Modernizing Core Banking Infrastructure: The Role of AI/ML in Transforming IT Services

Bharath Somu,

Architect-I, ORCID ID: 0009-0008-6556-7848

Article Info
Page Number:16928 - 16960
Publication Issue:
Vol 71 No. 4 (2022)

Abstract

Modernizing Core Banking Infrastructure: The Role of AI/ML in Transforming IT Services In today's rapidly evolving digital landscape, retail banks are increasingly focused on modernizing their core banking infrastructure. As part of this effort, financial institutions are moving forward with a component-based architecture and interoperability layer, supported by data lake and new-age analytical frameworks [1]. Adopting a component-based architecture framework mitigates the high cost of technology replacement and effectively handles scalability and security issues. A component-based architecture with an interoperability layer facilitates easy integration with new outside components, offers rapid access to real-time data, and supports the utilization of new-age analytics frameworks. Significant investments are being made to improve customer relationships, bolster risk frameworks, and optimize governance, budgeting, and strategic planning. Along with the component-based architecture, financial institutions are amassing data lakes that provide centralized storage for unified data management and retail banking analytics. A new-age data science and analytics framework will help parse large volumes of data spread across disparate, multi-structured data sources into structured data formats, allowing organizations to glean actionable business insights [2]. Banks can strategically use these insights, thereby significantly improving customer experience and engagement, agency performance, asset quality, fraud management, and other key operational and business performance metrics. This paper summarizes the role that AI/ML can play in retail banking transformation through modernization of the IT services domain. The objective is to lay out specific AI/ML capabilities that can be harnessed to create a future-ready core banking architecture, either by making process/technology investments or by collaborating with newer, niche solution providers.

Over the past three decades or so, the banking industry has seen several disruptive technology shifts. The journey began with the development of defensive technology shields to protect banks from ravenous competitors; the emergence of the internet age technology paradigm, in which banks were challenged to upgrade their technological infrastructure; the introduction of innovative customer-facing tab-based visualizations and interactivity, which obligated banks to significantly transform their offerings; and the mainstreaming of smart phones, which necessitated a paradigm change in consumer engagement. The most recent disruption to engulf the industry, 'fintech', is fundamentally altering core banking technology, services, and operating models, ultimately threatening banks' relevance. In response, banks are investing massively in IT services and technology to evolve beyond traditional high-margin service providers toward digital transparency, extensibility, and scalability with a move to an 'API economy', digital rating platforms, cloud-based third-party innovation ecosystems. Banks need to respond to disruptive external threats by building a resilient, agile, cohesive, and responsive core banking engine-as-a-service operating infrastructure and structural deposit collection, risk management, and profitability-optimizing architectures. In this new core banking technology and services landscape, banks will find it difficult to remain relevant. Cognitive AI will be necessary to extract quality insight from the vast amounts of data generated by business processes, consumer engagement, risk modeling, regulation, and compliance. Native AI, a part of the core banking service structure, will need to be a differentiator offering real-time insights during consumer engagement, risk detection, and evolving the compliance architecture. AI-enabled IT Ecosystems, powered by blockchain technology, will need to establish credibility across domains, geographies, and industries to be successful in creating pre-emptive, quality insight and oversight.

Keywords: Core Banking, Digital Transformation, AI in Banking, Machine Learning, IT Modernization, Banking Automation, Predictive Analytics, Customer Experience, Legacy System Upgrade, Intelligent Automation, Fraud Detection, Data-Driven Banking, Cloud Computing, FinTech Integration, Real-Time Processing, Risk Management, AI-Powered Decision Making, Operational Efficiency, Smart Banking Solutions, Cybersecurity in Banking

Article History:
Article Received: *15 October 2022*
Revised: *24 November 2022*
Accepted: *18 December 2022*

1. Introduction

Banking has undergone phenomenally dramatic and deep-seated change historically, and presently information technology is the call of the day. Banks, by its nature, are information-oriented organizations. Therefore, to get rich dividends on their primary business, i.e., accepting deposits, lending investment, and transferring value, banks are constantly collecting and storing digitalized data. Information and Intelligence gathering, storing, and dissemination capability should be improved significantly in this new era of electronic banking. Artificial Intelligence (AI) can help to get a strategic advantage and achieve a major competitive edge. Banks worldwide have begun active investigation and experimentation in this field and have already seen some AI-based rewards. Creative and intelligent decisions are rendered instantly using customer data, deposit, and loan history.

Fig 1: Top Core Banking Software

For example, automatic decision banks in lending institutions operate unsettled payments and overdue clients. Intelligent virtual agents besides ATM would save millions of human hours and extend service reach at odd hours with the emergence of highly advanced speech recognition and natural language processing. Mustered knowledge from highly confidential information through examining thousands of documents visually, structured and unstructured data, non-cohesive data gathering will result in a major directional advantage. Today, with more comprehensive procedural knowledge being digitalized, machine learning, knowledge management systems, and natural language comprehension systems would be beneficial in analyzing their internal functioning and information producing better decisions and expediting response time with the added benefit of achieving zero downtime [1].

Knowledge coding in expert systems will provide intelligent cockpit viewing to personnel at all levels. Graphics and visual display of records would result in better comprehension. AI would revive investments in unstructured and unprofessional documents stored due to the absence of machines and mechanisms for assimilation and authentic substantiations. Mining cases of fraud, risk occurrences, and trend detection with long-term patient effort in domestic and overseas banks might also be reaped benefits with AI support. Even after redefining the bank's business objectives, enhanced networking, and larger investment in the latest technology, banks would have to overcome implementing real-time data warehousing products and services without disruption along with the intrinsic cultural shift.

2. Overview of Core Banking Systems

With the establishment and development of the banking system in the Republic of Macedonia, a core banking system has been implemented in most of the banks, for processing deposit transactions in a timely manner and generating different reports for these transactions [3]. However, because the core banking system is not designed to deal with information not related to the deposits and deposit transactions, the information about all other transaction flows in the branches are maintained outside the core banking system in different unsupported external software. These software are developed using different programming languages in relation to the one used for the core banking system, and are not enterprise solutions, leading to problems such as duplication of data, impossibility to maintain the integrity of the data, lack of flexibility and scalability, difficulty of exchange and users access to data, no segmentation of a complex process in a simpler one, unused resources, high operational costs, high investments to overcome issues in the existing system, and poor cooperation with third party providers [4]. In order to transform the banking information system (BIS) to respond to the present business requirements and to provide synergy between different software, the existing deposit information system is transformed into high-performance software using custom-made tiered Java EE web-based enterprise solution, along with machine learning and artificial intelligence features for prediction of deposit transactions approval, introducing flexibility and compatibility with other third party software.

The analysis phase covered the current situation of the BIS, core banking system and possible solutions for it. It was concluded that the insufficient flexibility of the existing system posed the biggest issue, followed by lack of hardware resources and high maintenance costs. From there, it was determined that, in order to eliminate all issues, the system should be replaced with a custom-made one, built as a tiered Java EE web-based enterprise solution. The installation of the target system was planned to be completed in stages, in order to eliminate computational requirements and support most of the current operations. In parallel, some independent programs (internal and third party ones) for elimination of some current functions were built. This program replaced the existing information system with a newly built one in a period of less than a year. The selected way of modernization of the current system proved to be extremely successful. Knowledge transfer from the outside team to the internal executors and success of the training process contributed to the reduction of effort regarding implementing special training forms from the bank. Everything implemented in the deposit transactions approval process turned out to be applicable in later stages. This led to a correctness assurance of processing savings accounts opening transactions.

3. Challenges in Traditional Banking Infrastructure

Modern banking systems have, over the years, moved from an initial interest in computing, which consisted mostly in batch data management capabilities, archiving, and basic accounting of information, to a dominance of computing in the way of doing banking. New generation of banking applications developed in the last 10 years are lagging behind the pace of business and technology innovation. Traditional IT restructuring attempts in banking have focused largely on modernizing the underlying stack of technology on which banking applications are hosted and run. More recently, a new class of bank-wide enterprise architectures has emerged, based on the principle of designing, implementing and deploying flexible contention-based processes that manage change and information propagation in the banking business. In this class of solutions, business processes are implemented as algebraic equations in a functional notation. However, efforts to refresh legacy banking applications have failed for a variety of technical and organizational reasons with deployment often requiring deep restructuring of business unit organizations. Other set of solutions, which adopt an industrialized approach to creating and running banking applications, are based on the principle of exchanging-depth computational pre-integration of business processes at different functional, organizational and physical scales. During that effort the banking core reactivity instead of selecting functional modules to bolt on the existing core, offering mechanism to create a rapid and short-lived banking services in the chaos of a fast innovation. Not only must banks rethink existing propositions, but they must also question fundamental data realities. Shared processors such as graphics cards, with many cores, have recently enabled greater density of compute units. Stacked sensors, memory and processors chip, have let the financial industry interleave three-dimensional chips and narrow-band signal optical bundles to meet new high-frequency trading information latencies. These advances in technology reshape the possibilities of banking IT enabling banking services to go from decades to seconds. There exists a singularity in IT/information processing where, using very large number of chips at extremely low latencies, banks could regain dominance against too-big to fail tech giants. This computing acceleration however comes at the price of much greater uncertainty of service and firm.

