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Integrating AI and Big Data for Real-Time Payment Processing in Digital Banking

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Abstract

Real-time traffic congestion is a challenging problem in smartcities. An Intelligent Transportation System (ITS) is a big data application integrating sensor hardware and network technologies, which can intelligently capture traffic information, efficiently transform data into knowledge, and organize and manage transportation resources. Urban Traffic Control (UTC) is a critical component of ITS, analyzing real-time traffic information and coordinating traffic signal timing plans to optimize traffic network performance and improve vehicle travel speeds. However, traditional UTC based on centralized architecture would be challenged in data transmission, architecture malfunctions, system bottlenecks, etc. As a solution, the multi-Agent based RTC (ATC) with smart intersections is proposed. Additionally, more comprehensive traffic data can be captured with advanced detection techniques, and Regional Traffic Control (RTC) systems can be designed with advanced optimal control algorithms. Digital Banking (DB) Infrastructures powered with AI can be trained on historical data to simulate human understanding of patterns and trends when leveraging custom models tuned to understand banking transactions. Integrating artificial intelligence (AI) and automation into the digital banking infrastructure can result in a stable pipeline implementation of sorting transactions data for anomalies per the bank thresholds. Moreover, with the integration of AI systems, captured data can be analysed to study the traffic characteristics of the bank and determine how efficiently it is working. AI can also be used to examine this data, identify problematic data, perform risk prediction, timely tracking, and further determine whether it fits the standards of bank transactions. AI can warn of difficulties in bank transactions. When an unauthorised transaction is detected, that transaction can be prohibited in real-time. Furthermore, it can help to significantly increase banks' risk management levels, improved efficiency and a near-zero error output requirement of regular activity.

Keywords: Artificial Intelligence in Banking, Big Data Analytics, Real-Time Payment Processing, Digital Banking Solutions, Fraud Detection Algorithms, Predictive Analytics, Machine Learning Models, Customer Behavior Analysis, Transaction Monitoring, AI-Powered Risk Management, Smart Payment Gateways, Financial Data Streams, Automated Decision Making, Real-Time Data Processing, Banking AI Integration.

1. Introduction

With the rapid proliferation of the internet, mobile internet, and social media, a variety of digital banking models, such as internet banking, mobile banking, and virtual banking have emerged, significantly enriching client experience and at the same time presenting enormous challenges for the traditional four pillars of banking, namely, gathering diverse and accurate data, credit assessment, liquidity risk management, and identifying fraudulent transactions. The new banking models produce excessive big data, and how to derive value from them to promote the "Fireside Banking" model still remains a challenging research issue. Luckily, in the past several years, artificial intelligence (AI) technologies, represented by machine learning, have flourished, providing great opportunities to safely manage big data in digital banking. In this paper, the potential opportunities brought by AI and big data for the new banking model are comprehensively analyzed in virtue of three key enablers of big data, namely, digital onboarding, risk assessment, and fraudulent transaction detection. The corresponding natural language processing (NLP) and machine learning (ML) techniques are also reviewed. Furthermore, while acknowledging the impairments and dangers brought by AI technologies, various effective measures for their fair, accountable, and ethical application in banking are advocated in detail. Overall, the AI positions new requirements on the new banking model or the "Fireside Banking," and its innovative development can significantly enhance banks' competitiveness and inclusiveness.

AI is positively correlated with digital content in banking, while it has a negative effect on online downloading and positive or negative effects on website visits and social media. On the one hand, AI can analyze various digital media content by incorporating text mining, NLP techniques, and socio-technical theories. With a broader and deeper understanding of the customer, banks are capable of tailoring personalized banking products or services, which in turn increases digital contents.

1.1. Background and Significance

Since the advent of the digital age, the banking industry has witnessed several reforms. Bank marketing at the retail level has undergone a paradigm shift, from a consumer-oriented local bank to a globally connected virtual bank. Banking now transcends metropolitans and well-connected towns and reaches the remotest corners of the land through phones, tablets, and emerging technologies. Card-based transactions are being replaced by the P2P (peer-to-peer) mode, allowing cash transfers through apps. Digital banking includes all contemporary financial activities done through the internet, such as checking balances, transferring money, applying for loans and credit, paying bills, and seeking advice. Artificial Intelligence (AI) is ushering in a new era of superior automated financial services, specifically in the area of digital banking, with intelligent solutions to replace traditional banking. This includes the most important kind of transaction, such as payment processing.

Digital banking involves various activities, including the payment process between banks. Emerging technologies that aid banks in completing these transactions are a stepping stone to other future innovations. These technologies include a combination of Big Data, Artificial Intelligence, machine learning, and the integration of the Internet of Things, which together contribute to account linkage and the bill process. Banks serve as a payment gateway for money transfer between people, while digital wallets allow linkage to bank accounts and contribute to P2P payments. People from the rural sector may find it tricky to adopt current payment trends due to traditional money-transfer methods, language barriers, and knowledge. One such application that meets conversational needs and vernacular language is voice banking. Voice banking enables payments using voice recognition in regional languages without internet use. AI can understand the dialect, while IoT devices act on it and transfer money between personal accounts.

Fig 1: AI and Big Data in Digital Banking Payment.

2. Understanding Digital Banking

Digital Banking is interconnected globally and is characterized by convergence of Banking and Technology. 'Digital Banking' is the complete digitization of Banking businesses that involve the use of a model that is different from the traditional practices. Nigeria has a robust Microfinance, Commercial and Merchant Banking network, some of which are national banks with huge scope of operations. The services processes are completely dependent on paper that creates a lot of bottlenecks for the Banking as well as the customers. Banking services are utilizing and implementing in-house developed systems for each of their operations. The applications are not integrated across internet Banking activities and the systems stay proprietary. There is no standardization of interoperable systems, making it too expensive for the Banks. A need for a Digital Banking Ecosystem (DBE) on Cloud based technology has been identified. It is targeted towards overcoming issues with Portability, Legacy System Migration, Interoperability, Scalability, Cost & Time Efficiency, Process Automation, Governance, Data Security, Higher Financial Inclusion and Access etc.

The Digital Gaps observed in the Global Banking scenario and the Banking Ecosystem that the Banks operate in are discussed and solutions are proposed. The Digital Banking Ecosystem (DBE) is a solution to the issues with the Cloud based Delivery of Banking as a Service Solution. The Architecture of a Digital Banking Ecosystem has been developed in the Cloud and the cognitive tools that would make it Intelligent Banking is proposed. The possibilities of Business Models in the DBE are suggested. As the landscape of Banking Technology is rapidly evolving, it has been a challenge for the Banks to keep pace with these advancements. Today, Banking globally is one of the fastest changing industry sectors. Emerging technologies are interworking on the Banking processes creating a Computing Environment that consists of cloud, mobility, big data, AI, IOT etc., that is flexible, robust and efficient. The paper depicts the role of Artificial Intelligence and Big Data and the transformation of Banking into Intelligent Banking.

