privately maintained Infrastructure-as-a-Service (IaaS) solutions, such as computing power or cloud storage. Cloud solutions avoid heavy upfront costs through a SaaS model which typically incorporates lower monthly payments through subscription-based services. The upfront investment into an On-Premises solution can pay off in a variety of ways, including but not limited to: price-leadership, unique offerings, better customer experience, or lower operating overhead. Coupled with deal-slashed profit margins or a poor brand image Cloud solutions may be rendered unviable. Therefore, when deciding upon using a Cloud solution, an FI must accurately weigh the estimation of costs and returns prior to entering serious negotiations with Cloud providers.

Moving to Operating Costs, there are multiple factors to account for in weighing the total costs and potential viability of the entity's offering. Both In-House Component Infrastructure (IC) and Integration Infrastructure (II) will need to be planned out before heavy investments are made. Large cloud providers include many components necessary for AI/ML integration against additional monthly costs. Larger players are tied to their own proprietary ecosystems and may therefore increase costs for integration. Tying an institution into a proprietary cloud system may lock them into higher costs over time or entirely obfuscate the switching options they had pre-integration. On-Premise solutions would have these components integrated beforehand which would lower the overall infrastructure under operating costs. However, the need to purchase a license upfront creates an additional cost-differential in favor of cloud providers.

### 4.2. Scalability and Performance

When organizations invest in AI/ML-enabled infrastructures, they expect the new technology to be able to grow in capacity and improve quality as its usage increases. Scalability is the system's ability to increase performance when more data, users, or machines are added. Performance is the amount of useful work performed, usually compared to processing time; in addition, Business Value is important to consider as a resource in AI projects. Processing time has a well-defined meaning measured in seconds; however, business value is difficult to quantify because of multiple influencing cost and benefit factors. When measuring scalability and trying to include all relevant factors, it is almost impossible to conduct scientifically sound experiments and compare results. But as a proxy, we define scalability at the two levels data-wise and workforce-wise, while performance is divided into three subcategories: timing, business value, and resource usage. In addition, engineering quality factors directly influencing performance have to be analyzed: preprocessing parallelism, retraining only, batch size, subsetting size, and features to use.

When AI systems grow in horizontal capacity, it is important to understand how their processing performance increases. In other words, the question is whether any performance bottlenecks appear that lower the efficiency of the system. AI models can generally hardly be redesigned to run faster when more data are added, a phenomenon which can keep existing R&D: Training data pipelining, adding forecast input features, tuning hyper-parameters, and re-architecting models or employing training mechanisms all require costly ongoing expert attention on a major AI project. On the other hand, analysis and well-designed experiments exploring how the execution of models is affected by the infrastructure's expansion have to be conducted to sweat out the newly gained processing power for AI systems.

### 4.3. Data Security and Compliance

Although the adoption of AI/ML across the bank associates has accelerated rapidly, almost all the bank associates are still concerned about data security and compliance. In order to ease the process of aligning organization with regulations in relation to data security and usage while deploying AI/ML, two methods could be chosen. In the first scenario, MLOP tools are deployed but maintained only by the model owners across the organization. In this case, the adoption of tools is driven by the model owners' willingness to change their processes and adopt MLOPs. The bank associates that are slower on adoption can be assisted by more experienced model owners during this time. On the downside, every model owner may create their own homegrown procedure making it harder to scale and develop familiarity. On the other hand, a second scenario can be implemented wherein standard procedures with associated training are presented to the model owners. In that case, the model owners can start with minimum customization and have a head start on scaling the processes. This provides the opportunity to raise the baseline compliance level across the organization faster. Advanced capabilities can however lead to certain areas across the organization that are too advanced. Hence, it prevents the use of more specific advanced features of the tool by model owners that are really in need of them.

One well-known pitfall of collecting AI/ML architectures is the reaction of the developers, who typically feel the sum of the architectures is not representative enough of their architecture. Normal habits, like using customized functions, adapting a library, or omitting code sections when they do not contribute to the task at hand, often become excuses to refrain from adding this to the common collection of AI/ML code. Although educational approaches to get the model owners to appreciate the grander sharing goal have been undertaken, this effort cannot remove developers' need for privacy. Creating a library of AI/ML building blocks requires a greater level of insight into the code than most libraries normally require. Essential for the approach followed was the instant insight feedback and explanation it allows the model owners. With emphasis on trusted architecture inspection, privacy is ensured grid-based search and sampling is explained thoroughly and the search and overhead scales linearly.

## 5. Integrating AI/ML with Data Lakes

A modern enterprise-level bank can generate tens of terabytes or even hundreds of terabytes of structured and unstructured data. Twelve to fifteen years have gone by since the emergence and quick implementation of data lakes. The current company scenarios for data lakes can be boiled down to the following problems. First, a steadily increasing number of data sources and formats are being added, resulting in instantly overflowing data lakes even during data collection, importing, and storage procedures. The term data swamp, which denotes defunct data lakes, has sparked heated arguments once more. Second, several new significant data sources are accessible, and the capacity to handle various data types, such as videos, is somewhat absent. The challenge of generating a vessel for unleashing these types of data is urgent. Third, only traditional batch data jobs and dead-end aliases share processing platforms with data science teams and data engineers to manipulate various data in an unsatisfactory way. Fourth, there is a growing demand for handling on-demand real-time processing for key data to meet business and regulatory tops. Additionally, the traditional warehouses cannot support this functionality either.