4. The Emergence of AI and ML in Banking

The emergence of AI and ML technologies within the banking industry is in conjunction with the digital transformation of banks, the emergence of FinTech companies, and the financial services opening up to the third parties. In order to keep and expand customer deposits and business, banks have rapidly developed their apps in the past years in hope to become the bank for consumers time-to-time. However, competition is higher than it has ever been. In the continuous battle for gaining tapping demand and making the users stay, users' increasing needs for better UX have been implied by the app engagement metrics. Particularly in China, over 50% of banking app users keep "uninstall/off" for the app within one month of downloading it, reflecting up the importance for user engagement and retention hence downstream profitability [1]. The constantly upgraded onboard processes, lighter weight experiences, and product rich content are strategies that incumbent banks have tried to lift UX, among which personalized contents and experiences have managed to take a mark. Controlling and enhancing user experience (UX) have become an inevitable task for all the banks and financial technology companies worldwide [5]. The dominance of UX has been emphasized in discussions concerning the App engagement and retention hence the market share. Non-prominent banking app UX has been pointed out since global banks started to widen their app gardens, while with the crawling commercialization pressure, product orientation and therefore UX have become the core battleground for banking companies to attract consumer deposits and retain consumers, hence acquiring sustainable revenues. UX refers to how a person feels when interfacing with a system. Thereby it becomes a challenging task on how to quantitatively analyze UX, hence the UX-related data ahead of a banking company app improvement. In consideration of the privacy and security issue, conventional analytics have been dominant and widely preferred, whereas there remains a blind spot for actionable insights from app UX data on the bank app, since in perception UID data such as session ID, access time, lat/lng are widely configured to ensure users' privacy.

5. AI/ML Technologies and Their Applications

AI and machine learning (ML) are already large parts of many industries, and they're increasingly being applied in banking applications. Banks and other financial institutions use ML to improve risk management, fraud detection, compliance, and customer experience. AI is still a relatively newly-emerging area of tech, but it's already transforming IT services in the banking and financial services sector. A primary advantage of using AI/ML technologies is that they allow huge amounts of complex data to be analyzed to rapidly produce actionable insights in response.

ML is now a large part of many industries, from retail to tech to telecommunications, as ML-analyzed data can become competitive advantages. With growing amounts of business data being made available every day, a huge pool of untapped datasets is now available for smarter financial analytics. Banks must take advantage of their data and invest heavily to modernize their IT infrastructures to stay relevant and ahead of potential industry disruptors and challenger banks. AI/ML technologies afford banks the ability to upgrade their services by automating their data analysis processes, enabling quick adaptability to changes in the real world. Using AI/ML technologies for predictive modeling can mitigate traditional service risks.

$$I_L = f(C_L, D_L, E_L)$$

Eqn.1:Legacy Infrastructure State Equation

- I_L = Legacy infrastructure performance
- C_L = Legacy computing capacity
- D_L = Data throughput in legacy systems
- E_L = Operational efficiency in legacy systems

Traditional financial data is fundamentally different from structured data like sales transaction records. Banking data can be unstructured or semi-structured, such as customer communications, emails, or messages. Banks have also historically lagged behind industries like retail and tech in data processing, and as such, their access to AI/ML visualization and data science tools is also limited. Nevertheless, banks sit atop some of the largest datasets available, and they have unique information on market segmentations and securities for hedge fund managers and private equity. Banks also have huge investments in data engineering and data acquisition, having hoarded masses of data, leading to an expectation that they should be employing AI/ML for maximal ROI and risk minimization [1].

5.1. Machine Learning Algorithms The banking sector is adopting a developing fad of AI/ML due to the rapid growth of big data in recent years. Accordingly, AI/ML technology has a broad application prospect in many fields. As a result, research on AI/ML algorithms and applications in finance and banking has been amplified over the past decades. However, up until now, there has been no comprehensive survey of AI/ML algorithms in banking applications. This survey classifies the AI/ML technologies used in banking into three categories: supervised learning, unsupervised learning, and other AI/ML algorithms. After that, these AI/ML technologies are summarized for 15 representative banking applications in different categories, including credit-related applications, fraud detection applications, risk-related applications, bank management and marketing applications, text analysis application, and control-related applications [1].

Before the introduction of AI/ML in banking applications, a short overview of the banking industry structure, data in the field of banking, and data precursors for their ML predictive models is presented [6]. The introduction is followed by a survey of various mature and popular supervised ML algorithms, unsupervised ML algorithms, and traditional AI modeling tools that can also be used in banking. This survey presents basic concepts, data setups, advantages, and challenges. At the end of each subsection, an empirical application case study of the AI/ML algorithm in question is showcased through explaining the research objectives, methodology, data, and results and implications. The text aims to provide readers with a good understanding of the current state-of-the-art AI/ML techniques and how they have been applied in the banking sector.

After decades of fast development, the banking industry has a significant impact on society and people's life with a large quality of services. The banking industry provides trustworthy and convenient financial services that enable individuals and institutions to save and invest. Yet, the world has changed dramatically since the 1980s, which has introduced unprecedented challenges to banks. In the dawn of the 21st century, banks were the first blamed for the financial crisis when the stock market collapsed to an unprecedented low. The wide proliferation and fast growth of the Internet and the introduction of the cloud improved living standards and productivity worldwide but also led to disruptions in life and even political unrest. To catch up with such fierce competition and obviate dilemmas, banks are now focusing on AI-related products and services.

5.2. Natural Language Processing Natural language processing (NLP) enables the mechanical understanding and treatment of natural language. The extraction of information from unstructured data is crucial, offering a wealth of knowledge in terms of state indicators and parameters. However, among different data sources, unstructured data is rarely used as sapient measures in process automation. NLP techniques enable the transformation of unstructured into structured data and help detect incipient risk indicators in financial documents [7]. Recent developments in the field of NLP provide highly sophisticated and scalable models as hyperparameters for various tasks using different embedding schemes. These models can be utilized in banking especially to gain insights about picks and falls, ectodermic mechanisms for valuation model inspections, disclosures, pricing model specification, contract structuring or compliance aspects in AML, risk, or consumer lending.

To foster the spirit of sharing research ideas and discussion, this section elaborates on related studies and sheds light on the state of affairs in two interconnected research areas: NLP applications in banking and the emergent field of multimodal document analytics. The area of applications covers the need for insights through NLP applications and their state in the banking domain. On a more theoretical level, the limitations of current document analytics are identified. The vision and research agenda are introduced concluding with discussing its relevant implications.

In the business context, there is great demand for conventional data handling methods, largely developed in ML, AI and NLP fields. The banking sector has vast amounts of data that are often badly structured, such as contracts, correspondence, reports, assessments, industrial documents, etc. Shared feature spaces or global representations from different modalities ease coherence tasks needing insights from the entire document, which is particularly relevant in the financial sector. Given the importance and the currently poor handling of textual and visual data in the banking sector, it is argued that multidisciplinary research in this area has to be done in close collaboration with the banking domain.

5.3. Robotic Process Automation In recent years, Robotic Process Automation has been implemented across multiple enterprises in diverse areas such as accounting, auditing, human resources, banking, public administration and other sectors, where they have successfully automated repetitive and tedious tasks across many applications thus providing organizations a cost effective, scalable and efficient approach to automating processes. RPA has been leveraged by organizations for its lightweight approach and fast implementation. It allows automation of screen-based applications that are not web-based, providing a broader set of applications to automate, and easily integrates with existing IT landscape and does not affect the underlying systems. With well-planned Robotic Process Automation, businesses can achieve reduction in processing time (sometimes dramatically), operational cost savings, faster return on investment (sometimes in months), reduction in operational risk and compliance breaches [8].

RPAs have been championed as the primary driver of the digital transformation wave, starting with the advent of GUI automation tools. In low scale deployments and scripted, controlled environments, RPAs worked smoothly providing the first experience with widespread implementation of automation in enterprises. Hence the attention of researchers has turned into automatically identifying RPA-eligible tasks as a key enabler in RPA's success, where solutions rely on supervised machine learning and a small ratio of the domain knowledge in the form of rules. As the deployment of RPAs scaled up across the world, complexities arose such as operating in the wild web application, semantic changes in input data, and requirements of improved knowledge management [9]. RPAs were unable to fulfill business needs beyond the initial simple implementations, and thus when combined with other advancements in AI, they prompted the demand for new research directions and contributed to the hype around Intelligent Business Process Automation.

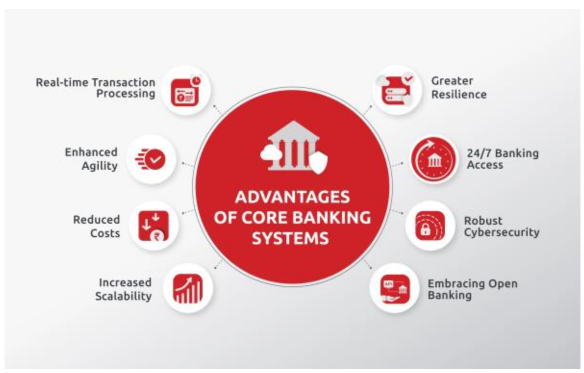


Fig 2: Modern Core Banking Solutions

A class of solutions typically referred to as Business Process Automation solutions could take a step further from RPAs by automating the decision making in business process. The success is again tied to pre-existing activity event logs. Still machine learning bottlenecks remain; for example, deep learning models were trained to model business processes from event logs, one of the main components needed for more advanced automation. As automation of more domains is sought, interest in natural language processing advancements has dramatically increased. Enterprise chatbots are now considered capable of performing many day-to-day routine, thus more tedious and labor-intensive tasks on behalf of their human users. Starting from simple question answering customer support bots, enterprise chatbots have evolved towards fully autonomous digital assistants.

6. Benefits of AI/ML in Core Banking

The banking industry is experiencing a wave of digitalization, with consumer preferences shifting towards online banking services and banking processes becoming more automated. Worldwide acceptance of technology has ushered in a new era referred to as “FinTech”, which has been driven by operators who recognized that current banking operations are cyclical [1]. The banking mechanization began with an offline single-processing system and has evolved into a multi-processing method consisting of Ingress Processing Units, Auxiliary Processing Units, and Egress Processing Units. Modernization continues to occur at all levels of data processing. Some financial services have been modeled already, including bank assurance, financing, trading, investment, and wealth management. New mechanisms for sharing forecasts occasionally need to be developed real-time, and the system should be designed to fulfill such requests quickly and efficiently at scale.