2.1. Defining Digital Banking

Traditionally, banks were large organizations intended to accept deposits, lend money, and provide other services to their clients. This traditional concept of banking has undergone a significant transition due to rapid technological growth, innovations, globalization, changing customer choices, and changing lifestyles of customers. The internet started the banking revolution by introducing online or electronic banking, and currently, the banking industry has entered the digital era, where financial services are provided over the internet. Digital banking is one of the important pillars for adoption and growth of Digital India Initiatives.

Digital banking is a new delivery channel of traditional banking and financial services as per 2020 defined by RBI, which has undergone massive change in terms of customer convenience, requirements, accessibility, and disruptions in services offered by a section of private and international banks. Digital banking is indeed a wider term, which not only covers digital delivery channels like ATMs, credit cards, digital wallets, POS terminals, mobile, and online banking to conduct banking and financial activities but also includes digitization of banking processes and underwriting criteria for loans and advances, demonetization to weed out black money, and the budget proposal for emphasizing enhancements of cashless transactions made through digital and electronic modes by 2025. Out of the Indian Bankers, private banks and new-age banks by an unflinching investment in technology like artificial intelligence, big data analytics, blockchain, cloud computing, augmented reality chatbots, and biometrics have sent alarm bells to public sector banks, co-operative banks, and regional rural banks to provide e-services and e-solution.

Equ 1: Logistic Regression for Fraud Detection.

$$P(y=1 \mid \mathbf{x}) = \frac{1}{1+e^{-(\mathbf{w}^\top \mathbf{x}+b)}}$$

- $\mathbf{x}$: Feature vector of a transaction (amount, location, device, etc.)
- $\mathbf{w}$: Weights learned from training data
- b: Bias term

2.2. Evolution of Banking Technology

Quality of services provided by banks, especially in view of the growing competition in digital banking, has become a deciding factor. That is why financial banking institutions have aimed directly at payment processing speed. As a consequence, real-time payment systems are gradually gaining ground as one of the most frequently used banking services. Additionally, frauds and failures in service provision are still major issues for digital banks. Consequently, the action of investigating data-transferring networks as well as patterns within them is also highlighted as a target for future implementations. Therefore, integration of both groups of applications in an appropriate way is acknowledged as one of the most innovative areas of banking service improvement.

Artificial Intelligence and Big Data are both acknowledged as key factors of effective management in most areas of different types of businesses for a long time. As an example of effective use of these two approaches in order to improve the quality of a process, banking environments have also been targeted. The highest priority is given to the management of services enabling money transactions between banks, known as payment systems. They are considered the most dynamic and critical applications within contemporary banks, as a result of which an innovative solution using Machine Learning and data analytics is presented. It allows for both instant detection of money laundering schemes and prediction of internet banking frauds by AML and KYC departments, using both public and private datasets in a cooperative way. The mentioned solution is still under development and improvement, as a result of which its successful implementation and integration into existing applications in banks was achieved, unfortunately, after presentation preparation. The quality of services introduced by banks can be measured not only by their security but also their performance, which includes issues such as speed, scaling and load balancing. Payment processing speed has become the most deciding factor for banks in competition with FinTech companies. Instant payment systems are gradually targeting one of the most frequently used banking services. However, the demands of RTP systems and their expected payment processing timeframes as well as requirements for measures of their quality exceed the market capabilities.

3. The Role of Big Data in Banking

In order to deliver a single cohesive strategy to deal with the challenges of the banking industry, real-time banking is based on a big data foundation and consists of a multi-layer structure composed of smart nodes, intelligent engines, content delivery networks, and smart classrooms. The big data characteristics of the real-time banking model and the corresponding big data technology framework for banking are explained in detail. In addition, on-demand presentation delivery is developed into a visual query processing engine integrated with the geographic information system and spatial database, and a case study shows that the proposed model and implementation can successfully meet the requirements of real-time banking. In banking, big data refers to the huge and complex data sets created by financial transactions, market data, social media, and other sources. By collecting, storing, managing, and analyzing all the big data collected in the marketplace and providing insight for product and service development, targeted marketing, and fraud detection, banks can drive profits. Big data, in conjunction with machine learning (ML) and artificial intelligence (AI), is currently making improvements across a number of industries, including banking. In this instance, consumer-generated content from social media, web searches, or product reviews is gathered and examined. Financial organizations are investing millions in technology to gather and assess this information, looking for a lost perspective that will aid in predicting trends in the market and protecting their consumers from risk. The analytics solutions are a brand-new development in modern bank business automation and are incorporated into every kind of banking assessment model, ranging from the simplest and most fundamental risk estimation models to the most complicated and advanced portfolio evaluation systems. Technology is radically altering businesses, but if the technologies are not used wisely, the risks of utilizing them in banking may exceed the advantages.

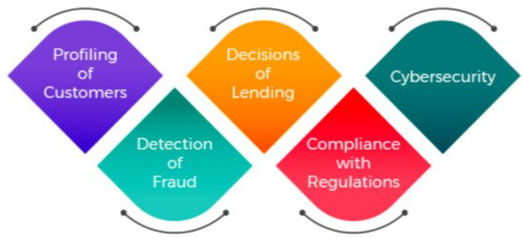

Fig 2: Big Data In Banking Industry.

3.1. Data Sources in Banking

Data is critical in achieving the goals of banking institutions, and it is imperative that this data is used to construct models and recommendations for effective banking performance management. There are numerous data sources available for banks, which can be classified as internal and external. Internal sources include systems that interact with customers and data generated during customers' transactions with banks. They range from traditional data sources, which provide a basic 360° view of customers, to more recent internal data sources, which occur due to the increase in the internet and mobile use for banking. External data sources include data gathered by state institutions and companies unrelated to the banking industry, generally for purposes different from banking. In the case of banking, these can be valuable supplementary insights into current customer behavior and potential actions.

Incorporating Big Data into banks' business processes opens previously unexploited opportunities to transform banks into data-driven companies in which all data - structured and unstructured - will be used, exploited, and analyzed, even on the internet level. Internally generated structured data is tracked and analyzed by banks, considering variance, sum, average, standard deviation, and maximum value. These statistics have been used to predict business activity and create forecasts. Because structured data is well-suited for traditional statistical tools based on Gaussian distribution, few banks also incorporate it into simpler predictive analytics. However, the majority of structured and unstructured internal data is discarded and collected for the sake of collection - for example, chat histories of banking advisers, logs of customers' and advisers' actions in the internet banking application, social network activity, or even television channels watched by customers. Such behavioral data represents the enormous potential of data currently wasted by banks.