Though two-thirds of the current mainstream technical solutions were probably developed based on data lakes about three years ago and have obtained a considerable market share by a few vendors, the previously mentioned difficulties varied for different banks. A well-crafted migration road from the data granulator to a six-layer AI/ML-enabled real-time bank, in which a high-throughput and low-latency data lake serves as primary data infrastructure, is offered, together with the dire challenges and pleasing keynote. Approximately ten AI/ML products will locate top-tier dimensions, including video-based on latency face checking and document recognition. They are running continuously in top executive dashboards after delivery, while about two dozen data science teams monitor these products and contribute new models and techniques to improve accuracy and efficiency.

### 5.1. Data Preparation and Processing

The preparation and processing of data is the first significant component in implementing AI/ML in banking infrastructure. Businesses create and acquire a variety of data as part of their daily operations. It is crucial to gather the raw data from many sources in order to build and train banking business models. Data from various areas of the business, such as consumer data, product data, credit analysis data, loan process data, and risk management data, are gathered. Text logs, metadata, and data from relational databases and NoSQL databases are all part of the raw data. Thus, constructing effective data connectors that allow for a seamless data connection into the system is necessary. In order to keep the implementation costs in check, it is essential to design an effective data selection strategy for data collection. The data must be transformed into a suitable structure for analysis and ML workflow before it can be used for any modeling and statistics. The quality of the data is considered throughout this phase more thoroughly since different types of variables may impact the result in different ways and because the quality standards may differ for each data type. The following details are involved in the data preparation and data integration. 1) In data preparation, the focus is on understanding the data and the gaps in the data. It is also checked if the data is useful for the analysis. Obtaining several statistical insights from the data using summary statistics is usually a preferable first step. 2) Quality analysis: Data fidelity is analyzed using techniques designed based on the rich knowledge of the process and various forms of domain knowledge. 3) Summarization: To make initial observations using visualization tools. 4) Data integration: Data from multiple sources are stained onto the same schema for further analysis. 5) De-duplication and conflict resolution: Ensure that the data is clean and of good quality as the input to the analysis.

## 5.2. Model Training and Deployment

Both on-device and cloud AI/ML models are required to process all instruments in near real-time. This necessitates the selection of appropriate deployment hardware in alignment with model output types, including outputs ranging from informative bubbles to raw time-series data. In particular, the commercial cloud platform is in charge of data transfer and model hosting across the firm. It executes inference requests in batches to take advantage of the hardware's computational efficiency. Meanwhile, the streaming data pipeline and real-time model inference serve as the on-device AI/ML layer to interface with dynamic datasets, while generating early warnings and alarms that trigger human intervention.

To prepare the cloud AI/ML service deployment, cloud environments and resource specifications are provisioned to facilitate the automated deployment of components other than the learning models, such as application programming interfaces (APIs) for incoming requests, data pre-processing and post-processing logics, and monitoring and alerting for hardware resource utilization. There is usually a significant application effort associated with AI/ML service deployment, regardless of model distribution frameworks. Therefore, the modularization and automated deployment of all service components is a crucial capability upon which the success of a firm's AI/ML strategy depends. In contrast, deploying streaming models presents a considerably higher challenge due to the complex onboard component variety and intricate interfaces with upstream streaming engines in terms of both message formats and data-driven processing control logic.

The cloud deployment team is composed of cloud product owners and developers from several teams, such as infrastructure management and development, model development, model conversion, and workbench development, all of whom need to collaborate closely. The role of the deployment team is to gather requirements, coordinate development and testing across different teams and components, and develop application logic around model outputs. Any misalignment or issue needs to be resolved promptly to ensure that a working cloud AI/ML service can be delivered within the two-week sprint cycle.

To expedite the on-device deployment of time-series models, it is recommended to adopt a simulated observation library of a model governance platform to record messages exchanged among components ahead of time and assist with model testing and quality evaluation. In addition, the model conversion and deployment of on-device models require frequent iteration as model versions are updated. Consequently, to minimize the burden of conversion and deployment, it is suggested to automate the workbench package generation and testing phases of the on-device code generation, and construct CI/CD pipelines to incentivize collaborative engagement of cloud and on-device developers.

**Equ 3 : AI ROI in Banking**

$$ROI = \frac{(B_s - B_o) - C_i}{C_i}$$

Where:

- $ROI$ = Return on investment from AI/ML infrastructure
- $B_s$ = Business success metrics with AI (revenue, efficiency gains)
- $B_o$ = Baseline business metrics without AI
- $C_i$ = Cost of AI infrastructure (initial + operational)

## 5.3. Real-Time Data Streaming

Real-time and continuous measurement of data is provided through streaming. Low-latency and high-cost streaming architecture is implemented through target processors and framework acquisition. Streaming architecture with data source connectors is integrated. Structured query language is used to visualize the analytics using an embedded server. AI/ML capabilities in institution banking infrastructure are utilized through data ingestion for strategy execution. Framework architecture for data ingestion is built along with embedded components for real-time data ingestion. Real-time data visualization using SQL queries is developed through software implementation. Requirements and architecture for technologies supporting broader, Piloting Environmental, Virtual agents, and AI pipelines are provided. Attendance information is extracted from video, audio, and presentations through multilingual automated speech recognition (ASR) and natural language processing (NLP) technologies. Usage of the program is tracked through server logs and metadata APIs. Summarization of video/audio is performed using neural-network-based techniques. Deep learning models are explored for emotion detection and facial expression estimation from video feeds. Voice analysis along with video is performed using CNN-RNN-based techniques for misbehavior cyberspace detection in a hybrid way using visual and linguistic features. Event detection for notification triggering and archiving is developed using augmented classifiers with visual attention and graph networks. Finite impulse response (FIR) processing for the detection of different types of audio data is implemented using deep learning models. Extraction of data entities and key-value pairs for cloud spreadsheets is performed with CNN-RNN architectures. Distribution of high-dimensional feature vectors for the appropriate quantile query approximation is developed using tree-based clustering with deep informatics. Differentiated retrieval of multimedia data with multimodal features is developed using cascade retrieval. AI/ML pipelines are deployed as serverless functions with attachable testing and validation modules to verify the functionality of other functions. Programming patterns for reusable and scalable unit operations for multimedia processing are developed at a high code abstraction level using streaming query language.