However, the financial system is under constant attack from nations, oligarchs, terrorist groups, hacktivists, aggregate stocks, Anons, and spammers, and it is uncertain whether AI can help in defense. Bank transaction links are complicated, with an accumulation of custodians that range from the initiating party up to the top custodians who handle the service network. The bank usually interacts with up to 30 custodians, as measured by a real world bank. An Agent system has been proposed to facilitate interactions over the custodians by distributing potential requests. It is reasonable to expect that with real-time simulations, risks can be assessed and team compositions can be suggested. A second AI-based Mechanism has been created to cope with sensor data streams.

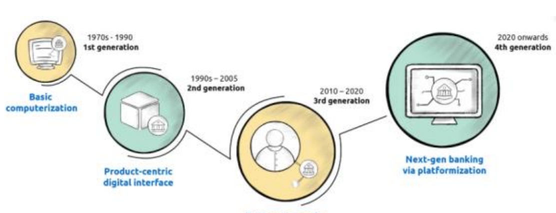
Financial risk management is in an early reform stage where some companies are starting to explore ATS for the whole valuation and risk management basis [2]. Nevertheless, inputs are required from professionals, and while the technologies exist, they are not as extensively deployed. Client due diligence is a process with worldwide standards that is semi-automated already. Technologies already cover many aspects, and there seems to be no need for further developments. Moreover, consultations rely on proprietary knowledge that cannot be replaced easily. Using AI/DL for heart tax has been implemented with great success, including fully automated and human-in-the-loop approaches to get the best of the two worlds. However, good models exist that do detect fruits like a footprint in spite of the noise. Systems have been implemented to control that with legal provenance on requests that could alert the authorities globally.

6.1. Enhanced Customer Experience Natural language processing (NLP) has undergone significant advancements recently, enabling more natural human-computer conversations. It helps process huge amounts of unstructured data in text or voice, which is most of today's data. These capabilities are essential for virtual assistants, data analytics, and big data systems, making banking more intelligent. As virtual assistants evolve in their human-similar capabilities, they will serve as knowledge engines for customers and banks, enhancing understanding and meaning of financial services.

In many regions, digital conversations are becoming the main communication between financial institutions and customers. They provide more personalized, seamless, effective, and immediate services compared to mobile banking apps and traditional phone calls. With this change, customers can enjoy the true 24/7 mobilization of financial services from any location on any digital device ([1]). However, such large-scale and real-time services with human-like conversations are challenging for banks, which can be overcome by introducing intelligent virtual assistants.

Increasing customer demand is the fundamental driving force behind financial services digitization. Globalization, social networks, mobile internet, big data, and finance have all impacted people's understanding and perception of financial services. Essential needs include easy access to finance, offering more innovative financial products and services, managing personal wealth better, and providing personalized and timely analysis and suggestions on wealth management. For banks, meeting customers' demand is the first step. As their banking services and products digitize and decouple, they become more significant, diversified, and customized. This trend will place greater pressure on improving service effectiveness, quality, and efficiency. Nevertheless, modern banks are operating increasingly complicated systems to cover more diversified, detailed, and complex interactions. It is challenging to achieve both omnichannel integration for a single gate and more human-like services to meet diversified demands.

6.2. Risk Management and Fraud Detection Estimates suggest that digital SMEs have been among the sectors hardest hit by financial fraud during the pandemic, with many encountering difficulties in securing immediate payment solutions. The first issue presented by the e-commerce sector is the importance of real-time transaction monitoring. In this environment, merchants must ascertain not only whether a certain API request is fraudulent, but also whether the transaction linked to that request is consistent with the customer’s behavior within the webshop. For instance, should a customer change their order after requesting an API to confirm the transaction, the latest request will require further examination. The usual cycle of data storage and model training does not suffice in this ever-changing e-commerce environment. The second issue is the sensitivity of the models to changes in input data, ultimately referring to adversarial drift. Neural networks tackle the fraud detection task via a series of mathematical operations on the input data. These models can thus be altered to produce varied output values even if the input changes negligibly. Consequently, e-commerce companies attune feature values for their input data to shave off input that results in false positives. However, the models also entail the risk of changing the meaning of portfolio values, introducing distributional and data-drift challenges over time.



.Fig 3: Big data in healthcare

With rising digitalization across various sectors, financial stability has attracted increasing attention from governments and the financial industry. High-profile financial events have raised doubts concerning the design of financial markets and investment products, the integrity of the financial market infrastructure, and the conduct behavior of financial institutions. Though financial risks are inherently and fundamentally present in the financial industry, they are also tremendous. Financial risk refers to exposure to potential financial loss, such as the risk of default on a loan and systemic risk affecting an entire financial system [1]. Since the financial system is always under assault—internally, externally, fundamentally, and temporarily—too much speed in a decision-making chain and too little data chart may not make any difference; risks would simply become bigger. Thus decisions made automatically might not be trusted until corresponding financial responsibility is borne.

6.3. Operational Efficiency While the operational performance of banks was traditionally measured using cost ratios and asset quality measures, the advent of information technology led to the inclusion of IT-enabled efficiency measures such as the percentage of commercial loans made over the Internet or the percentage of inquiries answered by ATMs [2]. However, these measures reflect only a subset of overall efficiency, largely ignoring the efficiency of legacy banking systems (usually referred to as core systems). These systems receive comparatively little research attention. Core systems make the business critical processes possible, which is reflected by the definition of an operation support system as a system supporting a process whose failure can cause large losses in revenue or risk exposure. Hence, they are closely linked with the operational performance of banks. A comprehensive architecture-based model called Core Systems OpERational Efficiency (CSOPERE) is developed for the measurement of the efficiency of a banking system's core services (CS) as an input–output based index. The basic approach of this model is in line with the well-established non-parametric Data Envelopment Analysis (DEA) bootstrapping. However, a bottom–up architecture-based modeling novelty is introduced to ensure the satisfaction of the central assumption of return to scale continuity of the core service efficiency. On the basis of a broad international sample of 74 banks CS infrastructure data covering all relevant dimensions and deployed capacity estimates, a detailed CS efficiency benchmarking is performed. The improvement potential of the analyzed banks is estimated in detail including individual suggestions.

7. Case Studies of AI/ML Implementation

In late 2021, China Merchants Bank (CMB) proposed a 2035 'Vision' —"to build a world-class investment commercial bank, a world-class wealth management bank, and a world-class digital bank." CMB has identified 'Digital China, Intelligent Finance' as a key strategic direction, and actively pursued the development of artificial intelligence. CMB posits that it has pursued a 'full chain thinking' approach in terms of automating fully customer service tasks through AI systematically, comprehensively, and from end-to-end. This paper aims to provide a general analysis of implementation of AI in various enterprise services of CMB, the degree of its convenient improvement to customers, the various challenges faced in practice, along with possible remedies using cases related to overseas AI deployment. The purpose is to aid the reader in better understanding AI's current impact on enterprise management.

Globally speaking, financial institutions realized over the past decade that they have a 'people' problem. Having trusted members of a core banking transaction processing system which surrendered them valuable long-term business relationships was noble in the 1960's. In 2020, lending members these same trusted people were still contacting via tele-via-message-in-person-checking one dame thing. This legacy business model was ill-suited to a world that needed instant on-line-real-time-peace-of-mind-money management. With the emergence of AI-based solutions capable of addressing tricky issues, the rules for engagement have changed drastically [2]. Above AI has also elevated the notion of client self-service in all its aspects. Bank contact centers are long established and accepted as an integral part of banking. Nevertheless, except in cases where manual intervention was warranted via an escalation route, it was a cumbersome, slow, frustrating, unnervating, and inaccurate means to gather information and to execute transactions. The means by which to securely access hold, exchange and transfer assets are far more sophisticated now. Personal banking, business banking and employer payments can all be carried out securely and instantly globally well into the hundreds of millions of dollars and pounds on an end-to-end-anonymous basis. AI is common knowledge. AI alone would dictate a re-think on whether call centers deserved a place in a 21st century bank [1].

7.1. Successful Transformations The UK-based Lloyds Banking Group is on the way to carry out the biggest overhaul of its digital banking platform in a decade, abandoning its legacy core banking platform in favour of a cloud-native solution. The service processes financial transactions in a SaaS environment. Lloyds, with a customer base of 27 million, will make a long-term investment in excess of US$ 1.55 billion, targeting the transfer of 40 million current and savings accounts to the new cloud-based system in the first phase in 2025/26. Eventually, all products supporting operations in Lloyds Retail and Wealth divisions will migrate onto the new platform.

India's top bank, the State Bank of India (SBI), has conducted its own big bank system transformation on a wholesale basis. In the bank's case, from 2015 to 2022, it shifted away from 23 cascading legacy platforms, going live with a new integrated enterprise banking core back-end architecture including various components. Now with a homegrown cloud-native platform at the back-end, as well as a front-end App constructed on NoSQL and cloud-native microservice architectures, SBI claims to have the capacity to handle 1 billion accounts if additional investments in infrastructure are made to scale up.

Various other banks across the world are making their migration project plans. Few banks doing end-to-end core redesign are on the verge of completion. Similar changeover plans are likely to continue in the banking sector well into the 2030s as cloud-native core modernized infrastructures providing AI/ML capabilities become the new standard for such banking functions.

7.2. Lessons Learned There are some insights which can be derived from the acquaintance with AI and its applications in a public sector bank/service organization. In India, AI is mostly and currently used in the back office processes where repeated actions have in high volume. AI also aids in the fraud detection in branches through a transactional analysis of recorded voice data. In the O.D. transaction, the results may be hinted from the development of 'basic banking services' like banking at point of sale, NEFT, Real Time Gross Settlement etc. From the analysis, it can also conclusive that the advent of AI is and should be there in Service Organizations to enhance the efficiency, provide quality services, work load and to remain competitive. There are wide areas within certain sectors that AI can improve where banks could reduce the routine mundane works carried out by clerical officers and the bank staff can use their intelligence in framing new strategies with premium banking products which can be customized on the basis of needs of the customers. It can also be inferred that once the technology is implacable, a proper and time period determined process of getting the awareness must be carried out to elicit the maximum improvement from the current position. There are many future arenas to be explored having a positive impact from AI adoption where banks could issue a personalized ATM card Business Intelligence on CRM, PostDocument Rendering, Medical Credit and collection, Loan Analytics, Chat Bot Development, Fraud Detection and Claim Processing through Speech Analytics, Gene Testing, Sales Process and CRM Analytics, Branch Location Optimization, Credit Risk Monitoring, Customer Scoring and Cheque Clearing through Image Analytics, Collection/Insurance Fraud Detection Scoring, Surveillance through Face Recognition and Transaction Classification, Workflow Engine, Customer Segmentation and Assessment of Profitability and Smart Assist Agents and Customized Wealth planning.

