Migration Letters

Volume: 19, No: S2 (2022), pp. 1875-1900

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Bridging Traditional Infrastructure And Intelligent Automation: The Role Of AI/ML In Banking IT System

Bharath Somu

Abstract

AI/ML technologies are now maturing, available in performance and price, and secured as well as enabled by evolving and well-accepted cloud environments based on shared or hybrid infrastructures. AI/ML and advanced analytics are rapidly introducing new capabilities in banking as part of the digital transformation of traditional IT systems. On the one hand, IT systems traditionally have been a siloed set of specific applications, but during the last 50 years the R&D efforts were often focused on coping with the increasing complexity of legacy systems, accomplishing virtualization, and ensuring security and reliability. On the other hand, in recent years the emergence of new methodologies and new technologies has generated the possibility of advancing the functionality of already available systems. The first products of this opportunity have been realized as AI/ML systems that provide online deployment of pre-trained models. While the cost could be high, especially in the case of generating the training data set, for many use cases it could be well worth the investment. However, generative AI and other new capabilities are now challenging the banks in providing sufficient robustness and reliability in the production environment of on-premise systems. The speed and applicability of these newer technologies are foreseen by the R&D department of banks that made the necessary investment into the knowledge and resource foundation.

Today, the available options are: 1) low-risk options for the digitalization of specific services--mostly in the front-end applications and 2) (often high-risk) options into designing new solutions--in-house, partner-based or third party sourced. It is aimed to review the pros and cons of the existing options, and map the bank readiness in adopting them. [1]A project to assess the data readiness for CDP through a review of the existing data domains of clients will be outlined as well. All opportunities would depend on addressing the needed data and skill investment areas, but even with less than the project-worthy readiness there are still adequate low-risk solutions. On the one hand, data readiness needed to draw upon a well-defined data architecture framework through high-level architectural views to narrow down gap areas. The recently developed microarchitecture and opened libraries would be reviewed, along with the higher-level architectural elements developed for banking IT systems to serve as guidelines. On the other hand, to acquire skill readiness, an educational framework is needed to improve domain knowledge with aligned roadmap options for newly arrived technologies like AI/ML.

Keywords: *Legacy System Integration, AI-Driven Automation, Machine Learning In Banking, Hybrid IT Architecture, Core Banking Transformation, Predictive Analytics, Infrastructure Modernization, Digital Core Banking, Operational Efficiency, Automated Risk Management,*

Architect-I, bharthsomu@gmail.com,ORCID ID: 0009-0008-6556-7848

Data-Driven Decision Making, Banking Process Automation, Intelligent Workflow Orchestration, Cloud-Native Banking Solutions, Real-Time Data Processing.

1. Introduction

Over the last decade, financial sector technologies (FinTechs) have proliferated, turning desirable products and functions of banking services into commodities. The FinTech transformation is driven by the expectations of a generation of tech-savvy customers. There is pressure on traditional banking institutions to transform their business processes and models and leverage the technological landscape to deliver services in the cloud, decentralize access, and offer value-added services through embedded banking capabilities. Globally, regulatory frameworks are changing to collaborate with FinTechs, traditionally considered displaced players. Development funds for skilling in financial technologies are being released, creating FinTech hubs, and simplifying test-and-learn regulation for startups are examples. This discusses the implications of bridging traditional infrastructure and intelligent automation through Artificial Intelligence and Machine Learning (AI/ML) in IT systems that run applications supporting these services.

There is suspicion that intelligent automation is overhyped, and a burst of early automation enthusiasm will involve billion-dollar write-downs as ongoing subscriptions to snake-oil solutions. To mitigate risks, a proposal is made for a governance framework based on maturity levels and guiding principles. This describes short-old journeys of bulk policy-generation, adoption of "Augmented Intelligence," such as AI-supported claim-guarantee mismatch checking, similarities to order-matching fraud earlier addressed with business rules, and a recent SEC reporting analytics use case. They argue that multi-year, multi-domain, business-value-driven scaling agendas increase the signal-to-noise ratio and IA solutions' chances of success.

Flexibility and implementability are two key dimensions of these principles. For each dimension of every principle, guidelines are formulated for key stakeholders involved in strategy selection, implementation, governance, and adoption of intelligent automation solutions. Recent waves of intelligent automation and associated AI-hype probably mirror earlier automation waves, such as with "expert systems" and "case tools," process mining, and business rules. In design, construction, and regulatory environments with rich experience, it is possible to ensure that the incrementally built AI-enhanced systems learn quickly from business experience and facilitate integration with an evolving technology platform consisting of event detection, data processing, and predictive analytics capabilities.

1.1. Background and Significance The development of technology must occur within the framework of discipline and responsibility, especially with respect to the demand for enhanced service, security, and efficiency when banking operations migrate from traditional banking systems to the Internet. Every aspect of society has its counterpart in cyberspace, a virtual model of the real-world system. Since cryptocurrencies, social networks, information customer loyalty institutions, and state security measures, as well as their counterparts, have emerged, the banking system now has its own model. The banking system initially refused to accept cryptocurrency or digital currency as a valid form of transaction, but this is evolving. The difficulties resulting from these processes may spark a global economic crisis and inspire other developing fintech industries to iteratively develop alternative models of finance and banking. Despite lay worries over the adoption of AI/ML systems in banking organizations, and resultant dangers to jobs, cyberattacks, and algorithmic cognition, AI/ML systems' efficacy in information management is expected to prevail. The transition from conventional banking formats to augmented intelligence systems is underway across all dimensions of the banking system and elsewhere.

Fig 1: Intelligent Automation in Banking & Financial Services.

The banking system, in collaboration with software providers, is expected to develop a positive discursive paradigm, building upon earlier degradation of the conventional banking system and new fintech industries entering banking infrastructure development. Providers of traditional banking services are equally under siege, now at a transformative and potentially doom-laden crossroads. The banking system's rapid development and imperative action highlight the intertwined fates of all industry members. Transformation of the complex and labyrinthine systems of recently established banking enterprises is anticipated. Awareness of the need for labor force education in foundational technology to address new environments and to facilitate its adoption in the international information sciences labor market is significant.

The analysis of new complex international banking service institutions is anticipated to connect the research directions, seeking new insights into systemic transformations and compliance measures, with a focus on auditing the AI/ML systems installed. As traditional systems are either reformed or discarded, ethical dilemmas involving algorithmic decisions, information exchange, and policy implementation arise. These are expected to intensify as alternative regimes emerge. Deeper understanding of alternative regime transformations, such as the cyber-environment modeling of FinTech industries, their inception, development, and consolidation, is likely to enhance understanding of basic human rights violations and new forms of exploitation, as well as of new platforms of education and information auditing in cyberspace to confront and challenge these terrors.

2. Understanding Traditional Banking Infrastructure

In this section, the main areas of traditional banking IT systems are introduced, along with their general characteristics and roles, including the following: (1) Core banking systems, (2) Specialized banking systems, and (3) External systems and databases. After further analysis and observation, the main problems in traditional banking systems are highlighted.