**6. Use Cases of AI/ML in Banking**

AI/ML-enabled infrastructure is increasingly being adopted by banking and financial technology firms to prove their viability in the extremely competitive financial and banking services sector. Based on current trends in AI, this technology is helping banks and financial companies improve customer experience and efficiency while reducing their overall costs. By consolidating massive volumes of both structured and unstructured data, AI acts as a long-term investment strategy for banks and financial institutions. AI helps automate numerous banking services such as self-service, data processing, and payment processing to give customers a personalized experience while cutting down costs and time. Banks and financial institutions are utilizing chatbots as part of their digital strategy to address daily customer inquiries and provide 24/7 customer service. AI ensures that applications sprint ahead with the ever-growing demand for online financial services and instant assistance. It helps banks and financial institutions extract real-time insights from massive datasets to closely monitor transactions, thereby reducing fraudulent transactions and ensuring customer security against phony transactions. AI is also being utilized to predict client behavior, understand product usage patterns, and better analyze customer experiences to improve overall service experience and product viability. AI streamlines operations by automating labor-intensive tasks. With fraud detection playing an important role in all banking services, regulators in the banking sector face the challenge of anticipating rogue operations conducted by third-party contractors for financial gain.

AI can better analyze customers via transaction history and block suspected fraud patterns, thereby improving hit ratios and reducing the burden on risk compliance teams. Established data flow standards and categorization ensure that data can be correctly used by key performance indicators or machine learning models. The traditional method requires the identification of eligible databases within a long time frame, which also happens to be the time for data to grow. Competitors with better techniques can take advantage of this and make answers come faster and better. AI may be used to evaluate this data, identify problematic data, perform risk prediction, timely tracking, and further determine if it fits the standards of bank transactions. It can warn of difficulties in bank transactions, prohibit inappropriate transactions in real-time, and significantly increase banks' risk management levels. AI may handle the loan process when banks lend.

**6.1. Fraud Detection**

Fraud detection is one of the most important application areas of AI in banks. Money laundering and fraudulent transactions might lead to huge penalties. Banks are increasingly spending more and more on upcoming AI-based systems, which help detect these abnormal events automatically without much human intervention. Financial frauds are one of the major threats faced to global economy development as most of the transactions are nowadays done digitally. It is one of the major cyber-crime affecting the financial concerns of every individual or organisation and hurting their well-being. Loss in billions of dollars every year is the result of the above activities. The target is to detect frauds during the customer transaction by the bank. There are numerous fraudulent ways of bank accounts, but an indicator is not created for them. Financial frauds are very complicated, thus remaining as open questions. Creation of an indicator for money laundering is a very hard, complex task because of the fact that each bank has different target records. At the present time, the two major commitments of the banking systems include gathering huge amounts of data and the ability of executing fast query procedures. The centralised ML methodology is the most powerful AI/ML-enabled infrastructure approach in banks, which is responsible for the uptake of financial frauds during customer transactions. The majority of the existing analysis and research are based and performed on the banking records given in the competitions, without inclusion of deep bank-asserted data. Since different banks have the diverse nature of fraudulent patterns, sharing data among them is not encouraged due to privacy concerns. In particular, it is risky for national security as it may reveal sensitive information about individuals. Thus, federated learning (FL) is exploited as a novel collaborative and confidential countermeasure. In the trustless, security-trustless environment, the robustness and stability of the FL system is verified mathematically. Generally, combining insights from different banks and financial institutions is an efficient approach against universal fraud schemes. However, it is hard for distinct banks or financial institutions to share sensitive data.

**6.2. Customer Segmentation**

In today's banking business landscape, the traditional approaches of segmentation have become inefficient in retaining customer relationships. The financial institutions must derive mechanisms using simpler methodology and technology to retain the correct cluster of loyal customers who generate maximum revenues. These institutions must focus on capturing both explicit and implicit data, as explicit data indicate the consumption of average daily balances, loan interest, time deposits, etc., which are important data points to analyze. By retaining the correct level of customer segmentation, the financial institution shall improve profits considerably by customizing product offerings according to the individual preferences of customers' datasets . Financial institutions constantly face the problem of better performance of existing customers. All traditional methods for reliable segmentation of customers are either hybrid with more than one methodology or consist of a collection of complex technologies with less focus on maintainability of systems. The purpose of the project is to evaluate the association of unsupervised machine learning algorithms in combination with RFM model to find the optimal number of customer segments on an ideal bank customers dataset with limited size. The banking sector is one of the innovative and fastest-growing sectors in Azerbaijan. As the customer base of the banking sector grows, traditional methods of customer segmentation would no longer be efficient. Instead, more sophisticated methods of segmentation are required to improve personalization of offers, products, and communication and to promote fairness. In combination with these models, newly deployed artificial intelligence methods can help to derive micro-segments of customers in a fast, automated, and cost-efficient manner. In an industry such as finance that deals with sensitive data, legal obligations for the implementation of AI in a responsible manner exist. Explainability and interpretability are important elements of responsible AI, yet adequate methods for effective explanation and interpretation of results are often lacking. This study addresses the problem of explaining and interpreting micro-segmentation by representation learning. A method relating to inverse regression and dynamical systems is introduced for the interpretation of relevant features and their influence on the outcome. Total customers EAP. Thus, in order to forecast better results using excellent machine learning with common models of per-class labels and to generate solutions regarding the correct number of classes. The banks need to be advised using this segmentation model not to be biased toward this dataset as there may exist bias towards less popular banks in this assessment during model building and verifying stage in order to better serve the existing set of customers with customized packages and proper model of services.