8. Regulatory Considerations

As banks leverage cutting-edge technology for Artificial Intelligence (AI) as part of the planned upgrade of their core banking infrastructure, they take a more fragmented approach to the solution than the approach taken when they selected a service provider for the current core banking software. Contemporary core banking solutions are bundled solutions that provide a wide breadth of capabilities, but banks are selecting solution providers for narrower parts of these solutions and building more of the overall solution using a wider provider base. This is a more risk-on approach than banks have previously taken on as it creates additional integration risk. To mitigate these risks, it is important that the bank pays careful attention to its selection process for technology and service providers.

AI is now being applied to various aspects of financial services, including credit assessment, customer service, transaction monitoring, marketing and advertising, and wealth or investment management. Banks and other financial services firms are underscoring the importance of Trust, Predictability, and Safety (TPS) in these applications as a way to mitigate the various risks a new AI application would create. There are several practical and technical ways to address these issues, the most important of which is better and wider datasets for AI model training. The bank can benefit from best practices from other industries, practices it may not have experience with. Practitioners familiar with these practices may not be readily available at banks and other financial services firms.

Banks need to share more data among themselves, but many of the data sources banks could benefit from, including economic data, competition data, and sanction lists, are public sources that banks already have. Additionally, banks may have experience in deploying large-scale solutions with AI, for instance, applying AI to anti-money laundering (AML) systems. The approach to TPS safety assurance in AI is likely to evolve towards a mix and match application of existing regulatory approaches taken on Capital and Conflict of Interest on top of an understanding of the cyber-security landscape for AI systems [5]. The more prescriptive the regulations, the lower the average state of trust in the entire banking sector is likely to be [11].

9. Data Privacy and Security Challenges

Digital banking is becoming increasingly popular. It presents new opportunities for banks and fintech companies to boost their growth immeasurably. However, the growth of digital banking has raised internet security issues, which need more attention from privacy guards and the bank itself. Hackers are resorting to new techniques for stealing customer data and credit cards [12]. Thus, banks and institutions must work hard to keep their clients' data secure from hackers as hackers will take advantage of weak countermeasures. Furthermore, many cyber attackers perform DDoS attacks and security exploits via social engineering in order to build a security-aware clientele. These attacks abound in the banking domain, and prudence and mitigation counts on utilizing the best available defense mechanisms to build resilience in information security systems.

In the banking sector, reputational damage and stock prices drop unravels faster than security tech spam. This is why banks are less dynamic to adopt and innovate with new technologies in everything from IT infrastructure and filtrating and storing customer data. Data protection was found to be the utmost critical item in the first two years following the first major breach. Misconfiguration of access control systems might have led to many dynamic threats from outsiders and insiders. Additionally, data provenance processing results might sometimes escalate privacy risks due to massive data sharing with third parties. Several data protection models have been presented to guarantee the privacy of customers' information. For instance, conducted an empirical study on trust assessment as an essential factor in modern banking systems. Their study demonstrated that a sort of information asymmetry can be addressed to build trust in the FinTech systems. Indeed, there is no better remedy than remedying at source for data being store, they claim.

10. Future Trends in Banking Technology

The modern banking environment is characterized by increased competition, evolving technologies, and changing consumer preferences. Consumers now expect banks to provide 24/7 intelligent, responsive services with complete flexibility, convenience, and security. To stay competitive, banks are compelled to adapt their core banking technology to upcoming trends. The ongoing trends in core banking technology are amalgamation of traditional banking with Fintech solutions, rising collaborations with artificial intelligence and machine learning (AI/ML), an improved focus on business intelligence (BI) and big data analytics, centralized online real-time exchange (CORE) implementations, and dual conversion approaches for core banking upgrade endeavors [5].

The COVID-19 pandemic has accelerated the urgency for banks to adopt AI/ML, especially for traditional banks – private or public – where cultural resistance may be stronger. Results of a 2020 survey highlighted that traditional banks plan to shift significantly towards AI/ML. If this is slow, the third-party Fintechs will eat away the incumbent's revenues. Recent history shows that retailers and BPAY providers have disrupted in-store payments at the POS. A considerable, non-core fee income for banks has been lost here [2].

In a thorough review of AI/ML technologies, a set of applications immediately emerged. The actual vs planned adoption (the gaps) of these applications were mostly of a similar pattern for all banks. However, the absolute gaps were much smaller for challengers. The Moore's curve of commonly employed AI/ML applied models explains part of the market dynamics; economics of producing superior, higher performance models under a data moats/algos war as aggregators of data demonetized lead to monopolies. To avoid competition, traditional banks cannot let the market evolve to stable monopolies for sensitivity analysis. The bank branches need to drive the quantitative research to the prevention of economic obsolescence in such sectors. Each banking strategy is paired with a taxonomy of characteristics, while the applications within each strategy branch are grouped according to broader functional robustness or homogeneity.

$$R_M = R_L - FD_{ml}$$

Eqn.2:Risk Reduction and Fraud Detection Equation

- R_L = Legacy risk level
- R_M = Modern risk level with AI/ML fraud detection
- FD_{ml} = ML-based fraud detection efficacy

11. Integration of AI/ML with Existing Systems

AI/ML has great potential in the banking and finance industry. However, it is a daunting challenge to leverage the power of AI/ML and be used in an effective and efficient manner. Banks must first establish the data and technological foundation. Data is most important, as AI which is trained with wrong or bad data will reach incorrect conclusions. It is crucial to gather and manage data with good quality. Furthermore, the historical events related to the application of AI/ML in a previous cycle are necessary to identify. The evolution of financial technology started from the first wave of bulletin boards. Although never died down, financial technology slowly lost its glamour and adventurous aspect. It was developed with an incremental, evolutionary approach. Later, the invention of Internet gave huge impetus to this industry. Member institutions of Yangtze River Delta Bank Co-Operative Union (CRDCU) are small in size. Small banks also have much less knowledge of the market, and have less competitive edge [1]. The generation of BGs requires well re-engineering the process flows in one bank first, and makes a debut in the market to capture more businesses, then increases the sky and process flows by acquiring other small banks. Banks have previously tried to build the robotic process automation (RPA) and artificial intelligence (AI) modules, but failed, because relaxed rules are hard to be digitalized. Creditors can approve a request by typing some numbers or selecting the dropdown menus, where a scheme using AI could classify these requests using the basic rules. CC is much more complex since it is, in fact, a draft version of the BG. Currently, it is generated and output in a word file with some basic contents pre-filled, while external content and flow left undefined. Automated generation of BG by integrating the tools of RPA and natural language processing (NLP) is an interesting project, and nothing similar is known in the industry. Consult chatbots are a hot area of study as well. A simplified project with general flows and data could be done in a short period of time which can be extended in the future [2].

12. Change Management in Banking Institutions

To implement appropriate change management in the banking operational functions, the change management process should cover all levels (communication, personalities, job function changes, etc.) in order to reduce the risk and maximize the project success. The organizational structure should support the change management process and a dedicated team and project plan with milestones and timeline should be put in place to measure and ensure project success. A training plan involving all employees should be established early in the process to tackle the functional changes of the system [3].

A migration strategy is also needed in order to counterbalance the risk of client dissatisfaction. Some IT relevant decisions should be taken early on in the process: the new IT current state should be defined; interfaces to existing applications should be defined; it should be decided how the data migration from the old system should take place. For some of the issues, a more hands-on approach is needed: for the tasks where the decision of “never do” matters, this would normally happen before the function interfaces are fully defined [4].

As for usability, adopting a new IT system is always a fairly personally traumatic period, with aggravated user acceptance problems in the case of complex systems. Also in short term delays in the required value added of the new system is probably the most common failure. To reduce these risks, careful planning and managing of the end-user training preparation, stakeholder presentation systems in order to get the user expectations clear with the work for effort estimations, opinions of required functionalities and so on would be needed sooner than speculations about them. Security requirements in banking computer systems are typically quite strict and non obtrusive, however with the trend of bringing more and more banking facilities to the product marketing side with open URLs or client-side computation, this area is generally foreseen some more contradictory requirements in the near future.

13. Training and Skill Development for Staff

To implement AI/ML-based products in core banking infrastructure, training programs are required for existing staff members. Certain skill sets like analytics, engineering, and research are required for AI/ML product development. Banks can recruit thoroughly educated graduates and then curate customized learning journeys for each of them in external training and internships to adopt this approach. These learned concepts may be incorporated successfully into the organizations during the orientation program. For existing staff with a dedicated interest in building digital capabilities at work, banks must strive to provide orientation and overview programs with the help of external partners. External trainers may be engaged to conduct workshops and webinars on AI/ML and its applications in financial institutions for other interested employees.

Some of the points should also be considered for success in this initiative. Recruitment with educational backgrounds such as statistics, engineering, and pure sciences [2]. Also, hire interns from renowned institutions. Dedicated training programs should be organized with the help of external partners. Programs may be task-oriented, evaluation-based, and offering levels of responsibility, and employees should be encouraged to become independent researchers in one domain by communicating with external partners to apply, design, and create subcomponents. Distributed Designated Learning Internships (DDLI), Research-Based Learning (RBL) pods, Midterm Resonate for Employees (MRE), and group technical development initiatives for hybrid teams from multiple backgrounds may also be organized.