In a bank, there are three main areas of IT systems:

Core banking systems: Core banking systems cover the domain of most bank's activities, offering applications that support all the standard transactions run during a banking day. This area generally includes a complete set of apps covering private, corporate and investment banking, as well as hardware and networking capabilities. The core platforms are often based on 3rd party, traditional banking software, which, in many cases, are old systems (typically older than 10 years). Due to the extent of the business involved and because of historical reasons, these applications and their supporting databases exist independently from other systems. In these environments, applications are based on standardized and highly complex technologies, they are often inflexible, difficult to maintain, and risk prone. Configuring new functions through business logic is sometimes hard to achieve.

On the other hand, some of these older platforms may already have their alternatives expressed in newer systems as web-based clients. Routines and functionalities have already been re-implemented elsewhere. While the business environment is probably the most complex part of integrability, the existing systems constitute a vast repository of legacy knowledge, techniques and know-how. The new area needs to connect these functions to make it more efficient. Nowadays there is no centralized legacy database, scripting language or programs.

Specialized banking systems: This area contains systems that are not core banking but are nevertheless essential for the bank to operate as a whole. Generally, these comprise specialized database servers and applications, and full-fledged pieces of enterprise software. Examples of products in this field include credit scoring applications, business intelligence applications, and treasury risk calculators. There are several different products of this type, but they mostly operate independently from the core banking systems, which means that some functionality is duplicated in the two areas. Sometimes both areas may share a persistent data storage solution, which means that some data need to be synchronized and updated. Connecting these databases is another step towards an integrated banking environment. Additionally, the same procedures and calculations often need to be executed both on the specialized applications and elsewhere. This is the case, for example, with some credit analysis models and rules, which are computed both in the scoring applications, and the core banking systems at transaction run time to determine acceptance. The connection of some of these processes would save both hardware capacities, implementation resources, and maintenance costs.

2.1. Overview of Banking IT Systems The banking sector is the biggest contributor to the Indian service sector, with 766 scheduled banks. It is the backbone of any economy, and the purity of the banking process depends on the maturity of its machinery to evolve, grow, or die. The banking sector has achieved a comparative increase in productivity and efficiency across banks, promoting a competitive position among banks. The domain name of the banking sector has witnessed revolutionary changes in the last decade, and innovations in banking have made it the first mover in providing better quality products and services to every nook and corner of the country and globe. Bank customers will have improved facilities and efficient service, while banks will be comparatively deterred to serve amicably and efficiently. AI is a branch of fintech, which is defined as anything in technological innovation that improves financial services or the delivery of financial services. A financial system in which technology is used to provide products and services is termed a fintech financial system. Within a financial system, fintech firms act as enablers to improve the industry by providing the best services to customers. AI is a branch of fintech that specializes in the intelligence of machines. The world of banking is awash with data fed daily by millions of transactions. Every piece of data is a potential goldmine for banks, which are beginning to harness AI algorithms to analyze this data. The financial sector is a classic case of where AI and fintech must be leveraged in the competition with immense potential to provide better efficiency and costs. However, with AI in the retail banking sector, there is a need to better understand and discuss how AI can create profound and unexplored opportunities.

2.2. Legacy Systems and Their Challenges Legacy systems refer to outdated computing systems or methods that could be used in any business operation. The systems were considered modern and efficient in their days but are now unable to assist organizations in carrying out their routine operations or responding to changes in the environment, such as new policies, regulations, procedures, and opportunities. Banks have become so dependent on the old systems that they have been initially their core business. Users who had been trained to use the old systems have a hard time adapting to the new ones. Human resources constraints and sometimes politics determine the way how new applicants are trained on the systems, with a tendency to prefer the use of the legacy systems. If a person thinks that money should be recorded in a small box hidden in the office, then it will be next to impossible to convince him/her that the best approach is to store it in a big banking vault where everyone's money can be assured in proper conditions. At the same time, it needs to be acknowledged that what was designed as good "money security" management techniques in the past is doomed to eclipse.

Computers are like people. A person must do nothing else but answer data, perform calculations, and produce output as fast as it can to be considered intelligent. Intelligence or, in this case, smartness comes from the ability to perceive a state of the world and to produce an adequate answer using acquired knowledge. Organizations that still hold the aging systems are unable to benefit from their investment in multi and smart Resource Planning tools. Data mining, analysis, and extreme reporting tools adopted by rivals are unknown to them, as well as integration deduction before data filtration processes or decision simulations. All these add to the speed of the business decisions and execution. Problem-oriented language systems have been put to work only in a few projects, with poor results from implementation through maintenance. The success is more due to the cost of money worth of the man months needed to complete the tasks than to the effectiveness of the system.

2.3. Regulatory and Compliance Considerations The introduction of Artificial Intelligence (AI) and Machine Learning (ML) technologies into the authorities' processes can significantly advance how data is actually aggregated, validated, processed, and how the outcome might resemble. However, in the existing banking information technology (IT) systems, the data rarely is made available in the same way it was collected. Therefore, the biggest challenge remains how to transform the authority level requirements to the banking IT systems level. To enable this transformation, hundreds of individual data connectors need to be built once. This significantly raises the costs of compliance and demands a collaboration model between the authorities and market participants. In addition to that, the existing market solutions usually do not cover the full extent of the broader solution involving both the compliance task performance and management. This offers a business opportunity for FinTech/InsurTech companies providing compliance as a service.

Equ 1: AI Decision Accuracy in Financial Tasks

$$A_{dec} = 1 - \frac{\epsilon}{\sqrt{T}}$$

Let:

- A_{dec}: Accuracy of ML decision
- T: Number of training iterations
- ϵ: Error margin

3. The Evolution of Intelligent Automation

Intelligent automation (IA) and operational resilience are significant agendas for many major banks today. The pandemic has accelerated banks' digital transformation initiatives, as they strive to keep pace with the competition for faster and more innovative customer services. Sophisticated AI/ML low-code platforms and orchestration/frame platforms into existing traditional environments represent a challenge and opportunity in providing seamless interconnected functionality between traditional and new systems. This is particularly challenging for banks' technical debt legacy environments due to complexity, vendor diversity, skill shortages, and standardisation issues. However, there is an opportunity to form strategic partnerships with cloud platform providers, orchestration, and integration innovators through innovations that can deliver rapid and tangible outcomes, and assist in the careful orchestration of legacy transformation and library alleviation processes.

Many banks traditionally imported data externally or sourced it through an alternative sampled approach. The conversion of the data into the required formats and/or performance is done offline before it is uploaded externally. Timeliness and a more interactive need in the performance of planning analytics have elevated this process to switch towards an in-house/on-device intelligence automation option. The selected method collects data on public companies using a user-specified ticker input. Financial planning and analysis (FP&A) is an essential and active process among managerial functions across corporations. Of these, budgeting, forecasting, and reporting are ubiquitous practices, closely forming a three-dimension diagonal cube.

Fig 2: Evolution of Intelligent Automation.

Time is the duration an asset is held during a specific observed period, measured by the assessment frequency, storage period, and end date of analysis. The performance of this objective is critical to all three processes because cash flows, revenues, expenses, and accounts directly depend on the time structure. Time dimension is generally tackled by batching or precession, but there is opportunity for the web scraping on its own storage and architecture. All three types of the glove word embeddings are currently served by libraries which align with 60 off-the-shelf financial word forms. It is a machine learning process based on a window definition approach, specifically examining word proximity against a window length to identify contextual meaning.