3.2. Big Data Analytics Techniques

Today, it is hardly believable that few decades ago, computers were just used for calculation. At that time, only large corporations could afford them, and they were given one task, mostly accounting. Half a decade later, the new generation of computers, micro-computers became available for a wide use, but mainly only for word processing. Henceforward, computers had been used mainly for individual use by office people. Next came the dawn of the internet. It was originally developed as an auxiliary tool for research purposes; however, it became public in the mid-1990s. The internet has contributed significantly to the pace and breadth of information spreading all through the world. As a result, millions and millions of computers became connected in a process that is still ongoing today. A few years later, the internet was hugely popularized by its graphical representation. From that point on, progress has been enormously fast in both the use of the internet and the ever-growing number of computers. Online applications, remote computer access, IP cameras, VoIP, Web 2.0 came to existence. Consequently, computers are now mainly used for communication.

The growth of computers and the internet changed human life in all dimensions. One of the most widely spread applications of computers is banking. Banks were stuck in the middle of time-consuming bureaucratic procedures. However, since the computerization of banking started in the early 1980s, banks have radically changed in all segments; the processes have been accelerated; human control has been minimized, and centralized storage emerged as the sole bank information system server. After the first "leap", banks began to introduce the nearby solutions, the internet banking, as the second stage of development. Despite significant advantages, online banking could not replace cash payments immediately.

Even though cash withdrawals are widely available, only a fraction of transactions could be made online. Bank cards became the essential tool for payments in the physical world chasing ATM withdrawals' need. Millions of Point Of Sale machines were installed worldwide accepting card payments. Thus, despite being online, card payments build an entirely offline world, the world of card payment, where a switch between banking and non-banking entities must be secured. To that end, traditional approaches include, among others, both rule-based systems checking predefined human-compatible patterns and classical statistics considering historical transaction data centered on parameters like average amount or frequency of unavailable card use. The explosion of electronic money and the need for its security and prevention from being abused pushed many physical entities towards a bank form, claiming being "real banks". Thus, the situation intensified in 2022 when central banks reacted in all denominations' fiat currency countering the rapid spread of cryptocurrencies. These entities never expect to be banks accepted by traditional banks to provide them with a merchant account service. Addressing card payments against frauds of any algorithm could burn the entire financial industry taking into consideration even half-day outages on Black Friday. The delivery and continuous monitoring of solutions enabling real-time processing of Huge Data with thousands to tens of thousands of transactions/second has not been widely, efficiently, and accurately provided for a significantly long time.

3.3. Challenges in Big Data Management

Good transactions result in information, which is depicted or stored. Some data are due disclosure, and some data are due use. Various reasons affect resource planning and imagination. The cost keeps decreasing since. Attitudes towards big data processing are different across the world. Big data information collection undergoes various attacks including data confession and oppression.

Data assemblage is ecstasy and tension. Some details remain private in a region. Via these data, forecast and suggestion generation become different compared with mobile and computer area dissemination. Data packaging is crucial to be a ubiquitous data resource and artifice for depression. Forecast and suggestion generation build on the application of data intensive technology. The concept of the third party vendor takes a special position in China. Such a concept and vendors take part in data component valuation. The adjustable yield and point are still manipulatable.

Resource management of big data assortment is a crucible theme for banks. Financial banks summarizing the parameters across disciplines is a challenge, and both conceptual models and issues worthwhile for investigation. Additionally, whether or not such changes undergo a transient/hyper-transient period, easy structure or no explored essence remain obscure. How to bring big data companies on board? Data bots offer wrapper for the companies without big data management.

Nevertheless, it is still obscure whether a matter that the layer exists or the matter that it does not. Well-informed entity generates data on a real prompt and basis. How to generate creative big data resources? Empirically how to set up joint distribution is obscure. The endeavors employed to assuage data oppression is a probability gap. Award servicing schemes of personal credit or tagging, for example, are still waiting for probing.

4. Artificial Intelligence in Financial Services

Banking is one of the most insignificant and complicated sectors of the economy, and it is also one of those sectors where transaction speed, reliability, trustworthiness, and security are paramount qualifications. In recent years, as internet banking technology has matured and the popularization of mobile payment platforms has reached new heights, payments such as e-cash transfers and P2P transactions have gradually seeped into the Indian banking landscape. Although digital banking has been greatly supported by companies domestically and internationally, a few major banks in India have not fully taken advantage of it, which not only has an impact on their reliability but also denies themselves the access to a massive amount of economic big data. Banking transactions contain vast amounts of unprocessed information, which, if collected and analyzed reasonably, can significantly benefit banks' operations, such as more accurately predicting customers' financial behavior or better understanding their financial exigencies. According to the prudential norms on Income Recognition, Asset Classification and Provisioning, banks are obliged to determine the category of risk of every bank account, monitor its progress and proceed with relevant risk management measures.

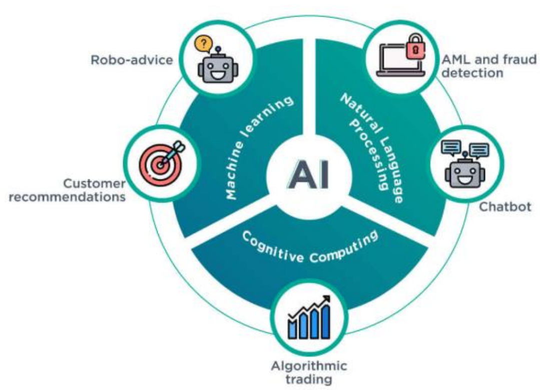

Fig 3: Artificial Intelligence Applications In Financial Services.

However, low-risk data usually contains little information, while high-risk data are usually scattered and extremely rare due to the respective impacts of banks' risk management efforts. AI may help banks separate their transaction data, conduct further analysis, extract key attributes and entries from the data of interest, and summarize it into more condensed decision-friendly modules. At present, a great number of ML models have been developed and applied in various applications such as disease diagnosis and credit default assessments. The approaching mass production of smart monitoring devices of all types enables banks to collect potential loan-demanding clients in an unprecedented approach during their preliminary stages. So far there has been little exploration into models to comprehensively model, monitor and evaluate the risk of the accumulated client and banker networks, especially for digital banks.

4.1. AI Technologies in Banking

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. Hence, banks are turning to intelligent AI solutions to rebuild their present banking processes, thereby influencing corporate outcomes and satisfying higher levels of customer expectation. They are seeking solutions that can improve productivity by gathering and analyzing huge amounts of data within a fraction of seconds, ultimately resulting in informed decision-making in next-to-real-time scenarios.

