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Chapter 4: Real-time payments and the convergence of artificial intelligence in transaction processing

4.1. Introduction

The next payment revolution has begun with the introduction of Real-Time Payment (RTP) systems. A RTP system provides instantaneous payment processing and transaction confirmation in near real-time manner. More than 88 countries have or are planning on developing RTP networks to provide their residents – both consumer and businesses – with entirely new payment capabilities such as pay-anyone from anywhere, no cut-off timings, and granularity and immediacy of payments. The arrival of RTP systems presents great opportunities and challenges for payment players. Fintechs need to immediately adapt their product roadmap to include RTP services. Payment schemes, gateways, and processors need to evolve their tech stack to perform instant routing, processing, and settlement of payments. Since any bank, fintech, wallet provider, or business could leverage RTP, consumer expectations on past "good enough" products are changing. Standards of the North American payment ecosystem were influenced by batch settlement systems like ACH and clearing houses, but today's consumers expect the features of a retail payments product to match the easy, on-demand expectations set by tech giants like Google, Pay Apple, and Tencent (Bodemer, 2024; Fathima, 2024; Lam, 2025).

Surprisingly, commercial RTP systems are now widely deployed across Asia and Europe. Applying any new tech stack to RTP is a demanding task in itself. The introduction of RTP is amplifying the consequences of piling on new technologies. Implementing an RTP system for a fintech is like playing 3D chess, and every new piece that is added complicates the game and the potential moves. Here, a new payment system in development in North America serves as an example to illustrate what is to come for RTP in one of the last places RTP is still being developed . The primary focus is on the impact RT payments and technology will have on payments that have already launched in competitive markets. This includes competitive, operational, and consumer impacts. Additionally, this focus area and others are discussed with the expectation that if RTP is not on the radar of individuals presently in the North American payment ecosystem, it will be soon (Taneja et al., 2024; Roy et al., 2025).

Fig 4.1: RealTime Payment

4.1.1. Background and Significance

The rapid adoption of digitized payment services across the globe has brought forth a key consideration in transaction processing systems: Real-time Payment (RTP) systems . These systems exhibit the ability to process payment transactions in an instantaneous manner, fundamentally disrupting the decades-long regime of batch-based settlement cycles in the payment industry. RTP systems are characterized by transaction-based, instantaneous crediting of transaction amounts to beneficiary organizations through Automated Clearing Houses or Central Banks, with stringent security mechanisms for bot-user detection. Payment messages use XML format, automatically characterizing senders and receivers, and the existence of machine-readable payment transaction schemes has tremendous prospects for deployment of artificial intelligence-based transaction processing systems, such as machine learning classifiers and computed mathematical modules in payment routing, transaction classification, and fraud detection.

Traditionally, RTP systems have emphasized 24x7x365 system architecture on a transactional basis, rendering the multi-module structure of processing systems insufficient to meet the sustained rise in transaction volume, throughput, and latency requirements. However, in the age of chatGPT-like functionalities in the FinTech sector, it is anticipated that transaction processing will be unified in a comprehensive deep-learning-based AI service.

4.2. Overview of Real-Time Payments

Real-Time Payments (RTP) is increasingly becoming a popular payment option amongst consumers, businesses, and the government globally. RTP system is characterized by the always-on capability, instantaneous clearing of transactions, a process intermediary, and immediate availability of settlement funds at the beneficiary participant. Real-time gross settlement (RTGS) is a conventional interbank payment system providing settlement of high-value payments, with payment instructions settled on a real-time basis after batching of the transactions.

Around 1,048 billion payment transactions were processed in the U.K. in 2020, up by 22.1% from 2019. Total value of payment transactions over the RTGS systems for the U.K. in 2020 was around £109.06 trillion. The pandemic period has provided a major impetus to the already fast-growing RTP solutions. Increased safety, reduced risk of physical interactions, and demands for seamless payment processing are some of the drivers behind this growth.

The risk to the settlement funds posted, that is credit and liquidity risk, on the operation of Real-Time payment systems is high, as liquidity drains at high speeds. Consequently, the chance of occurrence of unexpected payment spikes is high, exposing payment systems to additional risk. Therefore banks can decide to participate at certain times only or cancel participation altogether when the risk of draining out liquidity becomes too high. This phenomenon is known as the liquidity cascades. A liquidity enhancing solution that restricts signing time slots would be optimal to curb the liquidity cascades. A configurable restriction of the signing time slots that takes into account the current liquidity conditions is computationally feasible with distributed ledger technology. This prevents liquidity cascades and supports scalability.