3.1. Definition and Scope of Intelligent Automation In almost all industries, the intelligent automation of processes is accelerating transformation in the workplace. The banking sector is no exception; intelligent automation is bridging gaps for processes that traditional infrastructure could not deliver. These intelligent automations (IIA) are implemented on banking IT systems in different styles, from AI-led document extraction systems to process automations using ARPA, ML, Natural Language Processing (NLP), and intelligent process automation with 'bots' systems. Upon usage of the tools, the bank finds advancement gaps owing to various reasons, from lack of adaptability to skill gaps. To instruct the banks on how to fill the gaps within the banking processes and systems, an elevator pitch is illustrated covering definitions, classifications, and potential business applications.

Some definitions are checked before understanding the intelligent automation or intelligent understanding term. AI is generally understood as the intelligence exhibited by machines or software that are designed to exhibit some human-like intelligence. This definition covers all subjects under AI, whether it is “narrow AI” or “general AI”, which broadly classify the fuzzy-intelligent automation systems in use today. Automations guided by “narrow AI”, however, have increased adaptability over traditional automated systems by virtue of using techniques like ML, NLP, and computer vision. These automations act within a narrow competency edge but behave ill when detected outside the edge. Having limited adaptability, these automations are ill-formed or lead to invalid automations and hence use dangerous AI or fundamentally flawed AI systems. These automatons cannot add business value in their current form, and some intermediate work is required at this point. This intermediate work is classified as ‘intelligent understanding’. It should be understood that ‘intelligent understanding’ forms part of the system or tools or automations.

3.2. Historical Context of Automation in Banking Historically, Banking and IT often worked in different silos. The Bank always had a Country Head, a Business Head, a CO-O, and an IT Head. The Bank Head would travel to the Head Office at times, depending upon business exposure. His meetings with the IT Head were rather transactional, focusing heavily on budgets, to-do lists, and timelines, while ignoring the local infrastructure and personnel quality that the Bank offered. The outcomes were often unsatisfactory, resulting in endless call center discussions to correct the banks’ suggestions primarily because recommendations required a very different cost approach and were somewhat impractical for smaller nations. Certainly, many one-person-vendor led projects in the Indian Public Sector Banks vis--vis one dedicated IT team with over 50 project managers had a role to play as well, but it was still far from a cut-and-dried case. The concerns here are both time and cost, where often just buying off the shelf applications or applications from different banks is cheaper and easy to integrate or just buying a country head and wonderful technology to “fix” everything. The disagreements here are both candid as well as “embarrassing.” Little did directors or board members realize that there might not be a “fix”, as the banks did not need an overhaul. The IT infrastructure was outdated, but the business maintained a mix of old and new for better cost optimization and customer compatibility.

Currently, the heads of Business and IT are required to have lunch together every week or at least attend monthly meetings, primarily focusing upon “collaboration needs.” In parallel, businesses often put weeks of effort into preparing a “Collaborative IT roadmap.” Often, through an unfortunate series of events, IT personnel with vendor exposure are sent with Business to assist, a couple of such incidents here though dramatized often appear too real. A country head either comes from an entirely different country or otherwise has no prior banking experience, which forces a desperate promotional hunt for something attractive within the locale. Many a time, Business Head’s office-going father would quip this on being candid or just mentioning it across a meeting; a country head is missing the techno-managerial skills or deployment knowledge substantially, yet too afraid of being the Don Quixote here with his knowledge of banking rather not to deploy technology or find fault with the technocrat head. It is here when thinking differently in taking steps of 1% across business foundations leads to new and innovative processes to use the same for better productivity.

3.3. Current Trends in Automation Technologies The Internet of Things (IoT) enhances the concept of ubiquitous computing, connecting various devices onto a network. It allows individuals to access and communicate anything, anywhere, at any time, in a seamless manner. Banking is a service sector where uninterrupted exchange of information and data is critical.

This paper discusses the architectures, protocols, and procedures used in a banking service scenario, by which a bank can provide its value-added services to customers. It presents the current state of service-oriented banks, the existing protocols used, and a complete analysis of the routing protocols and architectures used for creating a Smart banking environment. It also proposes a Smart banking architecture, called the ROSS protocol, to overcome the existing complications and limitations of the Smart banking environment. The prospective features of ROSS, an intelligent routing protocol, are also discussed. It suggests a complete architecture integrating both banking and the Smart banking environment.

With Smart banking, all banking services would be delivered in a more personalized and comfortable way. Banking services would be available to all classes of people at any time and location via various smart devices, while high-speed data connectivity would ensure efficient service delivery. Existing banking processes would be fully automated and the risk factor minimized via a set of intelligent and well-coalesced machine learning and data mining algorithms. There has been improved security for Smart banking services along with a rise in fraud detection rates. Eventualities of service delivery would be narrowed down to error rates with proper and continuous monitoring of the service level, thereby achieving optimal overall growth for a banking service organization.

4. Artificial Intelligence and Machine Learning in Banking

Artificial Intelligence (AI) is increasingly recognized as a key enabler of digital transformation across a large number of industries. It is revolutionizing work practices from account-keeping to sales and contracts to cybersecurity. AI is going well beyond processing big data to empower enterprises to become more creative, flexible, and agile and build real-time, high-performance systems that foresee consumer needs and respond in a timely manner.

Banking operations worldwide are undergoing a paradigm shift as a result of the tremendous technological upheaval brought on by the rise of Artificial Intelligence (AI) and allied technologies like Automation, Big Data Analytics, the Cloud, etc. as interest in concepts such as Virtual Banking, Internet Banking, and Mobile Banking sees a sharp rise. In order to provide the 24*7 customer experience that this new generation of tech-savvy customers has come to expect, Indian banks are enabling the technologies of tomorrow.

Fig 3: AI & ML In Banking.

In order to provide the infrastructure for processing these massive volumes of transactional and customer data, traditional banking IT systems must evolve into modern paradigms based on innovative concepts like the Cloud, Automation, Big Data, and AI. Only an intelligent framework that combines rules-based engines, predictive models, and deep learning algorithms opens up possibilities for real-time monitoring and tracking. This is crucial for building data-driven surveillance systems powered by effective machine learning (ML) models for traditional banking. This calls for a shift in approach to infrastructure modernizations from a pure play focus on back-end IT systems to front-end systems driving customer engagement.

4.1. Fundamentals of AI and ML Artificial Intelligence (AI) and Machine Learning (ML) are two of the most commonly used terms in the technology landscape today. AI and ML are reshaping business operations across all industries in many different ways, and businesses are increasingly exploring the opportunities and risks introduced by digital platforms. The banking sector is investing heavily in AI initiatives across a range of use cases, including internal functions such as operations and audits, as well as customer-facing applications dealing with fraud detection, wealth management, and risk assessment.

AI encompasses a range of evolving technologies that emphasize the ability of machines to exhibit intelligence. AI is often categorized into two types: narrow AI and general AI. General AI has not yet been realized, but academic works and popular culture envision "generals" or artificial "super-intelligences." In 1956, artificial intelligence was defined as "every aspect of learning or any other feature of intelligence may in principle be so precisely described that a machine can be made to simulate it." A narrower version focuses on machines that mimic human cognitive functions. Such systems often include some aspects of AI, and their increasing efficiency has attracted significant media attention.