**Fig 4: Customer Segmentation Definition, Models, Analysis, Strategy and Examples**

### 6.3. Risk Assessment

Within the financial sector, more specifically in banking, machine learning is extensively used for modeling credit risks. It is believed that machine learning techniques combined with firm's data can surpass previous conventional statistical techniques in efficiency and performance in credit scoring and risk modeling. Risk assessment to the threat of loan defaulting is particularly crucial for banks especially in designing an accurate credit risk scoring model. A number of modeling techniques are explored and process efficiency and interpretability are considered. Additionally, proxy variables and those variables quantifying firm behaviour with machine learning techniques can improve the prediction ability of credit risk assessment models compared with only static financial ratios, default prediction models as a planning tool before granting a firm for a loan have been established. Utilities and techniques of machine learning techniques implemented for credit scoring are summarized along with discussions on challenges arise in implementation including interpretability of the prediction model, data deficiency subjects to prediction reasons. Banks need a risk prediction model which can estimate how likely an individual will default on his loans on a scale from 0 to 1.

Robust prediction models are critical in estimating the risk score of any bankable clients. The risk model can help a bank and its clients to understand what are the acceptable behaviours that will not harm their credit score. Pattern recognition, data mining and automated analytical modelling several derivatives of machine learning techniques. Applications of machine learning techniques and challenges and control in credit scoring and risk detection are reviewed. Risk modelling to the threat of loan defaulting is a prominent application of machine learning in the banking sector. Early identification of firms defaulting on loans is crucial for NPL management, earlier intervention is almost always accompanied by more effective remediation. To combat rising risks, classical statistical models have been augmented with complementing machine learning techniques. Application of machine learning to credit risk modelling is the nostalgia return of AI after decades of winter.

### 6.4. Personalized Banking Services

In all aspects of human life, intelligent services are anticipated to be ubiquitous. Along with high requirements for accuracy and dependability, the demand for personalized services is growing rapidly. Customers seek different financial products such as investment, insurance, and loans, which creates the need for personalized financial recommendations. The extraordinary growth of the internet and e-commerce has created a vast space for personalized recommendations for almost all products. The banking sector is witnessing phenomenal growth in online financial information access, with banks investing heavily to maximize revenues and the potential of artificial intelligence technology.

AI techniques in internet search engines, online recommendation systems, and targeted advertising are currently creating implicit information records and structured customer profiles, which can be effectively used for accurate and high-quality personalized banking services. The availability of low-cost competence for over 2 billion mobile phones, the existence of professionally skilled financial service providers, and rapid advancements in personal electronic consumer devices with great low-cost storage and computing capacity have all contributed to the current paradigms of personalized banking services across traditional banks and new third-party fintech companies. However, more advanced predictive mathematical learning algorithms which are scalable for big data, investigation of huge labor results, and information-cutting-edge hardware support for computer performance increases are required for the upgrade. In this condition, the prospects of AI/ML-enabled personalized banking services and possible AI technology use cases are explained.

The future of personalized banking services will use VL models that can construct sophisticated understanding and information conversion interfaces to sort new, unstructured, previously unseen multimedia-powered information. It can figure out complicated information along various lengthwise dependent phrases, while multi-funded reproduction and RL would permit behavior-level instantaneous dialogue and intelligent decisions over human-machine interfaces. Using this cloud-based, multi-source instruction mechanism which flexibly combines several short-term tasks information, third-party advisors will be available to enhance, monitor and tune traditional banks and financial market activities, including stock analysis, asset pricing, disease market probing, and chart authorization.

**7. Challenges in Implementing AI/ML Solutions**

The fundamental challenges to the local adoption of AI/ML remain many. Operations on data-sharing will require the ability to attack the underlying data-sharing issues, which are key enablers to use external data in any analytics problem. Privacy regulations need to follow AI development. What is status-quo knowledge, what is expected and easy to assess, and what is new and more difficult for the traditional role of regulators will also change. Concerns about overregulation and fragmentation, however, might not materialize if AI still remains proprietary and generally only the output is visible to most parties. In general, within "old" current ecosystems, there remain also hurdles and regulatory nagging about bias, transparency, algorithmic competence, and comparable performance of models for the current traditional process.

Designers of AI/ML solutions contend with general concerns related to quality, fairness, robustness, opacity, accountability, and often the compatibility of these with original or preceding IT environments, but there are also specific challenges in the banking context. Where possible, as a more generic recommendation, banking AI/ML implementations can be built modularly, with plug-and-play capability to avoid "big bang" changes in preceding systems and fears of bank-wide non-compatibility. The solutions should be as easy to use as software used outside the company and sufficiently documented. External parties should be no less engaged.