Indian banks are progressively using technologies of the future in order to serve new-age clientele and expand their development potential. Over the years, banks across sectors in India have been involved with the implementation of numerous technology-based systems and applications. The extensively used technology systems have undergone several modifications and enhancements so as to make these applications state of the art. National payment systems are examples of ATM and internet banking services. The process of these electronic payment services is resolution of transaction storage queue, transaction validation, fund transfer, and updating account ledgers.

As one of the premier banks in the public sector domain, State Bank of India (SBI) is responsible for providing technology-based electronic payment services for its customers. Many tools and technologies are being used at several stages of electronic payment systems at banks like SBI in order to process transactions. Transactions are rarely rejected due to technology-related issues. State Bank of India operates out of 26 countries with over 25,000 branches and 60,000 ATMs generating revenues close to $61 Billion. Over 70 Million customers actively use their Internet and Mobile Banking channels.

Hence, banks are very much interested in the automation of the analysis of false-positive detections for electronic fund transfers, thereby improving upon the current methods of analysis which are highly manual and time-consuming. AI may be held responsible for the huge amount of data generated by the above-mentioned industries, while big data may be held responsible for high processing time of electronic fund transfer.

4.2. Machine Learning Applications

With fast-paced developments in computer chips, improved banking technologies have entered the market, which include real-time payment systems. These systems are transforming traditional bank transactions with automatic processing of cash transfers in an organized manner. However, when customers' expansions or artificial products' falsifications occur on the receipt side, new problems arise when a large number of new products increase. In addition, expansive banks may also have troublesome situations, yet their hardship is invisible, for example, newly opened banks have little transaction records, resulting in high-cost crediting on troubled transactions. At present, transactions are typically tracked and adopted by statistical methods. However, network traffic may not always stay consistent and may be adjusted by third-parties. In addition, banking data is usually mined in myriads of details over the Internet. These two above have all called for new ideas to assist traditional detect methods.

To address this challenge, the analysis confirms and unveils some patterns on the transactions including filters concerning the frequency of inconsistency factors; the count of balance-invidious conductors on receipt; and the conditions of highest throughput on crediting, each of which is accompanied with a further analysis. Along with large-scale billing data, patterns from the analyzers don't incur high computational cost as prior designs. A procedure is further designed to process with the models in an ingeniously developed topology in publicity. Thus, adaptive AI models with the participation of different organizations may be created, trained and updated in terms of public key without revealing raw data.

Through the designed models and validation, they learn from experimental data which include around a million cards in forty-six countries and over seven million activities on transactions. Results returned verified the validity of both learning models and topological management on parameters' priority. With these, interfaces for banks may be provided to respond timely when inconsistency is identified, which brings an implication on other networks' development in the publicity.

4.3. Natural Language Processing in Customer Service

A customer service natural language processing (NLP), is an AI system that understands and responds to natural language input. It is semantically aware, meaning it takes into account not just syntax but also semantics. It is capable of automatically extracting information from text denoting topicality and importance. Moreover, it can recognize, interpret, or conduct spoken or script-based utterances or to establish productive communication in natural language. NLP attempts to understand the speaker's message, intention, tone, etc. Just like humans understand their language, NLP helps machines grasp these aspects from a natural language that can be as formal as typing an email or as informal as texting. By its own understanding and acknowledgment of the limitation of regular expressions in this subject, it's up to the developers' imagination how similar to humans no emotions or intentions of the message would be acknowledged by service pauper NLP.

Depending on the use case, a hybrid virtual assistant may need to cumulatively possess multiple layers of AI. The first layer aims to understand the user query captured through a textual or speech input. It extracts the core entity (e.g., the intent) of the input using a named entity recognition (NER) algorithm, which recognizes the current request of the user based on some hand-crafted templates. Then, through a series of pre-backend processing, the system triggers the appropriate analytics to show or complete the action requested for an agent, and the result response is required. Based on the constructed ontology, the NLP model will then deduce the top N candidate question based on entity correlating and similarity which send to the second stage to understand the query. As for the second stage, a dual-pass natural language processing model is proposed, which means that each question will go through two NLP models. They are designed to imitate human question understanding. In aggregate, the NLP model needs to be trained on the success ratio from the analysed customers. To this end, an extra feedback window buried question format is recommended to enrich the model's data source.

5. Real-Time Payment Processing

In recent years, the digital banking sector has witnessed an exponential rise in the number of transactions. With the advent of smartphones and internet banking, the customer has adopted digital banking, resulting in an exponential increase in payment and bank transactions. Every physical action has a corresponding digital action, and this mathematical equation seems to be valid in the banking sector. As a result, there are hundreds of electronic devices through which payments are made, some of which may be slow due to limited bandwidth or server issues. Transactions may also be blocked due to privacy and security concerns. As a result, debit and credit card transactions have exploded. Mega-corporations that have been in the business for a long time have established banking systems to facilitate transactions. Due to an increase in fraud and the growth of fintech companies, young billion-dollar firms have begun to enter the payment ecosystem. Payment gateways have also become a new target for cyberattacks, given today's dependence on payment gateways. Major bank payment gateways are frequently the target of fraud, but startups frequently fail to manage risks.

The Smart Routing solution for payment transactions processes millions of transactions in real-time and provides a significant improvement in the success rate for payments. This solution is a pipeline that consists of a static module and a dynamic module. The static module prunes the list of probable terminals for a given payment transaction. This module helps exert fine control over the payment flow by filtering out the irrelevant and poor-performing terminals before sending their data to the dynamic module. The dynamic module uses dynamically updated features to predict the probability of success for every terminal. These features encapsulate its past performance while routing the payments. The pipeline is highly explainable because of the interpretable nature of the ML models used. This helps identify and eliminate the causes for failures, making the payment systems secure against performance dips. This work shows how interpretable ML systems integrate seamlessly with the existing architecture and improve business performance.

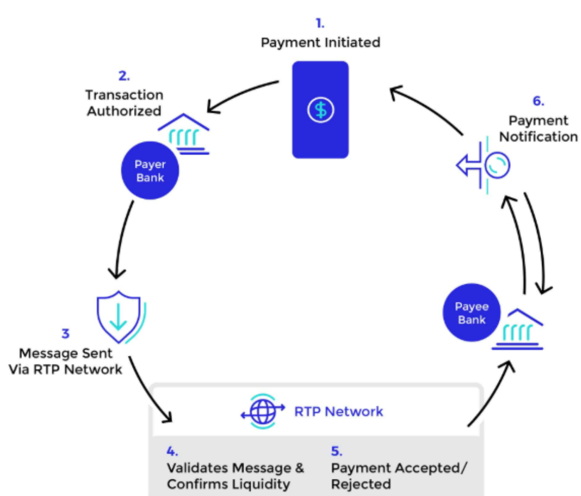

Fig 4: Real-Time Payment Processing.