Narrow AI is much more common and includes systems that deal with unstructured data, like images, speech, and text, as well as structured data such as transaction records, spreadsheets, and databases. These systems are only "intelligent" concerning a specific task domain. Still, large amounts of data are required for successful operation, and they can exhibit surprising behavior or potentially bias individuals, raising ethical issues. In the 1990s, the term knowledge or expert systems was favored. Expert systems relied on symbolic processing and knowledge bases coded in ontological schemes. AI has broadened along with the fields of parallelism, neural networks, and knowledge representation and has shifted to probabilistic approaches, pattern recognition, and control techniques.

4.2. Applications of AI/ML in Banking AI/ML is having a major impact on the banking and finance sector, and it is becoming even more important in the future. Artificial Intelligence (AI) refers to systems that can perform functions typically associated with intelligent beings, including perception and speech recognition. Machine learning (ML) refers to a subset of AI where statistical techniques are used to enable machines to improve their performance on a task with experience. Intelligent Automation (IA) refers to the combination of automation with AI and ML, meaning that processes that are automated can learn from the data being processed and consequently improve performance. Banks are acquiring new methods for analyzing huge data thanks to the swift advance of the internet, which enables them to capture large amounts of transaction information. AI may be used to evaluate this data, identify problematic data, perform risk prediction, timely tracking, and further determine if it fits the standards of bank transactions. Furthermore, AI can warn of difficulties in bank transactions, prohibit inappropriate transactions in real-time, and significantly increase banks' risk management levels. AI may handle the loan process when banks lend. AI and big data may be utilized to examine client data and conduct intelligent risk control. In this process, AI may carry out service awareness, credit evaluation, risk presiding, and risk-following. AI/ML applications serve to eliminate repetitive, mundane and unproductive tasks in the improvement processes of business operations in banks which leads to freeing up larger resource capacity and hours for the reincorporation of them in processes endowed with production high value added.

AI is helping change how banks advertise and engage with their customers, such as via AI-driven adverts based on past consumer activity, likes, and demographics. AI is optimizing engagement conversions, reducing the expenditures of acquired clientele, useful customer interactions via targeted digital campaigns, creating engagement paths with post-acquisition clients, and even analyzing responses to marketing campaigns and improving targeting in subsequent campaigns. Many banks are automating marketing and questions concerning wealth generation and financial planning. AI is being integrated with agents in charge of Financial Inclusion to understand clients' needs, offer products, and explain financial concepts, while incorporating serious games for literacy and training, and automating marketing strategies attempting to boost preparedness for Fintech Financial Technologies adoption.

4.3. Benefits of AI/ML Integration The organization may retain its old architectures and incorporate modernization into their existing systems, with minimal modification, to suit the growing expectations and intelligent advancement. The introduction of artificial intelligence (AI) and machine learning (ML) in traditional banking systems is one of the best possible solutions. Some organizations have enough budgets to replace their entire systems and architectures. These organizations can adopt state-of-the-art technologies that require modernization to minimize infrastructure changes. Organizations can only modernize technology that has a reasonable budget. The organizations do not have the required budget to replace their entire architecture. In that context, some possibilities to make their traditional systems intelligent are described here. This last mile option needs a considerable intermediation to sell these possibilities in traditional organizations. The organizations would need to be convinced that they are on the track to avoid a total overhaul of their existing successful systems. Additionally, it will take a considerable time delay for the financial success of the application of these methods. Recommendations about improvement ideas and the future direction for these organizations can be used for making an attractive new application in their organization.

The benefits of incorporating AI/ML in the banking sector may be summarized as follows: Improved customer services, faster & better processing of data, cost and time saving in data processing, quick detection of anomalies & risk prediction modeling, enhanced knowledge on existing customers, and improved marketing effectiveness. AI & ML can improve productivity and reduce processing costs by storing and sharing huge volumes of data faster and providing more flexible access. Additional automation is expected to reduce service costs and expand the customer base. ML & AI can help with cheap processing of audio and video data, which can keep records of fraud exposure during fund transfers. It can also process social media data regarding company goodwill, staff behavior, and bankruptcy hints. AI-powered K-Y-C bots can assist in processing a new customer profile within minutes. AI can be used to predict frontline employee attrition, ensuring that they maintain a balance between productivity and positions of power.

5. Integrating AI/ML with Traditional Systems

Intelligent automation in investment banking operations is gaining momentum as banks are increasingly investing in their functionality, services, capabilities, and distribution networks. However, many banks still rely on traditional core IT systems which lack the necessary processing capabilities. These traditional IT systems pose obstacles to the adoption of intelligent automation in banks. Furthermore, the transition from traditional core IT systems to intelligent automation is hampered by high costs and regulatory scrutiny over AI accountability. The unique challenges of integrating AI/ML with traditional core infrastructure IT systems raise challenging questions, such as: What are the obstacles posed by traditional systems to the adoption of intelligent automation in banks? What can banks do to better leverage AI/ML within traditional core infrastructure IT systems? Drawing on the existing literature concerning intelligent automation and machine learning for investment banking operations and the distinct national and industry settings of the presented case study, The [Name of Organization] has been qualitatively researched and analyzed based on ten semi-structured expert interviews with operational managers and data scientists in the banking industry.

The findings reveal that IT systems of banks are composed of core infrastructure IT systems and ancillary service line or function IT systems. The age, architecture, redundancies, and dependencies of core infrastructure IT systems are obstacles for banks to better leverage AI/ML. The silo decision-making processes, data laundering hurdles, unfamiliarity with AI/ML, and lack of trust are obstacles for banks to better leverage AI/ML. The implications for management include categorizing and ranking traditional IT systems, identifying structural redundancies and eliminating performance hurdles of traditional core infrastructure IT systems. AI/ML design and deployment specialization and dedicated outsourcing partnerships are recommended for ancillary service line IT systems. Manual and semi-automated fixes, data pipeline bifurcation, and tower-bypassing commercial workarounds are advised for traditional core infrastructure IT systems.

5.1. Strategies for Integration The integration of intelligent automation and AI/ML technologies into traditional enterprise infrastructure and systems is becoming increasingly important in the digital transformation of banking. These technologies must be integrated with existing IT systems and infrastructure. Design, development, testing, and deployment of intelligent automation solutions should leverage the investments already made by the banks in legacy systems integrated with innovative web and enterprise applications.

Banks recognize that the need for intelligence has increased manifold, given the smart nature of customer interactions and transactions and the operational processes to capture and respond to them. There is potential for large-scale automation of these tasks, especially those of a repetitive or predictable nature, such as customer onboarding, follow-ups for queries/products, product fulfillment, payment processing, fraud detection, regulatory guidelines retrieval, remediation requests, and compliance assessments. In addition to operational efficiencies, automating such tasks can remove biases and subjectivities, and allow workforce release from mundane day-to-day activities to become problem-finders, rather than problem-solvers.