Quantitative and complex generative models can reproduce data as needed but are usually difficult to interpret in some shapes and forms, useless in some AI/ML settings, and extremely demanding on computing resources. Bayesian methods are interpretable, much easier on questions of robustness and compatibility, but still relatively newly investigated and on the market. Concerns about the quality and compatibility of the performance of the "old" problems solved with AI/ML should be approached with clear demonstrations including against possible alternatives on past performance. AI/ML solutions should be benchmarked on an appropriate portion of whole data not using selected realization examples and in as fully "scientific" way as possible.

**7.1. Data Quality Issues**

Infrastructure in banking is being redefined by AI/ML-enabled applications to streamline operations or user experience. Development of AI/ML applications in banking typically starts with x-ray ingestion. This requires digitization of enormous amounts of paper documentation; it essentially ends with the training and validation of explanatory models. These steps can easily take a year or more while management expertise is needed to correctly frame the application. Once these early steps are complete, scrubbing the application is often neglected unless a glaring flaw in performance becomes evident.

There are numerous reasons for possible data quality issues including existing processes not being equipped for the underlying system becoming more digital, but this chapter focuses on issues primarily from a modelling perspective. One of the major issues with banking-related AI/ML deployments is data quality. This can occur at all stages of ingestion, pre-processing, and deployment. A key, non-technical aspect of AI deployments is a mismatch between performance goals and expectations. The AI may be expected to perform at a level that exceeds modelling state of the art. A careful audit of how quality control leverages expertise in systems of record is necessary to avoid suboptimal performance.

While banks are aware of data quality issues in operational processes, there are few if any upstream controls on the quality of data fed into AI/ML systems. Many AI/ML systems are effectively X-ray ingestions, ungrounded exploratory models feeding black box systems. This debt is thoughtlessly passed to downstream users, as issues in poorer regions or those more immediately reacting to COVID-19 have illustrated. Even apart from the effects of human bias, the mere fact that data was input and ML application deployed does not assure useful performance.

**7.2. Talent Acquisition and Skills Gap**

A growing number of financial firms have developed their own AI-driven, analytics-enabled solutions to meet their needs in the areas of trading, sales, marketing, risk management, and compliance. However, there is still great pressure on firms to acquire AI/ML knowledge and skills, which tends to be restricted to rather few data scientists. Outsourcing AI/ML skills to consultancies or tech firms is a possible option, though training efforts also strongly rely on case studies to disseminate experience. Labour market research suggests that more efforts should be focused on extracting skill usage from reports and job listings and linking this information to labor market ontologies to allow for offering training options . With regards to ethics and bias implications, banking is a highly regulated sector where bias detection is a must. Bias audits are recommended, as well as clear documentation including pre-commitment specifications for ethical algorithms. For ML adoption tracking, more research should be conducted on the various levels of usage of AI/ML across the banks, as well as on impacts for conventional analytics approaches in tasks such as fraud modelling and OCR.

### 7.3. Change Management

Human life has become exceedingly complicated, and so has business. There can't be one person in the entire company possessing the knowledge and ability of all involved activities. Moreover, a person's capacity can't meet the future demand. With the explosive growth of unprecedented quantities of data, domain knowledge, availability of processing power, sophisticated algorithms, and application frameworks, the models' influence and significance have expanded rapidly, pushing them into virtually every business area. While the incorporation of the computationally advanced and sophisticated models into business processes is broadening rapidly, especially in the banking, financial service, and insurance (BFSI) sectors, the governance processes keeping the models' performance, compliance, and risk management in check are struggling to catch up. Prior industry-established standards aimed at simplifying and codifying the governance processes are now themselves a bottleneck. There is a vivid and big picture of self-regulating AI & ML systems in the banking industry that addresses this gap and aims to enable sustainable and on-par governance, risk management, and compliance processes.

The system-level approach provides novel capabilities and solution opportunities. It can develop customized and scalable solutions for robust AI systems and governance challenges. This allows improvements in performance, cost, complexity, time-to-develop, time-to-review, and the ability to scale out. This enables the robust operation of the models as well as providing a new path for model risk management and governance organizations. Key governance capabilities can be integrated in a unified, in-house framework with increased automation. The self-regulating AI system approach can provide a unified in-house governance framework as well as the ability to customize for different application types. It can enable the run-time management and mitigation of the models. The system-level approach aims to provide real-time monitoring and mitigation capabilities to effectively manage AI models in production. AI models will likely play a big role in the regulatory and governance functions in the near future.

## 8. Future Trends in AI/ML for Banking

Artificial Intelligence (AI) is believed to be one of the key technology trends for banks in the future. More banks will adopt technologies such as biometrics, automation, chatbots, crowdsourcing, machine learning and/or AI to enhance operational efficiency and customer service/product offerings. By using AI and/or machine learning, banks can make complex banking functions available to more customers with a faster turnaround time. However, banking regulators in different countries will still impose strict rules, compliance and reporting requirements to mitigate against higher operational risks. Moreover, some banks will partner with Fintechs in areas such as Blockchain, payment systems and automated lending services. Some banks will also explore Blockchain and smart contracts to adopt a new payment ecosystem as Fintechs adopt these new technologies. Automated customer service technologies and robocar would further change how banks interact with customers and further disintermediate banks and/or their pricing power. Already, customers could interact with a bank, update their account details, change their personal particulars and transfer funds using a chatbot from home or from anywhere rather than visiting a bank branch during customer service hours for such services. Robocar technology has already been deployed in certain countries. Customers could drive to a car park containing a fleet of robocar and specify the destination or the time to arrival using a mobile app and the robocar will drive automatically to pick them up from home or specified pick up point. There does not need to be any bus driver, customer officers or taxi drivers anymore. The public transport system will become much more efficient and cheaper. Will for a future banking environment where the car park will contain a fleet of robocar with each of them with a banking license from the monetary authorities. These robocar will handle the financial transactions from depository, credit card payments, remittance transactions, currency exchange to stock/currency/derivative/options trading on behalf of their owners. Bank staff no longer need to wear suits and tie to work, while those with only a General Studies degree will become qualified bank robocar drivers. AI technologies advances through massive software changes. AI will increasingly be driven by machine learning techniques to improve its accuracy in processing bank transactions. It will be able to self-learn from new customer behaviours, new transactions and transaction end results.