A culture of hybrid work should be sustained, with flexibility in work assignments and job descriptions. Pioneering group activities and niche projects focusing on employees' unique intellectual and engineering qualities may also help. Additionally, there should be organizational acceptance for this initiative, and risks, costs, and benefits should be traded-off carefully to ensure the assurance of certain job supplies. Final stability on the work approach (fully autonomous or hybrid) may also help, and tech upgrades should be gradual and straightforward, with seamless integration into current systems and architectures. Ph.D. scholars may also be hired to lay a foundation for knowledge development and sharing of research in the areas of AI/ML-based innovation and technology upgradation initiatives.

14. Collaboration with Fintech Companies

The banking business areas that can be transformed with the emergence of FinTech companies, as well as the needs of banks regarding co-operation with FinTechs, are two issues that have not been explored sufficiently in this field. However, with a change in banking business strategies, the banking industries, especially in developed countries, will be entirely changed [13]. This change is not limited to banks' co-operating with FinTech companies. Hence, the banking business areas and the domains of co-operation with FinTech companies are presented in this regard. Additionally, the needs of banks, identified to improve their banking business areas, as well as address their business challenges via co-operation with FinTech companies, are presented.

Since the emergence of FinTech companies, banking has experienced fundamental changes. The community of FinTech companies has paved the way for the rapid growth of technology and its influence on every aspect of human life. This rapid growth has also made financial technologies the leading service production and offering technologies. Within this context, the banking business areas and the domains of co-operation with FinTech companies are presented. Hence, by identifying the banks' areas of business that can benefit from FinTech companies' services, research has been conducted to indicate the dimensions of co-operation on which banks can encounter FinTech companies, along with their services constraining banks' growth. As a profound shift is expected, covering different aspects of banking, this change would not just be confined to some limited aspects of banks' performance issues.

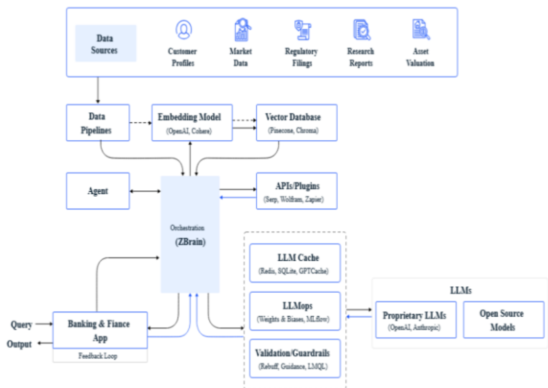


Fig 4: AI in banking and finance

In light of agreements, data storage standards adopted by banks are to be amended. In the upcoming years, these changes will force banks to rethink cooperation and re-examine information systems and outsourced services in terms of retail customers. An inquiry comparable to banks' adoption rate at the governmental and sovereign levels has not been reported. The development and wide range of performance response scores regarding Co-operation with FinTech Companies reveal a significant positive correlation with the service performance values of customers.

15. Impact on Employment in the Banking Sector

Major technological advancements such as artificial intelligence (AI), machine learning (ML), and blockchain already have had a massive impact on banks' IT infrastructure, changing the ways conventional IT services provide their services. Nevertheless, so far, the core (legacy) system of banks has hardly been touched by the implementation of these modern technologies. The existing systems worldwide still run on mainframes, even though the second generation of core banking systems has come into the market. The second generation aims to provide a modular design with well-defined application programming interfaces (APIs), but is still based upon conventional technologies. On the third generation, banks reconsider their entire IT infrastructure design. The new design distinguishes three core product pillars such as the interface between the interaction servers to clients (micro-ecosystem), and the database structure with an additional abstract table or graph hierarchy, and allows working with modern programming languages and tools (application servers) such as Java, Spring, Kafka, Redis, or Graph databases [14]. The resulting new IT infrastructure offers new possibilities and opportunities for virtually all technologies. Despite this, the basic calculations of individual accounts remain with literal transactions on abstract tables. Because at least worldwide or nationwide transactions will always be the final processes for credit creation or extinguishing (which possibly implies the contraction of one or more abstract tables), this approach does not imply a risk of a non-regulated market. On the contrary, based upon a dialogic network as database structure, much more automatic processing of personal information of clients will be performed that is essential for the processing itself. These changes in processes and systems also affect the staffing of banks and mean a paradigm shift in IT organization. Such a shift offers a totally different culture in which virtually all existing positions become obsolete. Banks will have to hire young staff with mathematics and programming background on the one hand and experienced employees with banking management knowledge on the other hand.

16. Customer Trust and Acceptance of AI

The dramatic recent advancement of artificial intelligence (AI) technology has been recognized worldwide, with funding and investment significantly increasing in various fields, including healthcare, investment, and the financial sector . In parallel, attention has been drawn to the ethical and societal impact of AI, particularly its use in financial operations, forecasting, and the banking sector. As a rapidly developing technology, it is anticipated that AI will eventually revolutionize the banking sector.

With the public growing more accepting of AI, banks are racing to implement and adopt AI solutions across various functions, such as risk management, fraud detection, marketing, and personalized services. The COVID-19 pandemic has only accelerated motivation for the wide adoption of advanced technology, including AI, to improve resilience in services and operating models. Rapid advancements in big data technologies, a broader array of available data types, modeling techniques, automated learning algorithms, and robotic systems have made it easier to acquire, process, and analyze massive amounts of information. Access to new data sources, machine learning techniques, and cloud solutions is likely to facilitate the incorporation of AI models.

For technology to work, customer trust is paramount. Now more than ever, consumers expect respect, transparency, and control in their interactions with a financial institution’s human and machine resources. The use of AI must be explained to their full understanding. This trust can be built over time through familiarity with AI use. In terms of design, interact, and educate with algorithms. Mistrust can stem from unintentional or unintended breaches of security and privacy, which should be avoided at all costs. Financial institutions should anticipate 51% of AI systems being unreasonably rejected and ramp up engagement, education, and compliance. At the legal and regulatory levels, a system of accountability needs to be established.

17. Measuring Success and ROI of AI/ML Initiatives

The banking industry's interest in Artificial Intelligence (AI)/Machine Learning (ML) is high, with increasing acceptance of enterprise-implemented AI/ML in many different use cases, ranging from fraud and money laundering detection to improving marketing targeting and IT operations. Although many banks have implemented simple applications, at many institutions, progress is stalling without being able to appropriately scale or recognize a return on investments made. This sustained interest in AI/ML comes at a time where the business and regulatory pressures on banking have never been greater. Demands to remain competitive with rapidly rising open platform neo banks with significantly lower operating cost and increased functionality/stability, increasingly stricter approach to control and audit by regulators, and rapidly declining profitability keep banks on edge and in a continuous state of investing in future state technology [1].

There exists a wide range of effective AI/ML use cases actively being implemented in banks and other financial institutions including credit card services and cybersecurity. However, broader questions of how a bank can maximize effectiveness through appropriate scaling of AI/ML technology inside their institution have yet to be explored in detail. Many of these questions are interrelated both within and between upper management, front office practitioners, and back office practitioners [2]. Deep learning is focused on the continual input of data and is able to use it by modeling a network of information dense mathematical nodes called artificial neurons, while machine learning alone would just consider the input data or consider the data as processed knowledge, which is the other two major paradigms of AI. DL is concerned with automatically learning representations of data with the aim of understanding data itself while ML concentrates purely with the determination of the rules for its transformation.

18. Ethical Considerations in AI/ML Deployment

AI/ML systems must adhere to ethical principles by design, which necessitates elucidating the intended use of the AI/ML systems and generating explanatory feedback on their performance. The Right to Explanation is a requirement that grants consumers the right to obtain information regarding how decisions were made by automated processes. That requirement is fundamental to the ethical principles of fairness and accountability [15]. AI/ML model deployment must take into account which behaviours are acceptable or unacceptable to clients. Interpretable actions must follow the client's context. Recommendations or predictions must be sufficiently transparent to convey what they pertain to and influence. AI/ML debugging should operate within predefined ethical guidelines. AI/ML training analytic systems must comply with ownership, privacy, and data usage regulations.

A reporting system should provide insights during training, validation, and servicing. It first must routinely report model validity metrics like training loss, test metrics, and forward pass and back-propagation time. Reported data must be contextualized to assist non-expert users in understanding model performance. Global behaviour auditing through indirect data sampling or metrics should assess model performance versus context. Labelling limitations should be quantified, for example, observation sparsity, baseline performance, or off-target observations. Lastly, by using control groups, results would be assessed quantitatively relative to previous behaviours and qualitatively relative to other systems or human performance.

Publishing interpretability measures or tools will empower the direct observers of AI/ML systems to perform their audits or design decisive correctness tests beyond mere guarantees and implications. This might bring a traversable, encyclopaedic AAM, but it will also invite abuse of procedural understanding, both scientifically and competitively. Therefore, a body of naming and shaming disclaimers will be needed for those situations and exploratory undertakings. This entire mishmash will have to be far and wide accessible yet sufficiently comprehensible; perhaps multilinguality should even be crafted in from the start.

19. Global Perspectives on AI in Banking

Artificial intelligence (AI) technologies have been widely adopted by banks. As with any new technology, banks are concerned about their ongoing relevance, especially when changing technology shifts the boundary of what are the privately held capabilities that differentiate one firm from another. This chapter examines how the usage of AI can be perceived as a signal of capability that influences speculative beliefs and reputation formation within the banking sector. The analytical model incorporates the possibility of AI investing and imitation, and it is shown that banks adopting AI in core banking processes gain advantages in terms of reputational measures. However, the benefits of switching to AI will introduce instability and oscillations in reputational measures .

It is concluded banking is a domain where investment in a new technology can become self-reinforcing as the banks acquire competitive advantages due to an increase in the AI adoption rate of their rivals. Banks can stave off oscillations by investing in AI at a slower rate. Broadly speaking, understanding metaphysical risks—including those induced by the emergence of the socially-shaping AI—will require cooperation across academia, technology, and finance.

The chapter shows how the usage of a technology can serve as a signal of capability that affects speculative beliefs and reputation formation within firms. It focuses on the banking sector and on how the investment in AI can change firms' beliefs and relative reputations by analyzing the basic dynamics of beliefs formation within the framework of a mathematical model that incorporates differential belief formation processes. The analysis highlights the intricate interplay between substances, institutions, and technologies that defines modern banking.