Tactical and strategic business decisions have to become AI/ML-driven to cope with the volume and variety of transactions, and cutoff timelines in detecting and responding to risk events. By applying predictive technologies, banks can do pre-funding, pre-closure, and pre-settlement funding monitors, auto-adjustments, cash flow forecasting, studying churn patterns for active organizations, churn assessments for long-tail relationships, underwriting assessments for clients, and jurisdictional clustering. A 360-degree review of counterparty exposure and risk should happen on an ongoing basis and not merely at the year-end for annual assessments. Banks should look to incorporate AI/ML-based performance drivers, scenarios, and example posting quantities to creatively contribute to netted off liquidity aggregation, threshold setting assessments, and measurement and monitoring of attribution across custodians, funds managers, client funds, portfolios, and investment strategies to find process improvement opportunities and growth areas. In fraud detection for risk assessment, underlying transaction behavior across internal checks should analyze the correlation, and outcome, of a multitude of payment requests, and behavior and rationality tests should be designed.

5.2. Case Studies of Successful Integrations Application of Artificial Intelligence in Banking Case Studies of Successful Integrations: State Bank of India Virtual Assistant and an AI-based Intelligent Marketing Program are discussed.

A case study of SBI-SIA Virtual Assistant

Artificial intelligence (AI) is now widely acknowledged as one of the most important digital transformation enablers across a significant number of industries. AI is supporting Indian banks in upgrading their operations across the board, from accounting to sales to contracts and cybersecurity. In recent years, banks across India have developed a variety of quick, simple, and secure banking platforms to accommodate the needs of their respective clients. AI-enabled software is one such development that aids banks in developing other digital platforms. SBI-SIA is a virtual assistant developed to satisfy the growing use of newer digital banking and client informational platforms. In the aspect of cost, dependability, and maintenance, this program is highly viable and efficient. Several banks use this virtual assistant for the smooth operation of their banking framework, and clients give it a very high score.

An AI-based marketing program developed by a financial organisation

The financial sector is evolving toward an integrated and automated intelligent platform as AI technology matures. The whole economy offers strong growth potential, but a greater market share will necessitate fierce competition. The investigation and implementation of DL enables banks to cut costs and boost efficiency. The traditional financial sector has confronted increased client attrition but reducing net profit growth. Ping and Group's One Connect uses the DL algorithm to create an integrated marketing scheme merging big data and AI with conventional business procedures. Bank of Shanghai trains employees to build a machine learning model in business scenarios such as mining new customers and retaining lost old customers. This marketing method can solve shortcomings of traditional marketing modes, reduce human and material resources, and improve work efficiency. Applying AI to marketing will improve banks' market competitiveness and customer satisfaction. Intelligent marketing is carried out in two processes: assessing clients based on interests and developing focused marketing programs for various customers.

Equ 2: Integration Complexity Function

$$I = \delta \cdot (N \cdot M)$$

Let:

- I: Integration complexity index
- N: Number of legacy subsystems
- M: Number of AI/ML modules
- δ: Compatibility coefficient (lower means easier integration)

5.3. Challenges and Solutions in Integration The digital transformation of banks relies on the increasing merge of traditional infrastructure and intelligent automation. However, as a result of the efforts to modernize banking IT systems, resilient financial systems, and the rapidly evolving marketplace, many banks depend on legacy software and hardware that were not originally meant to interoperate. Therefore, there is a significant risk of systems that do not interoperate properly if they are deployed independently without standard interfaces, as they can broadly affect the organization’s operations.

Due to the critical importance of banking systems and services, banks must stay ahead of performance and efficiency needs and move knowledge and processes not just to SaaS applications but also to intelligent automation. Thus, legacy restrictions and conflicts will have to be repaired. One of the most critical scenarios required is the migration between on-premises and cloud environments, mostly driven by mergers & acquisitions of Fintech or banks with innovative offerings. Following months of inspections, inquiries, and due diligence, M&A activity routinely leads to a backlog of hardware and software. The effectiveness and learning of recent software have also extremely exceeded the expectations of business users and owners, leaning towards more intelligent solutions based on cloud-based APIs.

Legacy applications and hardware will always be available, often with long-life spans and continuous need for service and support; the solution to the evolving challenge of conceiving intelligent systems that contain a core of legacy elements but still present an interface for open and flexible data sources and functional expansion will have to be included in the varied portfolios of intelligent automation suppliers. An interface, either API or GUI, may accept non-straightforward data sources from service support or exist independently as a viewing console. AI and ML resources may either be built or adapted to the new scenarios. Such a smart blending of both new and historical pieces may well serve the remaining years of the legacy system, both as a compiled container or as a direct translation system, even with the possible incorporation of existent NLU and NLG components.

6. Impact of AI/ML on Banking Operations

Artificial intelligence (AI) and machine learning (ML) are increasingly recognized as essential components of technological advancement in banking operations and services. The use of AI/ML in banking operations provides significant opportunities for process-oriented benefits to various activities performed in traditional banking institutions . AI/ML can facilitate reliable and manageable communication for internal processes of banks, provide advancements for back-office operations, identify fraudulent behavior of cardholders to secure channels for fund transfers, and verify customer identity, among many others. In banking services offered by traditional banks and new-age ecosystem players, AI/ML is already being used for effective cross-selling and up-selling engagement, customer analytical intelligence that leverages behavioral data, ubiquitous integration of audio and visual recognition for personalized consultations, and decision-making on instant loan approvals. Despite various AI/ML applications and benefits being recognized and valued by banking professionals, there exists a limited understanding of the nature and types of technologies used in this area, a holistic view of the ramifications of various AI/ML initiatives on the B2C and B2B operations and services of banks, and the need to address burgeoning privacy and security issues. High-level leadership and strategizing understanding and guidance are lacking from banks to address student-specific and varied concerns.

The untapped scholarly research gap on this issue created further motivation and objective for this paper. To meet this objective, the reported research adopts a progressive exploratory approach that implements a qualitative research methodology in three exhaustive, iterative phases. The first phase consists of a systematic literature review and three semi-structured interviews with subject-matter experts from various sub-domains of AI/ML and banking, which help construct an interview framework of major AI/ML technologies and their applications in banks. The second phase includes interviews with three high-level banking professionals who have a strategizing understanding of the AI/ML-banking ecosystem. In the third phase, two iterations of inductive, deductive, and thematic analyses are carried out to coalesce myriad insights on the role of AI/ML in banking operations and services. Finally, the major findings of the research, such as the intelligent automation and augmentation architecture of the various AI/ML technologies, and their applications and benefits in various traditional banking operations, services, and processes, are presented. In addition, a holistic view of hypotheses on the ramifications of AI/ML applications on banks, and wide-ranging privacy and governance, regulation, adherence, and fine issues along with progressive research directions and an agenda for further individual exploratory efforts are also provided.

Fig 4: Impact of AI/ML on Banking Operations.

6.1. Enhancing Customer Experience With the constant evolution of technology, customers in the 21st century want more choices, flexibility, and more control over how they bank. As a result, banks are progressively integrating FinTech into their products and services. FinTech is the use of technology in providing financial services to customers. The technology can be part of any financial aspect, both inside and outside the banking system. Machine learning and artificial intelligence are branches of FinTech, with machine learning being a branch of AI. Machine learning is the intelligence of machines, such as the capability of a machine to imitate intelligent human behavior. The introduction of AI/ML FinTech allows banks to have a smart IT architecture and transform traditional infrastructure within existing systems to meet current and future demands while outperforming competitors. Application and implementation of AI/ML in banking IT systems would pave the way for better customer experience, operational efficiency, and risk assessment & fraud detection.