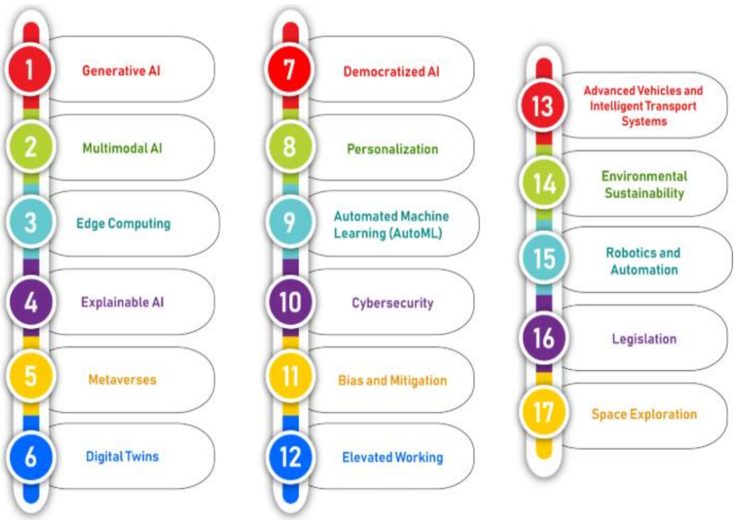


**Fig 5: Top Artificial and Machine Learning Trends in 2024**

**8.1. Ethical AI Practices**

Many advances in responsible artificial intelligence (AI) have concentrated on ethics committees, soft guidelines, general principles, or framework bills instead of implementing obligatory rules into hard law for responsible algorithmization. AI systems should not exhibit bias leading to discrimination concerning protected features, and there are strict requirements for the provision and documentation of a rectifying procedure or means. Regarding algorithmic systems for AI systems to recall ethical actions, the ethics governance service can query knowledge classes characterizing ethics in a database of ethics classes, formulate ethical spellings, and obtain a certified ethical reason. Such systems should be supported by the automated identification and monitoring of ethically relevant contexts. Automated creation and documentation of understandable explanations for algorithmic actions and the development of counterfactual explanations deserve further scrutiny as well. As mechanisms to comply with the right to a fair trial, request relevant data, and re-train AI systems are requested, the provision of informative and fair counterfactual interpretations of the impact of the decision on the decision candidate is demanded.

**8.2. Regulatory Considerations**

AI, Machine Learning, and Data Engineering have significant potential to shed light on a sector where data is abundant but not easy to interpret – the Banking and Financial Services sector. However, there are also inherent dangers in this situation rife with under-regulated data. A traditional, rules-based approach to regulation historically employed in the Banking sector seems ill-equipped to handle this situation. New types of regulatory and supervisory approaches are needed to keep up with these fast-moving developments. This paper discusses several relevant regulatory challenges raised by the AI/ML-enabled Infrastructure. It presents other technology-specific challenges, data challenges, and challenges raised by the high degree of data instrumentation and availability. Many of these challenges are interrelated. In identifying regulatory challenges, this paper is mostly agnostic about possible regulatory responses, but it notes potential activities and approaches where regulators may engage. Addressing the issues raised will make the emerging AI/ML-enabled Infrastructure in Banking safer and fairer.

Much of the research conducted on AI and AI regulation to date examines the AI debate and its regulatory challenges from various angles. These analyses cover the technical workings of AI, its social impact, the regulatory landscape and gaps, as well as philosophical issues. Some research emphasizes the role of the quantified self and its possible ramifications. Others explore data protection implications. A multitude of often-overlapping challenges can be distilled from these academic contributions, many of which can also be applied in the context of regulation in the Banking sector specifically. Regulation needs to catch up with fast-moving technology. Society has only just begun to grasp the ramifications of its increased digitization. Implementing fast-moving AI or global large language models in high-risk domains such as healthcare and the Banking sector raises urgent questions for which no clear answers yet exist. Regulations may need to be adjusted, and new laws might need to be written. It will be important not to stifle innovation too much, as the risks run by unregulated and unguarded self-driving cars demonstrate. The regulatory sandbox idea where, often under supervision, boundaries can be pushed and understood, and where if things go wrong nobody dies, may need to be explored.

Regulation of AI needs to become technology-neutral. Dynamic regulation, similar to how peer pressures governing financial markets operate, may provide better solutions than technology-specific laws. Regulation must be location- and institution-neutral. As regulation often lags behind innovation, regulators need to make their own use of AI, embedding them in the regulatory process. Regulatory and ethical concerns expressed against machine decision-making in an adversarial environment. AI must be explainable, interpretable and auditable. It generally cannot be reduced to a set of rules, nor must. The effects of capital laws or Basilea framework may be different depending on the institutional context. Blockchain is likely posed as a security challenge. While here to stay, uncertainty surrounds its long-term impact on banks and traditional finance. Roadblocks regarding self-hosting are likely and should prepare regulators.