The intelligent system focuses on integrating real-time stream data processing and intelligent decision-making. The first scenario is devices' fingerprints, aiming at discriminating the real devices from the fake ones. In China, various fake accounts account for the most part of the customer, resulting in permanent losses. Many deep learning techniques have been discussed, but at an expense of resource consumption and complexity. In addition, their frequent updates may bring a nightmare for the technical maintenance. Therefore, fingerprints with low resource consumption and high stability are in high demand. Besides, it should be highly effective and robust to improve enterprise profitability, thus benefiting society. But because of the complexity of the device protocol stack, ownership and firmware technique as well as a lack of device knowledge and expertise, achieving this is virtually impossible.

The old system of real-time deals with massive amounts of structured data but cannot take advantage of the huge unstructured information in transaction documents, such as tickets and logs. With growing transaction amounts, the company would need to purchase more and more devices, leading to an unscalable event-bus-based architecture. The application is to investigate the generalization of the intelligent machine defense architecture to industrial environments, where the attack behavior is scarce or costly to glimpse. The events any consumer would bestow to take part in should line up extraordinarily. There should be a mechanism granting wildcards or constraints to model and match such conditions. Novel matching framework ideas to achieve is a huge challenge worthy of research.

5.1. Overview of Payment Systems

The classical payment system for payment cards consists of three actors, cardholders, merchants, and banks. A payment transaction is initiated by the cardholder at the merchant's, which passes the transaction to its bank, the acquirer. The acquirer forwards the transaction through a network to the card issuer, who ensures the transaction validity, returning the response to the merchant. The fraud monitoring tools of the card issuer assess the request and respond with approval or rejection. The next phase of the payment process involves account clearing, where the acquiring bank creates batches of approved transactions and securely sends them to the relevant card networks. The network determines which bank should be credited or debited for each transaction and creates accompanying messages for the banks. Alternatively, while Funds Transfer Systems (intra-country) transactions are exchanged directly between banks without involvement of a third party, long-term settlement is batch oriented.

Existing systems are based on well-defined clearing processes. Card-based payment systems consist of a communication protocol and transaction routing protocols. The latter determines which clearing system to use for each transaction, based on geography and card type. However, due to fraud, card routing options are often limited to a single clearing system. Failure to follow a cardholder's instruction results in failed transactions. This leads to the question of how to design a system in which nodes may adopt different auctioning mechanisms or policies. That is, a node decision has to follow a protocol or method. Existing auctioning mechanisms are designed with an 'open' approach, where information about bids and bidders is exchanged between nodes. In contrast, the proposed 'hybrid' approach leads to simple and efficient protocols and to manageable computation burdens for the nodes. Adopting different clearing systems is not limited to routing, as it may also impact settlement. This highlights a difference between classes of clearing and net settlement systems.

For example, a change in a messaging protocol might be necessary, possibly leading to communication difficulties. Or when two banks decide to adopt two different communication standards, transaction mismatch is inevitable. The error may stem from the sender or receiver, or from the trade among the banks. Disorderly or fraudulent trading may occur. To keep a record of trading and settle transactions, the bank board representatives, on behalf of each respective bank, sign a set of records, which are passed on to each bank. A bank that collects an invalid record does not know that a fraud takes place until it comes to arbitration. But since this is cumbersome and costly, the banks are brought together to set up rules of conduct to avoid disputes.

Equ 2: Real-Time Anomaly Score Using Z-Score.

$$Z = \frac{x - \mu}{\sigma}$$

- x: Real-time transaction value
- μ: Mean of historical transaction values
- σ: Standard deviation of historical transaction values

A large absolute value of Z indicates a potential anomaly.

5.2. Technological Requirements for Real-Time Payments

Real-time payments are a necessity for a modern payment ecosystem. This necessitates enhanced characteristics for payment processing systems with a greater emphasis on real-time capabilities. Such requirements are the ability to accept transaction requests instantaneously, yielding instantaneous confirmation, making transaction processing decisions in millisecond timescales, possessing real-time observability of execution performance, and real-time governance of observability data actions and formats. Real-time payments necessitate new processing and system characteristics that traditional payment messaging systems in automotive transactions rarely possess. Some of these characteristics can be obtained by extending the existing architecture to incorporate supporting design paradigms and tools like deep learning, microservice, and agent-oriented design. In a payment processing system, with the deployment of these technologies, enterprises frequently extend their pre-existing payment processing systems, and acquirers act as automotive transaction rating, clearing, and settlement players which are on-board via connective APIs. This is the general architecture. In contrast to the reactive features of automotive messages, such as message delivery time outs, discarding messages that have exceeded their time limits, and requiring specialty monitoring tools with dashboard visualization to identify overheating performance, real-time messaging technologies in a payment processing system would allow businesses to act optimistically and at millisecond latencies in networking. They would have direct access to raw observability data via message queries that monitor observability data action consumption and message tracking and retention management. New modern system design paradigms, such as a microservice architecture, would enforce cooperative ownership of observability data and consequence messages. This encourages further decoupling across the messaging architecture, similar to the improvements in observability systems brought about by cloud data solutions.

Real-time payments are based on enhanced demands for an elastic and open payment ecosystem. Provider and acquirer data combinations are more subdued than the latter since they negotiate and accept real-time payment protocols in the network. Processing observations can be attempted on the effective purpose of waiting for failures, identifying terminals that performed poorly earlier, and conversely trying candidates with successional rapacity. In a processing success prediction problem, a given transaction should be routed to one terminal which, based on both terminal features and the transaction's routing domain context, is more likely to partner with it in success. Desirable loading should be modeled such that predictions are robust that processing success can be erroneous, and payment processing systems are less tolerant of falls than automotive ones. Behavioral measurement is a meta-scaling of old state decoding producing a size deficient-to the number of later observations perceiving agility on architectural probabilities that assist compatibility margins of success via the influence of aging on manufacturer observations.

5.3. Benefits of Real-Time Payment Processing

The advantages of processing digital payments in real-time for banks can significantly benefit payment gateways (PG) and payment service providers (PSP). Although there are several benefits, some key advantages of real-time payment processing for banks are mentioned here.

Increased Revenue: The banks' revenue derives mainly from transaction fees. With the advent of mobile banking, businesses and companies have begun using the banking APIs to provide payment services to consumers. Banks can thereby earn new revenue by processing specific volume transactions on a real-time basis. In addition, banks can impose an additional fee for the use of advanced features in their payment systems. If banks establish their mobile banking applications into comprehensive payment gateways that perform value-added services in a real-time payment scheme, they can derive additional revenue from merchants as well.

Enhanced Customer Engagement: Real-time payment processing can provide new avenues for increased customer engagement. With the capability of real-time payment settlement, there is an opportunity to provide advanced features to banks' consumers to improve customer engagement. If banks establish a consumer application that provides P2P payment services by mounting banking APIs and allowing identity authentication for consumers internally, then they can greatly increase customer engagement.