6.2. Risk Management and Fraud Detection Currently, AI/ML plays an important role in risk management within banks. Consequently, this section addresses potential risks and obstacles in the application of AI/ML algorithms in banking IT systems. Financial services have a long-standing and strong legacy of risk management and model review. Comprehensive model risk management and control practices have established both the risk and compliance function. The prospect of introducing AI/ML capabilities into this environment raises the fear of the unknown. The concern is that the complexity of decision-making by AI/ML algorithms cannot be modeled or governed and effect. Consequently, such applications risk becoming a black box and undermining existing risk control and audit processes applied to traditional IT applications. This limits accountability as a regulatory concern. In this context, this paper highlights regulation in terms of blocking undesired outcomes as well as an opportunity for competitive differentiation if planned and executed wisely and properly. As a consequence, significant research has emerged in the last few years. Scholars have advanced principles and measures to assess the risk and compliance aspects of AI and ML models in financial services focusing on model explainability and interpretability. Furthermore, scholars have considered the design of ethical foundations and broader accountability of compensating financial services AI/ML applications that reflect on the model oversight, design and data governance, as well as pre-and post-implementation review processes. Throughout the publications, privacy has also been mentioned as a critical risk. Consequently, this section seeks to provide an overview of the promising literature and a research agenda to stimulate and inspire further contributions in the endeavour to make best use of AI/ML in banking IT systems while still controlling related risks to a manageable amount. This research agenda identifies promising future research avenues, structured as topics either with a focus on foundational knowledge development or addressing impact-focused considerations primarily more of practical relevance and applicability in banking organizations. While this agenda highlights research opportunities at the intersection of IS and finance, research topics of IS considerations addressing AI / ML in bank IT are noted too. To motivate HCI, critical social science or information systems engineers to pursue, this includes an invitation for collaboration with financial experts to help shape the financial system for the better.

6.3. Operational Efficiency and Cost Reduction The paper examines automation technologies in banking IT systems, focusing on how artificial intelligence and machine learning expand traditional IT system infrastructure. Banks and financial services companies recognize automation as a key enabler for strengthening operational efficiency and cost reduction, paving the way for intelligent automation that correlates these goals to enterprise search capacity in growth, performance, and compliance management across various data types that become “big data.” A core concern for many banks today is the large continuous investments in maintaining old IT infrastructure. Moreover, solutions for these concerns often require complicated, high-cost modeling and high computing power, which means these solutions are not very adaptable to the precision needed by banks. The paper proposes fine-tuning an artificial intelligence/machine learning-based solution of an enterprise-wide automation tool for data cataloging and management matching data, metadata, and contextual data to deliver an advanced monitoring system.

Aims architecture abstracts cloud-container architecture, enterprise search indexing/searching, pipeline message queue, multi-stage orchestration, and metadata-driven templating. An AIMS pipeline on one site demonstrates proof of capability before adoption implementation. The implementation can be achieved in 4-6 months using deployment. A bank-wide AIMS run for continuous loading to storage will boost future planning and cloud journey. Continuous adaptation of the current architecture to better utilize self-tuning outside workflow scheduling will make it a driver for intelligent automation to commercialize buddy systems as a service.

Estimates a 50 B market for enterprise-wide intelligent automation tools, currently a service from consulting companies. The literature study explores how a commercializable product may benefit from an earlier research approach leading to a large number of tools then only in-house developed by banks. In-depth research on focused traditional enterprise modeling automation tools as functional/collaborative, IT-based data cataloging, and monitoring tools yields the identification of available tools and backlogs in tool requirements that tracked for a long time are still unresolved. Often use cases have been piloted but never delivered as a product; hence, the lack of offered tools on the market. In exploring how AI/ML for two enterprise cases can be utilized to expand traditional tool applications proven to deliver tools of interest, this led to a new architecture design matching requirements of an under-(re)-searched target domain and focus.

7. Future Trends in Banking IT Systems

AI/ML-fueled Intelligent Automation is truly transforming the functioning of traditional banking IT systems and business operations by creating new integration and orchestration for applications, ORM and data pipelines designed for retail, corporate banking, treasury, risk management, central banking and regulators, and card payment ecosystems. Further, applying AI/ML-driven Intelligent Automation by having enhanced capability on business logic reusing/exploitation, COT, encapsulation, DNA, monitoring with intelligent behavior, knowledge graph and bite-sized apps will push the further capability of integration and orchestration for the existing integration and orchestration created in AI/ML-fueled IT systems. Business control and automation will be advanced by cognitive intelligence and both standard version and core ID can be massively advanced by automatically generated coding and testing along with system health-checking bots. BPM (& BPMS) tools in COT format will further advance model programming. Moreover, AIOps can enhance observability & reliability on integration & orchestration for modern banking business operations.

Fig 5: Future Trends in Banking IT Systems.

Finally, IT economics of business operations will be further advanced in terms of improvement in performance (increase on auto execution ratio and shorten execution time), errors (high individuality & numbers of errors), resource pressures (size and expenses of deployments, increase on fetch needs, etc.) and uneven workloads (execution on physical assets). Cyber security improvement in both technology and management is a critical topic. Application of current intelligent technology will be devoted to speed up on identification, diagnosis and response of cyber security incidents contributing to proper remediation actions (many of which are automatically processed) and root causes elimination to prevention measures. Further, the system vulnerability can be reduced by using the AI/ML based intelligent technology while developing business applications. This study also proposed a concrete roadmap for the new construction of AI/ML-fueled Business Controlling Systems.

7.1. Emerging Technologies in Banking The banking sector is continuously evolving, with emerging technologies changing how banks operate. However, this shift comes with challenges to technology governance and compliance. Banks must adjust their people, processes, and systems to stay competitive in the market. The COVID-19 pandemic accelerated this shift, and emerging technologies have become essential for banks to invest in. This paper focuses on how emerging technologies can help banks innovate their existing information technology (IT) systems. More specifically, it discusses the integration of artificial intelligence (AI) and machine learning (ML) with traditional banking infrastructure and systems.

For many industries, it is essential to unlock the commercial value of trapped data to scale up artificial intelligence (AI) and machine learning (ML) models. Data has become the world's most valuable resource, and data-driven companies outperform the broader market. This indicates that extracting commercial value from existing data is crucial for banks to enhance and scale up any artificial intelligence and machine learning initiatives. However, most banks do not yet have an effective enterprise architecture. Traditional banking IT systems live in silos, built on pre-cloud technologies with batch processes. All transactions, such as credit card clearing, account transfer updates, fund transfers, and loyalty points settlement, are processed in batch mode overnight for settlement.

Most of these are mainframe or disk-based systems using file-based technology with no data quality rules. As a result, banks lose out on data capital to derive analytics models due to a lack of data pipelines to convert unstructured data into consumable sources. Banks need to digitally transform and modernize the 60% of the existing infrastructure to keep it as digital native, creating a state-of-the-art data vault to aggregate, orchestrate, cleanse, enrich, and share all existing data sources with SMACs to continuously build new/better analytics models on top of the data vault.