4.2.1. Definition and Importance

With the rapid growth of P2P and real-time transactions in recent years, payment systems are facing unprecedented challenges in transaction processing. The importance of providing secure and reliable service cannot be emphasized more. Therefore, the stability of payment services becomes a critical problem for Payment Service Providers (PSPs). Meanwhile, the distributed architecture of a payment system results in the difficulty of monitoring core components like a payment switch in real-time. PSPs are facing the dilemma of balancing the reliability and cost of investigation, which severely hinders their capability of dealing with payment failures and attacks. AI-driven Stability Analysis (StA) becomes a promising solution. Effective feature extraction which identifies features in both monitoring dataset and transaction dataset is widely something essential.

Financial service has been one of the early applications of AI. The widely deployed real-time payments transferring hundreds of billions of transactions annually have greatly profited from AI technologies. In the AI context, on the one hand, payment service providers carry enormous market scenarios for more accurate, real-time and multilingual predictions. On the other hand, uniform models on different input might create unwanted biases. Features are diverse, and dynamic settings overwhelm historical features. These variations pose challenges in generalization which demand analyzable and individualized models.

Natural Language Processing (NLP), graph structure reasoning and forecasting tasks are reengineered to Fintech scenarios. Money laundering and payment risk detection tasks have been reinvented as problems integrating financial graphs and time series. With MPL, interpreting features for graph and transaction-level makes financial models more applicable in compliance. Hierarchical attention mechanisms are also utilized to collectively analyze risks in both transaction context and network. Graph Convolutional Network (GCN) is integrated with Long Short Term Memory (LSTM) to fundamentally handle prospective money laundering.

4.2.2. Global Trends in Real-Time Payments

The adoption of real-time payments (RTP) is accelerating across the globe driven by technological developments and demand from consumers and businesses alike for improved capabilities across payment systems. This has resulted in a proliferation of RTP schemes worldwide, and the payment transaction processing capabilities of banks and other payment service providers are increasingly being challenged by the high volume and velocity of real-time payment transaction processing [3]. Rapidly growing consumer and merchant demand for new payment capabilities has also led to the rapid adoption of artificial intelligence-based systems for payment fraud detection and prevention, automated transaction dispute management, smart payment routing, and decision limit management.

Accelerated progress made in these new Artificial Intelligence (AI) initiatives is on a collision course with the established transaction processing capabilities and performance of RTP payment systems. The coming months and years will see the industry challenged to ensure that the very rapid advances and implementations of AI-based solutions in various stages of maturity will be able to interoperate with generational RTP transaction processing technologies. Alternatively, payment service providers may consider implementing new revenue-generating AI solutions only to discover that their currently installed payment system technologies may not be up to the task. In this context, the current state of RTP payment systems is reviewed followed by a summary of selected recent advances in AI-based payment transaction processing technologies.

Real-Time Payments (RTPs) are payment systems that allow transferring small to high amount of money from a payer to a payee in real-time, which can be settled immediately. In the typical case of Banks-based RTPs, the payer sends a request message to their bank (the creditor bank), who prepares a credit message and sends it through a gateway to the RTGS and finally to the payee's bank (the debtor bank). In real-time compatible RTP systems, timing constraints apply to the preparation and transmission of messages at each involved actor (e.g. bank, RTGS, gateway). In contrast to net settlements, in RTGS, each payment is executed in real-time (i.e. whenever a payment arrives at a bank, this bank implies a settlement at that moment and updates accounts/titles).

4.3. Artificial Intelligence in Financial Services

The financial services sector is experiencing a significant transformation characterized by rapid innovation fuelled by the convergence of enabling technologies and changing customer expectations. Artificial Intelligence (AI), cloud computing, Application Programming Interfaces (APIs), big data, the Internet of Things (IoT) and blockchain are at the heart of this revolution from a technology perspective. Changes in attitudes regarding personal data privacy and security, as well as rising expectations regarding both the quality of financial advice and the speed of transactions, are seen as having the most direct impact on the current transformation of financial services. These technological forces also have broad implications for other sectors but their implications are unique for the financial services sector, transformed by information and innovation rich in experience curves.

The financial services sector is undergoing unprecedented upheaval. Major innovation in the financial services sector is in part a result of technological forces including Artificial Intelligence (AI), cloud computing, Application Programming Interfaces (APIs), big data, the Internet of Things (IoT) and blockchain. This technological change is creating entirely new and alternative ways to deliver financial services and products. The providers of such services and products are becoming more and more blurred as the sector converges with other pervasive sectors. This, in turn, gives rise to contrasting consequences in terms of access, prices, quality, and choices. Understanding and appreciating the effect and effectiveness of these developments in financial services is crucial for development practitioners, regulators, and researchers.