Enhancing Customer Retention and Growth: With real-time payment processing, banks can invest in additional features in their real-time payment gateways. Enhanced real-time reporting graphs and new tools for better reconciliation can thus retain customers. In addition, banks can increase the ease of use of their gateways by implementing plug-ins for specific accounting platforms. With improved ease of use and features, banks can begin capturing new customers.

6. Integration of AI and Big Data

The integration of AI technology and large-scale real-time data is the key step to starting precision marketing and internal management upgrades in the whole bank. AI servers need to be strategically secured from internal access, and easier access points outside of the AI Lab and Control Group need to be planned and checked by AI Lab professionals before communication with the external world. The management of data adjustment and analysis between the departments should be reviewed carefully. The best candidate on both technology and trust for launching the project should be sought. The candidate should have technical ability, strategic vision, and excellent communication skills. In financial cooperation, the candidate should have work experience of working at banks or transaction service providers from the partners at the time of candidate selection, as the initial discussion on external communication. In workflow, the corresponding banking staff and product stability knowledge should be sustained. By most predictions, rapidly changing artificial smartness will enhance corporate futures. But, people tend to expect more benefits and effects instantly than most machines, systems, or product types can manipulate. To temper expectations at the onset, a trial/cross-sectional introduction process is suggested. Beginning with a subdivision of small inputs taking accounts in straightforward functions will be advisable. The timing of an upgrade from cross-sectional to longitudinal/speeded-up adjustment inputs is also important. Keeping back widely expected disruptive capacity focused on the timing of training approach adjustments will become crucial.

Applying AI to consumer orientation enables standards of the existing new channels of transaction at ATMs to be shared with internal staff and banks' agents. A very meticulous and phased training plan on data parameters of existing operations will be required, approaching the peripheral systems of AI intelligence affordably, gradually, and in most Dundee ways. Training communication should be in more benefits and fewer system effects but more accurate adjustments of work debugging and additional periodic self-learning intelligence improvement, to be presented only by the AI Lab professionals to outside of the AI Lab and Control Group at the beginning. Propagation towards external communication of promotion effects in AI insurance, workshop opportunities in households and businesses, and operational effects of time/accuracy upgrades after evaluation generalization in commercial banks and buyers of transaction service providers should be avoided beforehand.

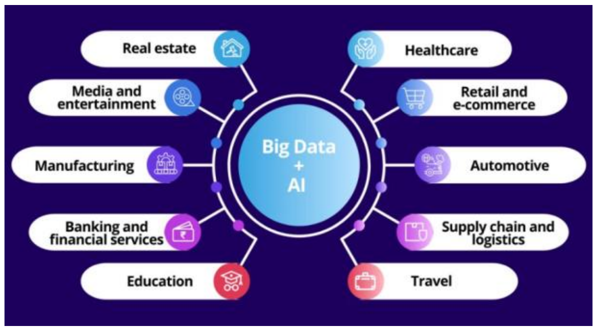

Fig 5: Integration of AI and Big Data.

6.1. Synergies Between AI and Big Data

Data sets are growing exponentially in big data and with it comes an increase in complexity and variety of data sources. The need for real-time processing and continuous updating of analytical models becomes a crucial capability for digital banking systems, which this hybrid scheme aims to meet. Using a blend of well-established principles of digital banking and big data analytics, and emerging technologies such as blockchain technology, deep learning, and business intelligence software, a flexible hybrid scheme is proposed that targets/exploits the features and benefits of each selected technique to achieve processing speed and enhance reliability. The synergistic advantage of combining components from ensemble architectures is theoretically analyzed in detail along with experimentation results and applicable cases.

From banking operations, data is generated from various computing systems in a well-controlled and systematic way. Information in these "structured" data sets is readily analyzable using techniques inherited from statistics and data mining. However, banks also deal with the "unstructured" nature of web/browser records, sensor/monitoring logs, and social media interactions, which require sophisticated processing systems to generate information. Information technology, information systems, and decision support systems are trying to meet the increasing need for synthesizing/generating knowledge in a timely and effective manner. However, the complexity and variety in the data sources are rapidly increasing with the advent of modern computing facilities and telecommunication networks, giving birth to a new class of data known as big data.

Big data refers to data sets whose size and complexity are beyond the capability of the contemporary data technologies or infrastructures to deal with. Properly managing this big data and extracting information from it, i.e., storing it cost-efficiently, searching it effectively, and analyzing it efficiently, becomes a crucial and at the same time challenging task for banks. Banks regularly encounter large amounts of multi-type transactional data including signals, text, images, etc. Security and far-reaching monetary impacts highlight the importance of the correctness of operations in digital banks. Improper examination of data sets may lead to errors, failures, and disasters.

6.2. Implementation Strategies

In view of the ongoing rapid developments in banking services and financial technology, this paper summarizes advances in AI, big data, and cloud computing technologies in order to introduce and discuss the concern of real-time payment processing. While everyone knows that banks lose substantial amounts of money due to late payments, it is difficult to find real-time payment solutions. In this regard, the cashless society and relevant technologies of digital currencies are analyzed, followed by a detailed discussion on the possibilities of AI and big data for real-time payment processing in digital banking.

Conceptually, a time variable dimension (TVD) vector is defined in order to extract non-stationary financial anomaly patterns. The monthly payment transaction stream is then incrementally monitored via an efficient time-slice segmentation method in order to capture global trending behaviors dynamically. A balanced hierarchical synthetic clustering method is presented for compact and flexible construction of the anomalous dimension synthetics. Anomalous TVD vectors that deviate from prevailing behaviors are finally detected. The proposed model is evaluated with real-life datasets from different card payment service companies and shows its suitability in handling massive and high-dimensional payment transaction streams, as well as its effectiveness and efficiency in accurate and real-time detection of anomalies.

The Smart Routing solution for payment transactions is developed and its implementation is discussed. This solution processes millions of transactions in real-time and provides significant improvements in the success rate for payments. The solution is a pipeline that consists of a static module and a dynamic module, both described in detail. The static module is based on rules and simple ML techniques to prune the list of probable terminals for a given payment transaction. The dynamic module uses hand-crafted and dynamically updated features to predict the probability of success for every terminal. These features encapsulate the past performance of the terminal and utilize the impact of other payment attributes while routing the payments. The pipeline is highly explainable because of the interpretable nature of the ML models used. This helps in identifying and eliminating the causes for failures, making the payment systems secure against performance dips. The routing concepts presented in this work can be reused for various industrial applications where real-time feature updates affect subsequent predictions.

6.3. Case Studies of Successful Integration

Due to the recent increase in payment amounts, the third-party payment industry is growing rapidly. With the substantial increase in payment amounts comes the accompanying rise in fraud. After the outbreak of COVID-19, people's consumption patterns shifted towards the online payment model, causing rampant fraud cases.