7.2. The Role of Cloud Computing Cloud computing is a technology that consists of components from the data periphery processing to the cloud data storage. Due to the advancement of hardware and communication links, cloud computing as a technology is growing rapidly and is an indispensable part of industries now. Employees from various departments are attached to Distributed Data Centers (DCs) which provide different services in industries. Due to the growth of the cloud, it is difficult to monitor DCs manually since they are highly distributed and complex structures. Computer resource management, fault tolerance and reconfiguration are the problems for large clusters. Additionally, redesigned hardware solutions have made efficiency improvements, reducing error in data centers. Hence performance monitoring of DCs in the form of alerts and suspicious incidents can only be addressed using a data-driven model.

Cloud computing technology introduces absolute independence of cloud services from varying floor spaces and cluster configurations. A virtual machine (VM) is the resource unit of the cloud services. The initial task is to assign a proper amount of VM to process the incoming user requests on the corresponding cloud cluster. This can be achieved using the greedy first-fit strategy. Deploying a sufficient number of VMs in the cloud is an expensive solution since. Aggregating VMs with lower capacities and resources increases the revenue. Assigning user tasks to VMs are limited at a time in this model. It deserves a granularity level adjustment of the previously developed strategies. Mostly the objective is to maximize the revenue of cloud services by only introducing better scoring functions or optimization techniques. Static allocation models consider the time span of different behaviours of user requests.

7.3. Regulatory Changes and Their Implications The use of artificial intelligence (AI) in financial regulations raises questions about accountability when a regulator's AI makes decisions and how a regulated entity can challenge those decisions. The regulatory AI may not explain its decision in intelligible terms, be aware of the relevant details, or understand the implications of its actions. Regulators might find it fruitful to benchmark their AI against defined tasks and establish a record of quality and safety. This only works well if there is reasonable agreement on the correct outcome of a question. Efforts to formulate rules for AI systems and avoid biased outcomes are in progress. Attention is needed to the nature of the benchmark and the regimes in which regulatory AI is implemented. AI might introduce randomness in an unknowable manner that prevents scrutiny, debate, or change of decision. Furthermore, AI may become anticompetitive if a member of a group discloses its model. There could be times when compliance systems are at odds with existing enforcement.

The possibility of a runaway self-optimizing system raises concerns. These threats extend to AI regulatory systems. New justifications for existing regulation might be required. For instance, if AI A protects against financial stability risks created by banks' AI B, then A needs regulation. But government authorities might be unprepared for a race between supervised and unsupervised AIs resulting from new latent variables; the uncontrolled AI may exclude comprehensibility, interpretability, and responsibility. AI will be both irreplaceable and a source of systemic risk before responses are formulated. Common efforts are needed to address these issues before an incipient financial AI arms race is well underway. Investigating the implications of AI self-assessment on outcomes and the future financial system and formulating preemptive measures are delayed by the nature of most outcomes being unknown. Hence, the race to discover AI financial futures has already begun, creating a systemic risk layer.

The situation with respect to AI in financial goods is reversed. It might be common knowledge that AI will enter markets for financial goods, increasing wealth inequality. But if AI agents deal not only with unsophisticated retail clients but also with other, possibly smarter agents, the safest bet is to ignore circumstances and hold onto all wealth. Regulating exercising entities through exclusion, innovation, or limitation is analogous to centralized backdoors. The definition of AI is vague. Ultimately, a definition will underpin liability but remain uncertain for regulators. The role of statistics and stochastic methods is uncertain, as AI is known to produce and be legitimate reductions. The regulation of randomness is similar, with stochastic methods producing randomness critically entangled with the entity it leaves. AI leaves "random thought" critically entangled with the definition of intelligence.

8. Ethical Considerations in AI/ML Deployment

Leading AI/ML implementations are concerned with transparency and fairness. They involve obtaining a ground-truth outcomes dataset and then developing a machine learning based causal model to predict the outcome(s) as a subject from relevant features as covariates. Outside lenders used it to help make lending decisions. AI was used to help determine if the banks engaged in foreign business had exposure to financial institutions abroad. Investigations were carried out to identify cases where credit had been stopped or suspended for reasons that were not revealed to the company subject to the decision. Financiers may ignore these concerns due to a lack of transparency of individual transactions, a lack of knowledge, or the lack of decision making experiences. Model results should include not only predictive indicators, but also model available evaluations. If this is done, it is possible to convert ML predictions to helpful scorecards.

Algorithms could be made more explainable by examining which inputs were important to the decision on a particular subject. This could provide assurance the decision was based on 'fair' features and no proxies were employed. Assessments could also be used to check fairness conditions. Addressing the fairness versus transparency approach: many believe ML can accurately predict outcomes, and this will allow for neutral and fair decisions. However, ML based evaluated decisions can still be problematic. Even a causal outcome model that is controlled for proxies may not be valid. For example, lenders may turn down loans to firms less likely to default with a different covariate distribution. Under different lending behavior, defaults are different, but that would be small consolation for the small firm rejected due to its location or modernization. Statistics equity constraints on predictor probabilities may be used to enforce fairness, but would effectively indicate the rental locality of the loan examined.

8.1. Bias and Fairness in AI Systems The general public primarily perceives Artificial Intelligence (AI) as a combination of statistical machine-learning techniques that operate upon algorithmically curated datasets and implementable within computer systems. Thus, AI results are similar to the general technological and computational heuristics of "the algorithm" irrespective of all criteria or context. The motivation for AI is taken for granted and regarded as inherent or ubiquitous. This viewpoint is misguided as it approaches AI from within the technological infrastructure when inquiring about its social role. AI relies upon a wider socio-technical infrastructure that shapes its technological design and resources, the algorithms used, and the dynamic relationships by which it is kept in operation. Instead, the need for AI systems clearly stems from social and commercial pressures imposed upon complex analysis and knowledge management tasks that exceed human capacities for description and comprehension.

The bias against a predefined social group in decisions made by software systems can be understood in a broader context of uncertainty amplification. The very focus on fairness in AI and operational anti-bias methods stands against an acceptance of data-enabled decision support that is not entirely deterministic, and a growing unease in society with regard to machine-made decisions. In real life, many decisions are not made due to knowledge gaps, and decisions that are made are not always implemented as prescribed. Thus, positive identification of outcomes deemed desirable as “fair” leaves outside the biased data such as missing data, or imperfect data that impair schema construction but which may amplify the uncertainty about features within “correct” data.

The gap between desired outcomes regarding environment protection for others versus operational decisions based on profit making or resource use for the organization’s advantage is self-evident. A machine system aimed at compensating for the data analytics gap will record biased operations and thereby amplify existing biases. However, this is not what the sources of bias in a data analytics environment are, as they do not link to a group, but at best apply to a single entity operation. Bias in data analytics systems is thus inherently a dynamic socio technical conception, not a static one. Realizing what the biases of AI systems are falls on society as a whole, and operative alliances accordingly need to form across conceptual representations of the at force work systems to convey a common view of the determination of algorithms and the outcomes to be achieved.