In recent years, there is a growing evidence base regarding technology adoption, deployments, and innovations in the financial services sector. Considerable attention has been paid within the academic literature to individual technologies, classes thereof, as well as use cases. The business implications of such developments are also being explored, including organisational performance. However, it appears that there is no academic research explicitly focused on the impact of technology on financial services classification or the consequences of classification on financial services in the technology-aware context. This paper seeks to address this apparent gap.

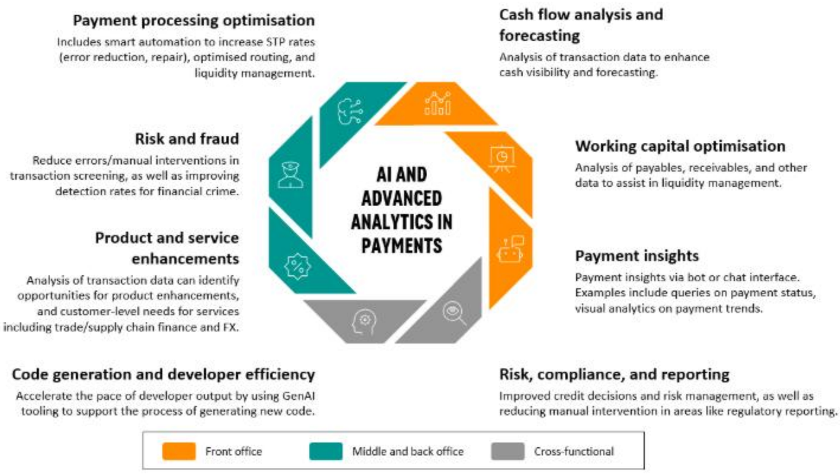

Fig 4.2: Artificial Intelligence (AI) in Finance

4.3.1. Overview of AI Technologies

Artificial intelligence (AI) has been a remarkable success in many applications, spanning from business sectors to advancements in computer operating systems with voice recognition and automatic voice responses, to the extremes of chatbots on various websites [6]. AI is the attempt of the machine to perform tasks that historically only humans could perform by arranging massive data in a way that smart machines can derive knowledge from it. AI promises a wide range of benefits with challenges and worries regarding job loss, social impact, and ethics. There are various AI definitions including smart machines, robotic systems, deep learning, natural language processing, and machine learning. More commonly agreed definitions suggest that AI is a technology built on simulating human cognitive systems including reasoning, learning, perception, problem-solving, knowledge representation, and language understanding. Each of the dimensions of AI can be categorized based on degrees of intelligence in tasks or domains, and on how the intelligence is achieved. Machine learning (ML) is a subfield of AI that is defined as the capability of a program to learn on its own with minimum human intervention. Reinforcement learning (RL) is a specific method of ML, simulating how humans learn new behaviors. With reinforcement learning, the agent learns the output function by trial-and-error among alternative actions; a rewarding scheme helps it discover the optimal function by rewarding, or penalizing, the actions taken. The application domains of AI are extensive with applications across the fields of security, finance, healthcare, agriculture, customer engagement, computer vision, business optimization, and so on. Smart systems designed to model human-like intelligence have been built which have changed the way business is operated. Some of the notable impacts have been noticed in HR, marketing, sales, service, and e-commerce.

4.3.2. Applications of AI in Finance

Artificial Intelligence (AI) is a systemic innovation that extends information processing, rich representations, deep learning of big data, multi-source edge-driven analysis and context-aware decisions. All these are key factors for intelligent finance technologies and services. Transmitter, carrier and transaction are three critical issues in finance. The former two have been conquered and applied for successful financial service innovations. Converging the above techniques, the analysis and decision-making intelligence become the third issue for finance innovations and services. Parallel to the development of intelligent techniques, intelligent finance analysis and decision-making are emerging, for example,. By offering a wide range of applications both for international, national or personal ownership and market, intelligent finance analysis techniques can be applied for event or issue based China stock market analysis, portfolio trading optimization based on personal stock ownership, industrial sector portfolios construction on risk and profit analyses, and recommendation system. Expanding privacy preserving approximation query answering in lipschitz ness and duality is much concealed for intelligent finance technologies and analytics to leap from success cases to commercial platform development.