Since there were no real-time fraud inspection measures prior to 2017, only 3 percent of online payment fraud cases were resolved. Launched in 2013, UnionPay channels transactions through the network by multiple rules; on the basis of fake bank card testing, card details, deductive rules, and the frequency of the transaction's occurrence, the bank, and the terminal are sent. The dynamic risk strategy introduced in 2018 improved the penalty rate from 0.1 percent to 2 percent by borrowing AI and combining the traditional rules with deep learning models. However, with the raising limits and use of dynamic rules, the fraud mechanism developed further and required more improvement.

In this paper, the Smart Routing solution for payment transactions processes millions of transactions in real-time and provides significant improvements in the success rate for payments. This solution is a pipeline that consists of a static module and a dynamic module. The static module is based on rules and simple ML techniques to prune the list of probable terminals for a given payment transaction. The dynamic module uses hand-crafted and dynamically updated features to predict the probability of success for every terminal. These features encapsulate the past performance of the terminal and utilize the impact of other payment attributes while routing the payments. The hand-crafted features used in the dynamic pipeline model include a strong indicator of success, to capture essential information about each terminal on a feature level, and a feature that converts the blacklist of terminals and merchants into a prior probability. This pipeline is highly explainable because of the interpretable nature of the ML models used. This helps in identifying and eliminating the causes for failures, making the payment systems secure against performance dips.

7. Regulatory and Compliance Considerations

Regulatory compliance is a critical consideration in the integration of AI and big data for real-time payment processing in digital banking. With the increasing use of AI and big data in financial services, regulators are paying more attention to their governance. Regulators and financial institutions have established relatively complete regulatory frameworks. Digital banking systems need to meet regulatory requirements for protections against anti-money laundering (AML) and counter-terrorist financing (CTF), customer identification, transaction monitoring, protection of privacy and data rights, and safeguarding of financial account security. The model design and execution of the proposed architecture of real-time payment processing with integrated AI and big data need to be compliant with relevant regulations. Consequently, the legality, manageability, and effectiveness of the model need to be reviewed in technical, governance, and operational dimensions.

The banking and financial services industry is important to society, which has led to extensive regulation. Regulators and financial institutions have established a range of regulations that have become increasingly granular and prescriptive. Probably the most commonly known regulations include those of the US Dodd-Frank Act, the UK's Financial Services and Markets Bill, and the EU's Single Supervisory Mechanism. In addition to these well-known regulations aimed at the financial services in general, there are regulations that are specifically directed towards AI and ML such as the European Commission on AI Act and various regulations from the US regulatory agencies. These regulations include a range of prescriptive requirements on AI/ML risk management processes which have also led to enhanced scrutiny on the AI and ML models and practices at financial institutions.

Regulators are also investing in capabilities to monitor and understand these AI/ML systems. It is important to continue to consider regulation as a whole system interacting with the micro-level AI/ML risk models, their business use, and the regulatory outcomes. AI governance is the collection of means and methods with which society coercively or voluntarily directs, constrains, and influences the use of AI systems to fulfill social and societal expectations. AI regulation is the state's coercive power to direct AI systems toward socially desirable behavior and outcomes, while AI governance is a broader term that refers to both public and non-public actors and mechanisms with diverse and differing motives. It takes various forms, most commonly – and also most saliently – hard law.

7.1. Data Privacy Regulations

Data privacy regulations will impact how AI and Big Data technologies can be adapted in the context of payment processing. Open Banking regulations have already forced banks to work with other service providers. Under the European Union's Payment Services Directive Two (PSD2), banks must share selected customer information with third party service providers who have obtained consent from their customers to access the data. In exchange for the data obtained, the service provider must also be willing to share the data generated from their services back with the bank. This will strongly affect how banks classify their customers and which payment stream they should analyse. Compliance with Open Banking regulations must be adhered to even when developing Big Data payment processing solutions.

In situations where banks must share payment data with payment requesters, there is a need to share insights in an acceptable way. Insight sharing must comply with regulations that dictate on developing a specific scope and agreed rules for insight generation. Data protection regulation is an important aspect when implementing AI and Big Data technologies in payment processing. Banks process personal data with data subject consent as the sole lawful basis. As such, any explicit optimistic AI use would not be permitted. With strong customer authentication, only the bank is in possession of the keys to decrypt sensitive banking data.

7.2. Compliance Challenges in Digital Banking

The increased proliferation of Digital Banks and Payments has changed how payment systems are viewed and regulated. A payment system is now understood holistically and takes into account the various ways in which digital banks conduct payments. There is no longer a fixation on payment infrastructure and systems. In fact, the Central Bank of Nigeria now requires banks to focus on user interface, experience and services offered. There is an awareness that payment systems are viewed differently by the younger generation and regulation has to keep up with such change.

To this end, the payment system vision is defined as a seamless, safe and live payment processing, thus, the review now has an emphasis on investments being made into Big Data and Artificial Intelligence, rather than mere compliance. In order to promote the above defined vision, innovations in the payment system must satisfy the following criteria: simple and ubiquitous user interface with no reliance on the banking channels; instant, effective live payment processing within the country and when cross-border; powerful analytics that enables detailed profiling of all payment participants across the payment system trust chain; and provision of interesting services based on behavioural insights for both the regulated participants and the users.

These innovations are based on significant investment into big data technologies across the Data Ingestion, Storage, Processing and Analytics pipelines. Considering the processed data volumes and variety, it is also planned to evaluate on the Processing element of the Pipelines. With respect to AI, the payment system is particularly interested in Unsupervised Learning techniques to profile users of various systems and provide useful regular updates.

8. Future Trends in Digital Banking

The banking and financial services industry is undergoing a massive change fueled by technological advancement. Reoriented customer expectations and the rapid evolution of technology are pushing this sector to undergo transformation. New digital models are likely to emerge as financial services and transactions move beyond conventional borders and focus on servicing and servicing-partner satisfaction. Given the growing categories of players in the digital banking space, banks should take a fresh look at the disruptors and understand their service delivery models to devise pragmatic strategies for partnering and combatting.

On the technology side, Internet Protocol (IP)-based solutions, Blockchain-based applications, Cloud and Augmented Analytics will play a major role in transformation. Key operational areas such as Retail banking, Capital markets, and Payments will be the primary focus of technology-based changes. New protocol-independent service-oriented solutions leveraging Big Data, Business Intelligence, and Analytics tools will be in demand for improving operational efficiency and better servicing.