20. The Role of Leadership in Transformation

In the context of banking, Artificial Intelligence refers to the computer systems' ability to mimic human intelligence and perform tasks typically requiring human intelligence such as visual perception, speech recognition, decision making, and language translation. It is the art of using computations and statistical learning algorithm in interpreting a data. Conventional data analysis always gives output only matching to input and are unable to predict out of the box. AI analyses historical data patterns to decide further data. AI in Banking refers to assessing, processing, and interpreting data on customers' actions in prescriptive ways. Along with interpretations, new and novel outputs are suggested to and worked on probability in Banking.

Fig 5: Core Banking Software Leading Companies and Solutions

Banks are adapting AI to create value for customers as per Banking 2050. RPA falls under the purview of AI based algorithms and is the use of software robots and artificial intelligence to support judgement based workflows. Initially developed for automating the mundane work such as batch entry, RPA has moved on to automate work which requires knowledge work but has itself become a target. RPA helps the banks in reviewing work output, QA reporting and on softer areas like survey analysis, policy rule validation and customer service chatbots [14].

The major components of RPA in banking includes RPA in correctness-checking, risk monitoring, and RPA for efficiency-checking. Bots check thousand pages of rule inputs and reference tables against customer interactions and flag that which did not check out. Bots search for cases of risk exposure early in work flows and interrogate inputs across large datasets to identify anomalous transactions red flag to be examined by human analysts. Bots check for percentage slippages by products across per line departments and even look for tree branch-on-branch lending or ask whether no person who had more than X transactions tried to submit forms only to be refused by X banks. Bots do character recognition, voice recognition and map geographical shapes to data for post-risk analysis. Bots also look for irregularities pattern in customer settlements with banks and whether such settlements had truncated follow-up chase on delinquent customers. Bots read customer survey-open mention inputs across channels for patterns flagging mention, persistency and omissions by branch, department, management, and cross-usage. Bots crosscheck policy rule outputs against live datasets and check whether not correctly defined policies have issued auto-cheque orders. Bots monitor responses to SLA standards by loan support calls across departments. Bots prep million datasets for audit/QA analysis and churn heat-maps across departments. Bots track and make play-books of cavier responses by less-than-extraordinary customer service representatives.

21. Building a Culture of Innovation

Innovation is an organization's capacity to treat careers in new ways. By making several concrete modifications in the operational approach of the assignment, an organization may create new knowledge to enhance services. Building a culture of innovation, however, is frequently disregarded because of the simple notion that innovation is integral to a strategy. Culture is described as a collection of intelligent encounters "institutively opposed to those of the past decade," which puts professional conduct notionally outside of civilization. A culture of innovation demands an eagerness to accept novel realities and a shift in prior mindsets by both leadership and personnel to make room for fresh ones. This openness requires the development of new viewpoints, abilities to see in new ways, investigation of alternatives, the courage to take risks, and forming new associations whose meaning has not yet been made apparent [2].

Culture is everything for building a culture of innovation, notwithstanding the technological advancements and new framework model development. To that end, members must become acquainted with a novel way of thinking. They must explore various possibilities for doing business. They must understand that it's acceptable to consider silly ideas and questions. They should experience working with different cultures and perspectives [1]. Sadly, these excitements and perversions may collide with the inherent group's rational worldview and execution-based culture, making a resistance culture. Furthermore, building a culture of innovation can create subcultures of hatred, resistance, and a desire to embarrass others. Thought leaders must lead innovation thinking along new conventions that open people to a fresh set of rules and new doing's and statements (tolerant of error, costly, strange ideas, etc.). To do so, the transformation must tackle oneself and keep the novel practice robust and fresh while building community structures that continue to open the client to novel methods and respect itself and humanity.

$$CX_M = CX_L + P_{ml} + S_{ai}$$

Eqn.3:Customer Experience Improvement Equation

- CX_L = Legacy customer experience score
- CX_M = Modernized customer experience score
- P_{ml} = Personalization via ML
- S_{ai} = Speed improvements via AI automation

It's a big project. But if executives are serious about transforming the organization outside, they must begin with the inside, primarily focusing on hard paradigms and on soft parables (culture). While technology typically outpaces and forwards in big startups, primate projects on culture will still be uncertain. Therefore, industry leaders should invest in technologies that make a culture of reflection and consideration visible within the organization. It can be carried out with a bank's decision center and a team of thought leaders.

22. Vendor Selection and Management

Purchasing and working with external vendors is a common practice in financial institutions. Vendor management encompasses all activities, decisions and documentation related to relationships with vendors. It includes the risk assessment or review process to help distinguish between routine and other specific vendor relationships. External vendors include companies that provide products/services or perform functions/service on a third-party basis. A vendor may be a corporation, partnership, limited liability company, sole proprietor, or other legitimate entity.

Vendor Risk Oversight is a foundation operational process. The Vendor Risk Oversight Committee, which is risk and compliance-focused, ensures that the vendor risk management policy, framework and procedure are adequate to manage vendor risk. The group is responsible for identifying material vendors and classifying them in accordance with the risk-related aspects of the services they provide or could provide. Vendor risk management and the vendor risk assessment function is provided by a compliance oversight group independent of business operations.

While vendor management at larger organizations is likely a mature function, it may vary from a simple, limited activity to an absent function in smaller institutions. In the absence of an established vendor management framework, many organizations may resort to reviewing specific contracts on a piecemeal basis with little awareness of the criticality of the vendor, lack of managerial oversight, vendor identification and tracking, and periodic risk assessment of the vendor. As seen in the failures cited earlier, low vendor risk awareness may result in higher operational and reputational risk for the institution.

Key areas of focus for vendor risk management assessments include identifying vendor categories, services, and access; critical vendor validation criteria; performance management and exit strategy; and documenting and tracking issues. Though vendor management hinges on understanding the vendor’s risks, this is only part of the story. While assessing the vendor’s risks and due diligence is critical, it is also essential to understand the components of the product, the main vendor of the business, and the secondary/third-party vendors that impact the stability of the product being reviewed.

23. Scalability of AI/ML Solutions

Artificial intelligence/machine learning (AI/ML) players demonstrate disruptive applications and valuable case studies fundamentally changing all banking processes. AI/ML solutions focus on obtaining in-depth insights into daily business operations, their energy consumption, and trading parameters, supporting information security teams to counteract internal and external threats, and optimizing processes like fusion data manipulation across various systems, compressing files, and assessing huge data sets in an unprecedented way [1]. AI/ML solutions evolve from internally risky projects with limited young client adoption and strict regulatory barriers to scalable full-use cases because of gradually increasing market share, confidence in the solutions provided, better client investment rationale, and successful regulatory adaptations.

Card methods provide close to accurate attributions for numerous clients to explain why providing long-term borrowing is useful for clients. Physical/asset-based lenders can widen their focus to financial investing by better recycling ongoing data for financial loans, creating dedicated companies recognizing the financial nature, and offering industry-unique solutions exploiting intensive data. Recently, banking/finance processes have triggered several successful AI/ML solutions supporting simpler product placements with adaptive UX journey offering entirely virtual clients and loans automated on the same day with a pre-clustered universe to receive triggers for buying/selling positions [2].

Given the enormous potential of AI/ML in growing existing bank profitability and defining new banks' edge, and considering universal aspects in AI/ML technology deepening its understanding, this section aims to make tangible the two most promising avenues with a bank's presentation. For existing banks, it demonstrates targeted processes, best practices, and explanations to enhance potential awareness concerning cluttered internal processes, incremental profits based on minor control changes, and a range of dedicate players' cost scenarios for AI/ML solutions. It illustrates new banks' profitability paths across various domains and how to exploit limited raw data sets to generate valuable securities.

24. User Experience Design in Banking Apps

Banking apps are mobile applications available on smartphones or tablets that help users manage their bank accounts and perform common banking transactions such as checking account balances, fund transfers, bill payments, withdrawals, and deposits. The rapidly increasing ownership of smartphones in the past few years has contributed to the noticeable development in the mobile banking sector. Banks seek to use the wide application of smartphones to create their mobile banking products to enhance customer satisfaction, loyalty, and bank image.

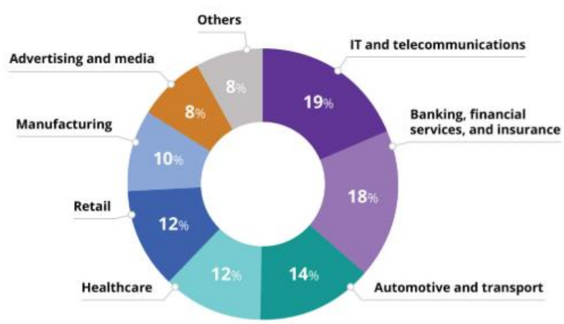


Fig : AI in finance

Like other Internet applications, banking apps can be successfully practiced only if users find them useful, easy to use, and secure. In addition, to attract new customers and create up-to-date values for current ones, banking apps should possess unique features and be compatible with various operations and mobile devices. Thus, scrutiny of user perceptions and evaluations of the success of a banking app is crucial for banks and organizations wishing to improve the commercial success of their banking apps. This study examines those critical success factors that may determine the success of a banking app in accordance with the IS success model, a leading model of information system success.

Mobile banking in India has made great strides as evidenced by the proliferation of mobile banking apps. The literature reports that the security of mobile-based banking services has serious concerns and is one of the most researched field in banking. Automated Teller Machine-Debit card rolling out is the reason for the adoption of Internet banking and generally e-banking. Fintechs are highlighting the need for competition and collaboration in banking. Recent trends on artificial intelligence chatbots in banking are discussed. A decade of research in e-banking is reviewed. All these literature contributions fail to evolve side by side the new developments in technology, regulation and competition [2]. So, this area is very important and timely to investigate it.