**8.3. AI-Driven Customer Experiences**

AI is changing the banking sector. Banks are using AI-driven data to offer the same, if not better, personalized and consistent experiences as giants like Apple. Facebook and Amazon have risen to dominate the financial industry by delivering unforgettable, hyper-personalized, and relevant experiences. By feeding the right data to AI, banks can create a better overall experience. AI is not just another technology; it's a massive architectural shift with huge implications. Understanding this shift allows banks to strategize for the future.

Consider what is meant by an "experience" in banking. At its heart lies a financial transaction, with various preconditions and postconditions that shape how it occurs. Banking experiences today may start with watching a review video on your phone, followed by online research, a conversation with friends, interacting with a chatbot online, analysis of dynamically generated advertisements, comparison on price-comparing websites, a meeting with a personal banker, and a quick visit to the ATM. New financial products arrive at the speed of a tweet from an influential expert. The time gap between product release and "how can I buy it" shrinks to less than an hour. Each individual experience can involve a dozen or so stakeholder firms, brands, and actors. Banks need to be at the center of the action and available at any touchpoint.

To meet the need for a frictionless experience, banks are leveraging AI. For nearly two decades, the wealth management arms of major banks have developed Middleware screen-scraping bots to consolidate data from hundreds of disparate sources in real time. Today, hyper-personalized AI is being embedded in cyber assistants that compose email replies, audit and correct chatbot policy responses, and provide users with tailor-made experiences across all brands. Banking experiences are becoming holistic; the quality of a single transaction experience can influence retention by up to 70%. Onboarding two products simultaneously can defer multiple times for future visits to the bank.

AI is helping banks orchestrate and offer holistic experiences to customers. To defuse the timing mismatch between product readiness and customer experience, banks first identify "early adopters" and present them with an organized experience and new product. The finance AI engine models each customer's real-time needs using 10 models across 5000+ input dimensions.

It then identifies one of over 540,000 “only once” events to lure them into a product-specific experience. Once a touchpoint is known, the experience normally comprises 7 to 8 tasks (steps) across 2 channels, displayed on 15 different screens over 45 minutes. Each moment can be tailored to customer profiles, learning preferences, and goals.

## 9. Case Studies of Successful Implementations

There are several case studies of successful implementations of infrastructure in Banking through AI/ML. Artificial intelligence (AI) has emerged as the most promising and rapidly developing technology in the world today. AI technology holds great potential for many enterprises in the banking sector to optimize business performance, enhance security surveillance, and mitigate reputational risks. AI is a prerequisite for stakeholders to become strategic, innovative, imaginative, nimble, and adaptable organizations. Indian Banking needs to be redefined to accommodate the implementation of banking AI technologies. AI has helped Banks to tackle data analysis challenges, voice and facial recognition, and clean data revaluation. AI in Banking increases business effectiveness and efficiency, enabling the banking sector to innovate smart strategies by leveraging AI technologies to garner the business realm  The study presented here discusses the evolution and types of AI, applicability in Banking, implementation applicability challenges, case study banks, business functionalities, input format for deployment, insights on technologies, and AI products.

This case study is based on the AI-based Virtual Assistant of the State Bank of India-Smart Interactive Assistant (SBI-SIA). AI is rapidly reshaping technology, including Banking, like never before, leading to innovative implementation. Indian banks are leveraging futuristic technologies like Artificial Intelligence, Machine Learning, the Internet of Things, and Blockchain to cater to the needs of new-age clientele and to scale up their growth potential. The case study explains how AI-based products are positioned in the Banking ecosystem through screening, advisory, bilateral, negotiation, and back-office assistance activities. With opportunities come a class of new challenges and threats to which the organizations need to be aware of, including malicious intrusion of types of digital communication and vulnerability in soft knowledge, lacuna in regulation, and uncertainty in controlling AI program learning by deep learning.

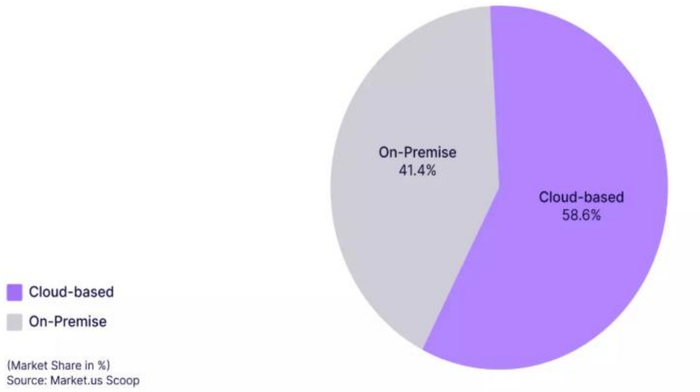


**Fig 6: Data Lake Architecture for Unified Data Analytics Platform**

### 9.1. Leading Banks’ AI Strategies

Bank of America and Citigroup have invested heavily in AI infrastructure, tools, and experts. Bank of America applies AI enthusiastically across its businesses, from risk management principles focusing on ESG factors to a virtual assistant. Citibank is exploring AI applications across almost all its businesses and functions, including compliance and risk, and finance and reporting. It has an engineering team dedicated to AI and machine learning, and is working with a start-up to create a small language-based model integrated with its ESG data and workflows. HDFC Bank is tapping into AI for elements of customer operations and to automate screening and decisions for lending. Because of its rapid growth, this bank may have a higher potential for AI-enhanced efficiencies relating to its ESG strategies, albeit with the usual concerns over the data quality and scope of training and on-hold changes. HSBC has launched an AI-powered index that tracks companies expected to benefit from improving ESG risk. A parent ranking developed by tracing the origin, or legal domicile, of corporate equity connections is known as the parent ranking. However, the parent ranking approach enables many similar companies to appear in all four corners of the world, leading to a data exhaust problem. JP Morgan Chase collaborates to integrate data-driven materiality into its ESG integration process, utilizing AI-driven technology to analyze reams of unstructured data to identify the ESG issues that are pertinent to all companies across sectors and geographies. Parallel efforts have been made to incorporate firm-centric intelligence on greenhouse gas emissions in SNC-Lavalin Group and First Nations ETF. Morgan Stanley uses AI applications such as natural voice recognition to convert conference calls and online news into data points, and to achieve patience rate change detection for sustainable investing and enhancing the accuracy of companies’ ESG metrics. NatWest launched Esme, an AI-powered solution to enhance companies’ ESG data and allocate capital to sustainable development for SMEs.