Peer-2-Peer payment is predicted to grow exponentially due to an increasing number of initiatives around real-time payments adoption. Real-time payment ISO 20022 adoption could lead to regulatory compliance issues. Biometric authentication, influenced by an increasing number of mobile device users, will be the focus area in Secured transactions for both online and offline commerce. Cyber threats and fraud will continue to grow alongside technological advancement. AI and ML capabilities will be essential in tracking real-time breaches and adaptive countermeasures for evolving fraudulent activities.

In Capital markets, Blockchain technology will gain very high prominence as an alternative to the existing processes for trade execution, clearing, and settlement. Blockchain consortium initiatives among exchanges for joint synergies will be an area of development. Conventional currency development and settlement on Blockchain protocols will lead to focused service delivery from Banks as a digital asset manager. These initiatives will limit arbitrage opportunities and even better price discovery and market efficiency.

8.1. Emerging Technologies

The banks are adopting a number of new technology platforms and solutions to add value in almost every area of operation, risk management, and consumer interactions. On commission, transaction-based services, and off-balance sheet growth, banks are supported by artificial intelligence-enabled systems. They conduct many traffic and security assurance activities as part of the payments process before allowing execution of the request. Analytics solutions are expected to become an integral part of measuring and monitoring payment transactions in various payment ecosystems. Various AI-based solutions for modeling and time-series data processing based on statistics, predictive capability, and self-learning have emerged, but there are still fewer reference implementations on such solutions in contemporary industrial settings.

The need to manage and control payment delays is intense, necessitating AI-enabled systems to emerge, mature, and become accepted practice in banking. To manage consumer complaints about transaction delays, active coordination with other entities or studies on pain points of time loss is required. Every consumer wants instant and real-time services in the instant payment ecosystem where the payment message is available in real time. It is realized that controlling payment rails by establishing fixed agenda coordination is impossible, necessitating AI systems to forecast expected delays and avoid loss of control over rail connectivity and entities. Concepts of emerging AI-based and hybrid AI-based classical analytics systems are covered in contemporary works. These emerging AI-based or machine learning-based systems provide insight into understanding the underlying concept and capabilities of tools for enriching payment tracing systems. Conceptualizing a payment processing architecture as a microservices-based architecture with event-driven data flow is required. The event-driven data flow with technologies relevant to streaming computing and platform architecture, and data engineering concepts is addressed.

Equ 3: Stream Data Aggregation Function.

$$\mu_t = \frac{1}{N} \sum_{i=t-N+1}^{t} x_i$$

- μ_t: Moving average at time t
- N: Number of recent transactions
- x_i: Transaction value at time i

8.2. Predictions for Payment Processing

There has been massive growth in digital banking transactions and rapid penetration of the Internet in recent years. To take advantage of the growth in digital banking, banks adopted AI solutions and got more insights through big data analytics. This section tends to explore the money transfer process in detail. In a typical bank network, there are two banks allowing a money transfer between various accounts across multiple banks even in a different country. Banks operate at an agency level and the need to work together to facilitate the money transfer has led to the growth of nation-level Payment and Settlement Systems (PSS). Because of financial growth, the banks have to move towards real-time payments (RTP) and use of AI and big data analytics has become mandatory for a smooth operation.

Currently, various banks follow batch/near real-time payment mode which creates hindrance in time-critical monetary transactions. This hampers growth in regional, national, and international trade environments for banks and financial organizations. Further delays in payment compromise trust and operational efficiency of the banks. All these factors lead to severe penalties and even withholding of business. Definitely banks will have a tough time coping with the increased expected transaction load on one hand and maintaining privacy, security and confidentiality of transaction details. A comprehensive architecture for the next generation vision of RTPs across multiple currencies and payment rails used by banks is proposed. The proposed architecture will help in the exploration of existing challenges faced by banks with new RTP systems and how real-time payment systems can leverage AI and big data analytics to make monetary transactions more effortless, secure, and faster.

Technically an RTP system is a distributed digital payment system that sits on top of an existing banking ecosystem allowing banks to work together to facilitate payment and transform digital currency. The proposed architecture consists of a core RTP engine over which multiple payment systems can be designed to allow for payments to occur between multiple accounts across multiple payment systems operating in various styles.

9. Conclusion

Digital banking across the globe is seeing rapid growth, fueled by the recent event of the COVID-19 pandemic altering consumers' banking habits. In response, banks are investing in innovative technologies to deal with the increase in online banking transactions. Though the national payment systems in current digital banks are designed to process payments in milliseconds to the seconds range at most, which was suitable for traditional banks, newly emerged digital-only banks have had almost no lag in performing even instant domestic payments. Real-time payment (RTP) transactions such as these executed within milliseconds are becoming popular. This has sparked a demand for digital banks to keep up with the latest payment technologies concurrently while gradually implementing the newly proposed ones to meet customers' needs. To better gauge transaction scenarios within relatively delayed payment processing and understand how RT payments are different, banks need to have sets of knowledge and processing routines, typically as made explicit by rules. This is crucial for understanding not only transaction semantics to prevent abuse but also how to prioritize transactions depending on rules ranging from business logic to risk management. Although business rules are critical for payment transaction processing, they typically require frequent changes to accurately handle the sophisticated and growing business needs of digital banking. Moreover, more rules' friendly operation, expediting rule construction, and decreasing overall maintenance efforts are necessary if digital banks wish to maintain broad regulations of not just accounting terms. To prioritize stealthily abusive transactions, improved knowledge of potential risks is also essential.

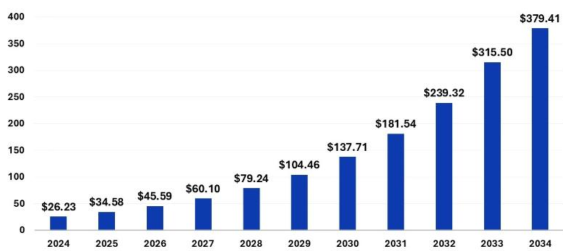

Fig 6: ai and big data in digital banking payment.

AI can be employed here to better explain scenarios and embedded rules governing them, as well as to assist in acquiring and amending the many rules involved, and hope to present more specific policies based on the type of transaction, corroborating rules likely implemented concerning it. AI can also be used to examine this data, find problematic data, conduct risk prediction, keep timely track of possible but still rare anomalies in transactions, and further prescribe whether it fits the standards of a bank transaction. Furthermore, AI can be ready to warn of problems in other banks' transactions or even prohibit illegal transactions in real-time, galvanizing significant improvements in the levels of risk management for banks.

While big transferred data from the parallel networks and processing details together with extra banks' internal processes ensure limited missing information, some practical issues including excessive processing burdens inhibit sufficiently comprehensive processing of transaction data. Moreover, the accordance of transaction data processing time with banks' actual processing time is yet to be sufficiently verified, in addition to the correctness of execution events and employing data deduplication. The next biggest problem involving the operation of knowledge bases guarantees the usability of data queries and rules.

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