25. Feedback Mechanisms for Continuous Improvement

The effectiveness of AI-enabled services in areas such as core banking infrastructure modernization, advanced analytics and fraud detection, customer support, and predictive maintenance will not match expectations without effective feedback loops wherein the system learns from its mistakes or insufficient accuracy and correctness. Baring feedback loops effectively limits AI-enabled systems to a "setup and forget" paradigm wherein they are only as good, timely, effective, etc. as they were when they were last updated or relearned from new examples. It also limits their ability to avoid technocracy: a realm where processes and controls dominate. Companies relying too heavily on technology may lose touch with the ever-changing needs of clients. AI systems that are unchecked and not supplemented with sufficient human intelligence may also lead to dead ends and cause collateral damage. Vigilance over important decisions made by AI systems is being aided by efforts to provide multiple perspectives and signals augmented by ethics teams and boards. This pushes firms to plan, design, and operate human-in-the-loop AI systems. Such centered designs enable effective systems with added value that act in accordance with firm values, with respect to clients' needs and interests. AI systems engaged in complex tasks in fast responsive, high volatility, ambiguous, and uncertain environments will demand more interactability even during tasks where they are effective enough without human interventions. Human participants will also gain increased functional and attributional responsibility. For more mundane and structured tasks, client focus and key performance targets will require personal explanation to users of the what, how, when, who, amount of effort, stages, constrained contingencies, etc. of the verdict suggested by the AI system. Throughout all tasks, AI systems failing to comply with requirements or running outside predefined bounds will demand explanations and foresight scenarios on the potential severity of the impact, the contingent decisions, information, and actions relevant to recovering and changing the system, and a range of remedial and adaptive actions to reinforce responsiveness and robustness. In constrained types of decisions, companies must also ensure that the system remains relevant throughout large ranges of the outcomes of relevant decisions, aspects of the data processed, and feedback loops implemented. Careful weighing between the fit however is hard, as continuous-system adaptivity may threaten organizational and regulatory compliance.

26. Conclusion

Infrastructure modernisation is critical in the era of digitalisation. Underlying enterprise infrastructures set the platforms and foundations for banks and financial institutions (FIs) to meet client demand and build competitive advantage through the adoption of digital technologies. Historically, across the globe, this core banking infrastructure has served banks effectively but is aging [2]. This increases risk exposure to banks and heightened difficulty in dealing with rapidly evolving and increasingly complex regulation. Banks have sluggish time-to-market and difficulty in developing new products/services to increase revenue. There's an urgent need for banks to modernise the core banking infrastructure which underlies their enterprise and operate as a digital bank. Modernising the core banking infrastructure requires banks to undertake transformative and disruptive change. Fortunately, rapid technological advancements in AI/ML and the maturity of cloud, lot, sensors, and user interface technologies provide banks with an unprecedented opportunity to overcome the challenges and build a core banking infrastructure that is elastic, scalable, cost-effective and secure. In this paper, an AI/ML-driven architecture for transforming and modernising the core banking infrastructure of banks and FIs is presented. For each layer of the architecture, the mix of technologies that can intonate AI/ML, open source/cloud/lot technologies, security technologies, interfaces, and smart contracts are discussed. The current core banking system of banks and FIs is analysed and the existing capability and limiting factors are articulated. While regulation in the banking sector is important and necessary, adopting excess regulation is counter-logical. For example, banks and FIs cannot unilaterally decide to devote their resources to expanding the capabilities for providing new products and services to the market or sourcing new suppliers for externalised services within the constraints of existing regulation. There's also a need to transform the business operations and levelling technologies around which the banking and FIs are currently built before embarking on pieces of disruption such as cloud-based core banking and quantum computing. The state-of-the-art of traditional core banking systems is described, and the AI/ML-driven hybrid architecture of smart core banking systems is presented. Lastly, emerging industry developments such as smart contracts and quantum computing are discussed and the transformational opportunities they offer to banks.

References:

[1] Kommaragiri, V. B., Preethish Nanan, B., Annapareddy, V. N., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Narasareddy and Gadi, Anil Lokesh and Kalisetty, Srinivas.

[2] Pamisetty, V., Dodda, A., Singireddy, J., & Challa, K. (2022). Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies. Jeevani and Challa, Kishore, Optimizing Digital Finance and Regulatory Systems Through Intelligent Automation, Secure Data Architectures, and Advanced Analytical Technologies (December 10, 2022).

[3] Paleti, S. (2022). The Role of Artificial Intelligence in Strengthening Risk Compliance and Driving Financial Innovation in Banking. International Journal of Science and Research (IJSR), 11(12), 1424–1440. https://doi.org/10.21275/sr22123165037

[4] Komaragiri, V. B. (2022). Expanding Telecom Network Range using Intelligent Routing and Cloud-Enabled Infrastructure. International Journal of Scientific Research and Modern Technology, 120–137. https://doi.org/10.38124/ijsrmt.v1i12.490

[5] Pamisetty, A., Sriram, H. K., Malempati, M., Challa, S. R., & Mashetty, S. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing

Security, Tax Compliance, and Audit Efficiency in Financial Operations. Tax Compliance, and Audit Efficiency in Financial Operations (December 15, 2022).

[6] Mashetty, S. (2022). Innovations In Mortgage-Backed Security Analytics: A Patent-Based Technology Review. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3826

[7] Kurdish Studies. (n.d.). Green Publication. https://doi.org/10.53555/ks.v10i2.3785

[8] Motamary, S. (2022). Enabling Zero-Touch Operations in Telecom: The Convergence of Agentic AI and Advanced DevOps for OSS/BSS Ecosystems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3833

[9] Kannan, S. (2022). AI-Powered Agricultural Equipment: Enhancing Precision Farming Through Big Data and Cloud Computing. Available at SSRN 5244931.

[10] Suura, S. R. (2022). Advancing Reproductive and Organ Health Management through cell-free DNA Testing and Machine Learning. International Journal of Scientific Research and Modern Technology, 43–58. https://doi.org/10.38124/ijsrmt.v1i12.454

[11] Nuka, S. T., Annapareddy, V. N., Koppolu, H. K. R., & Kannan, S. (2021). Advancements in Smart Medical and Industrial Devices: Enhancing Efficiency and Connectivity with High-Speed Telecom Networks. Open Journal of Medical Sciences, 1(1), 55-72.

[12] Meda, R. (2022). Integrating IoT and Big Data Analytics for Smart Paint Manufacturing Facilities. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3842

[13] Annapareddy, V. N., Preethish Nanan, B., Kommaragiri, V. B., Gadi, A. L., & Kalisetty, S. (2022). Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing. Venkata Bhardwaj and Gadi, Anil Lokesh and Kalisetty, Srinivas, Emerging Technologies in Smart Computing, Sustainable Energy, and Next-Generation Mobility: Enhancing Digital Infrastructure, Secure Networks, and Intelligent Manufacturing (December 15, 2022).

[14] Phanish Lakkarasu. (2022). AI-Driven Data Engineering: Automating Data Quality, Lineage, And Transformation In Cloud-Scale Platforms. Migration Letters, 19(S8), 2046–2068. Retrieved from https://migrationletters.com/index.php/ml/article/view/11875

[15] Kaulwar, P. K. (2022). Securing The Neural Ledger: Deep Learning Approaches For Fraud Detection And Data Integrity In Tax Advisory Systems. Migration Letters, 19, 1987-2008.

[16] Malempati, M. (2022). Transforming Payment Ecosystems Through The Synergy Of Artificial Intelligence, Big Data Technologies, And Predictive Financial Modeling. Big Data Technologies, And Predictive Financial Modeling (November 07, 2022).

[17] Recharla, M., & Chitta, S. (2022). Cloud-Based Data Integration and Machine Learning Applications in Biopharmaceutical Supply Chain Optimization.

[18] Lahari Pandiri. (2022). Advanced Umbrella Insurance Risk Aggregation Using Machine Learning. Migration Letters, 19(S8), 2069–2083. Retrieved from https://migrationletters.com/index.php/ml/article/view/11881

[19] Paleti, S., Burugulla, J. K. R., Pandiri, L., Pamisetty, V., & Challa, K. (2022). Optimizing Digital Payment Ecosystems: Ai-Enabled Risk Management, Regulatory Compliance, And Innovation In Financial Services. Regulatory Compliance, And Innovation In Financial Services (June 15, 2022).

[20] Singireddy, J. (2022). Leveraging Artificial Intelligence and Machine Learning for Enhancing Automated Financial Advisory Systems: A Study on AIDriven Personalized Financial Planning and Credit Monitoring. Mathematical Statistician and Engineering Applications, 71 (4), 16711–16728.

[21] Paleti, S., Singireddy, J., Dodda, A., Burugulla, J. K. R., & Challa, K. (2021). Innovative Financial Technologies: Strengthening Compliance, Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures. Secure Transactions, and Intelligent Advisory Systems Through AI-Driven Automation and Scalable Data Architectures (December 27, 2021).

[22] Sriram, H. K. (2022). Integrating generative AI into financial reporting systems for automated insights and decision support. Available at SSRN 5232395.

[23] Koppolu, H. K. R. (2021). Leveraging 5G Services for Next-Generation Telecom and Media Innovation. International Journal of Scientific Research and Modern Technology, 89–106. https://doi.org/10.38124/ijsrmt.v1i12.472

[24] End-to-End Traceability and Defect Prediction in Automotive Production Using Blockchain and Machine Learning. (2022). International Journal of Engineering and Computer Science, 11(12), 25711-25732. https://doi.org/10.18535/ijecs.v11i12.4746

[25] Chaitran Chakilam. (2022). AI-Driven Insights In Disease Prediction And Prevention: The Role Of Cloud Computing In Scalable Healthcare Delivery. Migration Letters, 19(S8), 2105–2123. Retrieved from https://migrationletters.com/index.php/ml/article/view/11883

[26] Sriram, H. K., ADUSUPALLI, B., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks.