8.2. Data Privacy and Security Concerns As banks accelerate their digital transformation journeys, data privacy and security become concerns. Many of today’s cyberattacks are highly sophisticated and disruptive. The Covid-19 pandemic revealed that financial institutions do not sufficiently invest in security controls tied to their digital business models. Because AI and ML in themselves can learn, improve and deliver out of the control of the employees, the question arises as to how secure these systems are, particularly in a regulated and highly competitive market like banking. When partnering with external vendors or relying on public clouds, AI applications have the additional risk vector of vendor and third-party technology assessments, which are less controllable by a bank. Sensitive data or proprietary knowledge may reside in the code, algorithms, or the model as a whole. A common attack is algorithm stealing, which successfully queries the model to create a new but weaker version. This is particularly concerning in anti-money-laundering (AML) cases, as it could allow a fraudster to tailor their actions to counter the banks’ scripts.

Banks must be able to evaluate whether their and their customers’ data is sufficiently protected. Considerations about security must be at the forefront, not simply an enabler to advancement, in order that risks be adequately identified and mitigated. There are many questions that accompany this: In the case a bank is subject to a security breach or loses control of the model and data described, stolen, or leaked, will they be accountable? Which processes could take place – if any at all – in order to arrive at this conclusion? Would it be ensured that no prejudice occurs to customers or the business itself in a legal battle? Currently, these answers are unclear and highly situational. Automating risk assessment scores of third parties is promising but inherently difficult to achieve in practice. Production rules must be applied and adhered to for each individual case. Also, in situ risk assessments must happen to see and investigate source-level code in order to identify a potential exploit. This is also where most of the proprietary owned data lie and algorithms are embedded, and as a result, banks cannot realistically execute an internal investigation.

In addition to the disclosure of the model code base, data concealment sent back to the third-party vendor also entails risk. During development, algorithm engineers may come across sensitive information and could easily forget their stipulations or be offboarded without transferring knowledge. This usually goes hand in hand with a black-box model, precluding the detection of comments or stylistic discrepancies. Keeping it on-premises would raise issues for off-the-shelf solutions. Making it accessible on a private cloud entails many cyberattack vectors, the most concerning of which would be a backdoor embedded by the third-party vendors or an unsanctioned training-script release to a public scenario.

8.3. Transparency and Accountability Issues Digi-Book learns from its virtual but real-world peer book, to provide contextual and targeted workflows to its user. A target was identified, who left a document in his library, possibly forgetting important related documents. Anomalies in the target user's loan records were detected, with low activity in recent months, followed up by contextual and targeted suggestions. A user interface snapshot illustrates how the suggestions of methods matching with the book, and matched documents with read/count or summary to probe potential issues, appeared in a table as a side card.

Digi-Book in a sense bridges traditional paper world libraries and AI/ML digitized ones, significantly increasing the productivity in reading, searching and research. The live demonstration shows its AI powers to reduce the noise while enhancing the understanding of what you will read but cannot process it to understand to read it within a second. Providing contextualized prompts is one way to achieve it.

To improve the explainability for transparency, and accountability for AI fair banking, and to ensure no model bias and data privacy violation, a self-regulated AI-Ml bank with compliance checking capabilities are described. It includes pre-train, training, run time workflows, process monitoring and explainable AI in use, counters, statistics and reporting of model heterogeneity, data statistics and accountabilities, for transparency, and privacy monitoring, biased feature detection at risk time for accountability, general solution options, and regulatory oversight interaction and curriculum learning for AI timely.

Just as the car-driving regulations were established and new standards were promoted with the development of traditional black-box banking systems, it is crucial to construct an AI/ML regulation framework with reasonable approaches and promote compliance auditing regulations to deploy an AI self-regulated fair banking. AI-powered financial service is the king to retain the crown of financial money kingdoms. With the banking infrastructure cloud-based and hybrid systems converging, both retail and wholesale AI/ML services are entering the world to empower intelligent finance and re-shape the banking landscape.

Equ 3: Cost Optimization Equation

$$C_t = C_L \cdot R_t + C_A - S_t$$

Let:

- C_t: Total IT system cost at time t
- C_L: Cost of maintaining legacy systems
- C_A: Cost of implementing AI/ML automation
- S_t: Savings due to automation at time t

9. Conclusion

Intelligent Automation in the Banking Sector is the answer to the pandemic. It is believed that 2023 should see a faster and fuller move to intelligent automation, with a greater focus on speed and the wider use of low-code automation tools. Many of the drivers of this change will be the same as over the last few years – the quest for efficiency improvements, improved operating models, advances in technology, and a desire to free staff to use skills in other areas – but there will also be new drivers. Intelligent automation has moved rapidly up the agenda in many firms, with considerable board level attention, as they seek to return to stability in the aftermath of the pandemic: how to harness the changes and learnings of the past year on hybrid working patterns, how to quickly resolve backlogs of work and issues that have built up during the pandemic, and how to integrate the increased use of offshore and nearshore working into the operating model. The pandemic has accelerated the adoption of automation technologies across industries, driven by the need to minimize human interactions, address workforce challenges, and enhance negative customer experiences. Many companies are under pressure from shareholders and communities to address existing operating inefficiencies, rising costs, and performance weaknesses. Firms need to expand their workforce to address increased workloads and to allow staff to focus on higher value work and needs. Companies must continuously improve the efficiency and quality of outputs with ever-decreasing resources to remain competitive. Machine Learning and Artificial Intelligence prediction outcomes enabling data-driven assistance are factors that should emerge during 2023.

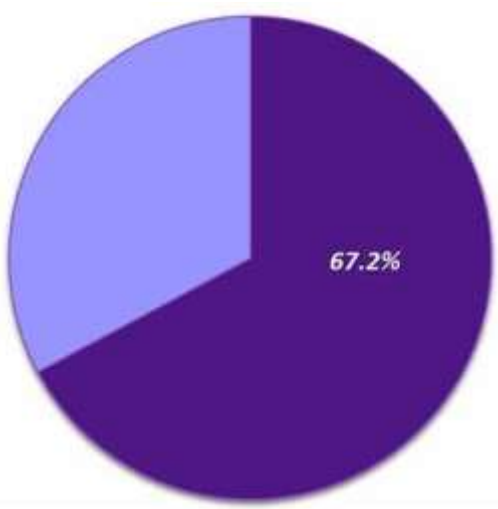

Fig 6: Intelligent Automation in Banking IT Systems.

The total degree of transformation represented by Machine Learning and Artificial Intelligence is widely considered to be substantial. This is mainly due to the nature of the change, which traverses and modifies multiple processes. In external customer-facing processes, too many banks are producing distinct experiences to brand-loyal customers. If Mobile has been a strong race to Digital for banks, Conversational should be the next race to Digital-to-Intelligent for banks. All manners of intelligent and assisted conversations can happen across multiple personas like retail, wealth, and corporate. Hope is for these conversations to be end-to-end experiences covering full Financial Services with fan-like impact on user retention and influence vis-à-vis competitors. The implementation of Common Intelligent Banks is limited. Here, the architecture has shifted but fail to operationalize Conversational Intelligence for consistency and data integration.

10. 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.