### 9.2. Lessons Learned from Failures

The banking industry is currently undergoing massive technological changes, transitioning from information technology (IT) to artificial intelligence (AI) and blockchain technology. However, due to the scale and complexity of traditional banks, the process is neither fast nor easy. During the transformation, it is difficult for banks to achieve effective management, and AI and machine learning (ML) are expected to provide powerful capabilities for management. Many large banks use AI/ML capability as one of their IT strategies, hoping to change the current state of disintegration in traditional banking structure. However, this capability has not been fully utilized in management practice. In fact, many banking firms have encountered obstacles or even failure, but so far no systematic studies have been conducted on failed cases in AI/ML-enabled infrastructure establishment. Therefore, analysis of failed cases is essential for providing insights.

How to use AI/ML capability to build infrastructure in banking firms is currently a challenge for scholars and practitioners. Compared with other industries, banking is highly regulated, and these regulations create winners and losers among stakeholders. Often, regulations restrict the design and structure of AI/ML-enabled infrastructure. Furthermore, banking firms dealing with finance and AI/ML capability invocation have added uncertainties exacerbated by model black-box and novel risks. More importantly, change management in traditional and established firms is always a challenge. In this increasingly uncertain environment, the transition of the organizational information system, especially software system, structure and culture, and business model is unlikely to be smooth. It is anticipated that such difficulties will result in complications and failures, and the examination and prescription of success cases are elusive, given that there are few successful cases and they usually include trade secrets.

Nevertheless, failures in AI/ML-enabled infrastructure establishment are often publicly examined. The banking and AI industries are highly concerned about failed firms, since each exam generates hundreds of media reports. Nevertheless, a systematic study on failed cases is absent. Knowledge gained from studying failures is vital. It helps organizations and nations avoid losses due to immature technologies and lose competitiveness in the following technical wave . Hence, studying failure cases in AI/ML capability-based banking infrastructure design is essential to provide insights and lessen the digital divide and data desert between developed and developing countries.

## 10. Conclusion

In conclusion, financial institutions can gain insights into AI/ML-enabled infrastructure and FinTech in their banking initiatives through the literature reviewed that focuses on the relevant topics of AI, ML, data infrastructure, application infrastructure, financial innovations, strategy, and business model innovation. The definitions, frameworks, and approaches provided can help in the development of this knowledge domain, which spans across multiple disciplines, with the goal of conducting more empirical studies to enhance our understanding of such important tools in the banking industry. In addition, regulatory and security issues, financial institutions' responses to the COVID-19 pandemic, and the public perception of the usage of AI in finance can be other interesting topics for further research. Banks have invested heavily and seek to use AI technology to intensify their competitive advantages, and have different AI functionalities that serve ALL bank business lines. It indicates that social media customer service, advisor chatbots, and accelerator applications targeting particular demographics are new trends in AI chatbots in wholesale banking. AI can improve compliance processes and transaction and client monitoring, but obtaining data and changing processes across customer touch points also raise challenges. AI is promising mainly in wealth management. Further studies into risk-related topics such as valuations, defaults, and risk scoring indicators would be referred to as valuable. Centralized versus localized views managing AI exponentially increase the difficulty of implementation and adoption; still, deeper studies with more databases would reveal interesting findings.

### 10.1 Future Trends

With the increasing trend of digitization and especially the wide application of Artificial Intelligence/Machine Learning in various aspects of life, banking gained no exception either. The evolution from traditional banking towards more customer-friendly options such as mobile banking, online banking, and collaborative banking paved the route for a number of FinTech and AI-based offerings in the banking ecosystem. AI/ML systems backed by natural language processing, self-learning engines, big data management etc., are considered the new-age analytics techno-systems and are thought to be a key to revolutionizing banking as they take a more data-driven approach. AI and ML technologies have already established their use cases in risk management, fraud detection, designing financial instruments, pricing risk, KYC processes etc. Apart from these applications in the banking domain, AI/ML-enabled systems are also widely explored for creating innovative trading algorithms in stock markets.

AI/ML-enabled infrastructure consists of data lake architecture with connections to the source systems such as the core banking systems, customer information repositories, transaction management systems, etc. Making credit decisions led by AI/ML models is only the tip of the iceberg. Banks can build an entire suite of model-based solutions for fraud detection, customer retention, cross-selling, upselling, etc. with AI and ML-based systems and can reinvent themselves as purely data-led organizations. Customer and transaction data, which can be record-wise structured as historical transactions, account balances, and customer operations are crucial for designing such model-based solutions. Other data sources, which can also be semi-structured, include records of customer complaints, past credit defaulter's case studies, survey feedbacks, call centre logs, etc. such non-structured data pose a need for integrating text mining, natural language processing, and summarization techniques in the overall ML-based model building.

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