[27] Avinash Pamisetty. (2021). A comparative study of cloud platforms for scalable infrastructure in food distribution supply chains. Journal of International Crisis and Risk Communication Research , 68–86. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2980

[28] Gadi, A. L., Kannan, S., Nanan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly

Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87-100.

[29] Dodda, A. (2022). The Role of Generative AI in Enhancing Customer Experience and Risk Management in Credit Card Services. International Journal of Scientific Research and Modern Technology, 138–154. https://doi.org/10.38124/ijsrmt.v1i12.491

[30] Gadi, A. L. (2022). Connected Financial Services in the Automotive Industry: AI-Powered Risk Assessment and Fraud Prevention. Journal of International Crisis and Risk Communication Research, 11-28.

[31] Pamisetty, A. (2022). A Comparative Study of AWS, Azure, and GCP for Scalable Big Data Solutions in Wholesale Product Distribution. International Journal of Scientific Research and Modern Technology, 71–88. https://doi.org/10.38124/ijsrmt.v1i12.466

[32] Adusupalli, B. (2021). Multi-Agent Advisory Networks: Redefining Insurance Consulting with Collaborative Agentic AI Systems. Journal of International Crisis and Risk Communication Research, 45-67.

[33] Dwaraka Nath Kummari. (2022). Iot-Enabled Additive Manufacturing: Improving Prototyping Speed And Customization In The Automotive Sector . Migration Letters, 19(S8), 2084–2104. Retrieved from https://migrationletters.com/index.php/ml/article/view/11882

[34] Data-Driven Strategies for Optimizing Customer Journeys Across Telecom and Healthcare Industries. (2021). International Journal of Engineering and Computer Science, 10(12), 25552-25571. https://doi.org/10.18535/ijecs.v10i12.4662

[35] Adusupalli, B., Singireddy, S., Sriram, H. K., Kaulwar, P. K., & Malempati, M. (2021). Revolutionizing Risk Assessment and Financial Ecosystems with Smart Automation, Secure Digital Solutions, and Advanced Analytical Frameworks. Universal Journal of Finance and Economics, 1(1), 101-122.

[36] AI-Based Financial Advisory Systems: Revolutionizing Personalized Investment Strategies. (2021). International Journal of Engineering and Computer Science, 10(12). https://doi.org/10.18535/ijecs.v10i12.4655

[37] Karthik Chava. (2022). Harnessing Artificial Intelligence and Big Data for Transformative Healthcare Delivery. International Journal on Recent and Innovation Trends in Computing and Communication, 10(12), 502–520. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11583

[38] Challa, K. (2022). The Future of Cashless Economies Through Big Data Analytics in Payment Systems. International Journal of Scientific Research and Modern Technology, 60–70. https://doi.org/10.38124/ijsrmt.v1i12.467

[39] Pamisetty, V., Pandiri, L., Annapareddy, V. N., & Sriram, H. K. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management (June 15, 2022).

[40] Innovations in Spinal Muscular Atrophy: From Gene Therapy to Disease-Modifying Treatments. (2021). International Journal of Engineering and Computer Science, 10(12), 25531-25551. https://doi.org/10.18535/ijecs.v10i12.4659

[41] Kaulwar, P. K. (2022). Data-Engineered Intelligence: An AI-Driven Framework for Scalable and Compliant Tax Consulting Ecosystems. Kurdish Studies, 10 (2), 774–788.

[42] Operationalizing Intelligence: A Unified Approach to MLOps and Scalable AI Workflows in Hybrid Cloud Environments. (2022). International Journal of Engineering and Computer Science, 11(12), 25691-25710. https://doi.org/10.18535/ijecs.v11i12.4743

[43] Nandan, B. P., & Chitta, S. (2022). Advanced Optical Proximity Correction (OPC) Techniques in Computational Lithography: Addressing the Challenges of Pattern Fidelity and Edge Placement Error. Global Journal of Medical Case Reports, 2(1), 58-75.

[44] Raviteja Meda. (2021). Machine Learning-Based Color Recommendation Engines for Enhanced Customer Personalization. Journal of International Crisis and Risk Communication Research , 124–140. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3018

[45] Rao Suura, S. (2021). Personalized Health Care Decisions Powered By Big Data And Generative Artificial Intelligence In Genomic Diagnostics. Journal of Survey in Fisheries Sciences. https://doi.org/10.53555/sfs.v7i3.3558

[46] Implementing Infrastructure-as-Code for Telecom Networks: Challenges and Best Practices for Scalable Service Orchestration. (2021). International Journal of Engineering and Computer Science, 10(12), 25631-25650. https://doi.org/10.18535/ijecs.v10i12.4671

[47] Vamsee Pamisetty, Lahari Pandiri, Sneha Singireddy, Venkata Narasareddy Annapareddy, Harish Kumar Sriram. (2022). Leveraging AI, Machine Learning, And Big Data For Enhancing Tax Compliance, Fraud Detection, And Predictive Analytics In Government Financial Management. Migration Letters, 19(S5), 1770–1784. Retrieved from https://migrationletters.com/index.php/ml/article/view/11808

[48] Someshwar Mashetty. (2020). Affordable Housing Through Smart Mortgage Financing: Technology, Analytics, And Innovation. International Journal on Recent and Innovation Trends in Computing and Communication, 8(12), 99–110. Retrieved from https://ijritcc.org/index.php/ijritcc/article/view/11581

[49] Srinivasa Rao Challa,. (2022). Cloud-Powered Financial Intelligence: Integrating AI and Big Data for Smarter Wealth Management Solutions. Mathematical Statistician and

Engineering Applications, 71(4), 16842–16862. Retrieved from https://philstat.org/index.php/MSEA/article/view/2977

[50] Paleti, S. (2022). Fusion Bank: Integrating AI-Driven Financial Innovations with Risk-Aware Data Engineering in Modern Banking. Mathematical Statistician and Engineering Applications, 71(4), 16785-16800.

[51] Pamisetty, V. (2022). Transforming Fiscal Impact Analysis with AI, Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance. Big Data, and Cloud Computing: A Framework for Modern Public Sector Finance (November 30, 2022).

[52] Kommaragiri, V. B., Gadi, A. L., Kannan, S., & Preethish Nanan, B. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization.

[53] Annapareddy, V. N. (2022). Integrating AI, Machine Learning, and Cloud Computing to Drive Innovation in Renewable Energy Systems and Education Technology Solutions. Available at SSRN 5240116.

[54] Transforming Renewable Energy and Educational Technologies Through AI, Machine Learning, Big Data Analytics, and Cloud-Based IT Integrations. (2021). International Journal of Engineering and Computer Science, 10(12), 25572-25585. https://doi.org/10.18535/ijecs.v10i12.4665

[55] Venkata Bhardwaj Komaragiri. (2021). Machine Learning Models for Predictive Maintenance and Performance Optimization in Telecom Infrastructure. Journal of International Crisis and Risk Communication Research , 141–167. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3019

[56] Paleti, S. (2021). Cognitive Core Banking: A Data-Engineered, AI-Infused Architecture for Proactive Risk Compliance Management. AI-Infused Architecture for Proactive Risk Compliance Management (December 21, 2021).

[57] Harish Kumar Sriram. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Mathematical Statistician and Engineering Applications, 71(4), 16729–16748. Retrieved from https://philstat.org/index.php/MSEA/article/view/2966

[58] Chava, K., Chakilam, C., Suura, S. R., & Recharla, M. (2021). Advancing Healthcare Innovation in 2021: Integrating AI, Digital Health Technologies, and Precision Medicine for Improved Patient Outcomes. Global Journal of Medical Case Reports, 1(1), 29-41.

[59] Data Engineering Architectures for Real-Time Quality Monitoring in Paint Production Lines. (2020). International Journal of Engineering and Computer Science, 9(12), 25289-25303. https://doi.org/10.18535/ijecs.v9i12.4587

[60] Pallav Kumar Kaulwar. (2021). From Code to Counsel: Deep Learning and Data Engineering Synergy for Intelligent Tax Strategy Generation. Journal of International Crisis and Risk Communication Research , 1–20. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/2967

[61] Pandiri, L., & Chitta, S. (2022). Leveraging AI and Big Data for Real-Time Risk Profiling and Claims Processing: A Case Study on Usage-Based Auto Insurance. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3760

[62] Kummari, D. N. (2022). AI-Driven Predictive Maintenance for Industrial Robots in Automotive Manufacturing: A Case Study. International Journal of Scientific Research and Modern Technology, 107–119. https://doi.org/10.38124/ijsrmt.v1i12.489

[63] Gadi, A. L. (2022). Cloud-Native Data Governance for Next-Generation Automotive Manufacturing: Securing, Managing, and Optimizing Big Data in AI-Driven Production Systems. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3758

[64] Dodda, A. (2022). Secure and Ethical Deployment of AI in Digital Payments: A Framework for the Future of Fintech. Kurdish Studies. https://doi.org/10.53555/ks.v10i2.3834

[65] Gadi, A. L. (2021). The Future of Automotive Mobility: Integrating Cloud-Based Connected Services for Sustainable and Autonomous Transportation. International Journal on Recent and Innovation Trends in Computing and Communication, 9(12), 179-187.

[66] Dodda, A. (2022). Strategic Financial Intelligence: Using Machine Learning to Inform Partnership Driven Growth in Global Payment Networks. International Journal of Scientific Research and Modern Technology, 1(12), 10-25.

[67] Just-in-Time Inventory Management Using Reinforcement Learning in Automotive Supply Chains. (2021). International Journal of Engineering and Computer Science, 10(12), 25586-25605. https://doi.org/10.18535/ijecs.v10i12.4666

[68] Srinivasa Rao Challa. (2021). From Data to Decisions: Leveraging Machine Learning and Cloud Computing in Modern Wealth Management. Journal of International Crisis and Risk Communication Research , 102–123. Retrieved from https://jicrcr.com/index.php/jicrcr/article/view/3017

[69] Kommaragiri, V. B. (2021). Enhancing Telecom Security Through Big Data Analytics and Cloud-Based Threat Intelligence. Available at SSRN 5240140.