As finance science is a multi-disciplinary knowledge system, from economics, sociology, political sciences, psychology behaviors, weather and even geographic or biomedical effects, its phenomena, issues, modelling or modeling are all open for multiagent gainful models or analogies. AI has been applied in finance with lasting success, but as with the recent AI hype cycle, a stronger interest in newer and smarter FinTech and their applications, particularly the focus on deep learning, generalization of robustness as well as attention mechanisms, have surged. Apart from its power and potential, AI in finance has been challenged in automated algorithmic trading, explainable AI, and most importantly the confidence and trust in machine-LADder

FinTech. Science discovers, models, simulates, and predicts phenomena, issues, and mechanisms, while AI analyzes, classifies, clusters, predicts, and derives actions and decisions. In finance modeling and machine empirics, the analysis and reasons to input composite models, model selection, F-distribution test for models testing are the hot topic among FinTech practitioners. It is, however, challenging to explain AI alsMEMRes or outputs, or the gradual process of deep learning of matrix hyper-parameters in a loss function in sequence based models.

Considering the system of finance as a layered grey leveled agent system, Transmitter, Carrier, and Transaction are the three critical issues respectively dealt with Finance, FinTech, and IntelliFinTech. Moreover, to conquer the agents' models and context secretiveness at all six levels and precision and correctness at the fourth level need robust converging techniques and techniques combination.

4.4. The Intersection of AI and Real-Time Payments

Using AI in transaction processing, such as filtering fraud checks against new real-time payments or taking advantage of price volatility for financial settlements, can bring substantial improvement to banks' bottom lines. Many banks in Asia have named this technology AI in real-time payments and have invested heavily in it. With this convergence of technologies, there are several trends in real-time payments that have emerged: trend of parallelism in settlement and reporting, trend of compliance automation, compliance analytics, and forecast of compliance load, trend of latency-driven rule set, on-demand rule classification changes, and rule testing in real-time payment processing, and trend of hybrid cloud settlements. These trends drive re-thinking of the status quo for real-time payments back-office systems. The AI-enabled back-office of the future is envisaged here. This is supported by an architecture consisting of three layers of infrastructure: a rule engine, a ledger, and applicability of cloud, including hybrid and on-premise. The re-thought systems meeting those three specifications best leverage the convergence of AI in transaction processing and real-time payments.

4.4.1. Enhancing Transaction Speed and Efficiency

Payments are fundamental to the functioning of the modern economy. Throughout history, payment systems have evolved from barter systems to increasingly sophisticated options through which payments can be carried out. In recent years, payment systems have undergone rapid evolution to accommodate the exponentially increasing volume of payments. Payment networks form a crucial part of payment systems. Many payment networks are adopting better technologies to process billions of payments accurately and on time. Adoption of technologies such as big data analytics optimizes the performance of payment networks. Payment routing is one such technology that can sift through millions of payment terminals and thousands of parameters to find the optimum terminal for processing a given payment. Existing commercial efforts in the area of payment routing are often privacy/knowledge-guarded black-box systems.

The Smart Routing solution for payment transactions handles millions of transactions in real-time/near real-time across different protocols and networks. The system grew out of the idea of using machine learning (ML) to determine the probable routing terminal for payment transactions. The payment processing pipeline consisted of both static and dynamic modules. The former is a rule-based module well embedded in commercial payment systems. ML methods, including decision trees and logistic regressions, were tried at the dynamic stage to predict probabilities of success for different payment terminals given a transaction. The method of successive corrections was applied to ensure that the different inputs for ML models are well conditioned. The model generally outputs probabilities of success of payment terminals. Business objectives deciding which terminal to route to can be customized. Therefore, depending on the environment, different terminals can be routed, e.g., one with a higher probability of success for capturing customer satisfaction or one which is at a maximum slowness point at the 99.99% of terminal completion time.

The solution was deployed in production with an overall success rate of ~91%, which was a significant improvement over the existing systems and desirable to the client. An API was developed to help answer queries in natural language based on the interpretable structure of the ML models used. Business teams benefit greatly by understanding the dynamics of success probability better and by going back in time to diagnose performance dips.

4.4.2. Fraud Detection and Prevention

Real-time payments (RTPs) in their most basic form allow payers to send funds instantly to any person or entity with an RTP account, in a way that is decoupled from traditional payment methods, whether that payment is for a specific good or service, or simply for account funding purposes. The convergence of multiple technologies may eliminate some human-driven and possibly manual processes through automation. Whether machines become the drivers of mass disbursements and settlements is yet to be determined. Automated clearinghouses (ACHs) settled payment files through batch processing overnight; RTPs now wire payments in real time while using batch processing and are slated to standardize an automated clearinghouse breakdown for RTP credits. Regardless of format, some level of manual review and intervention may always be needed in the transaction processing cycle. Some investigate sampled retrospective queries from secondary data stores to detect unwanted or incorrectly conducted transactions. Others, in real time, control parallel queues of executive query engines running AI-sourced transaction monitoring rules or self-learning over time. However, by nature of their timing and design, RTPs cannot be pushed aside for these approaches. Conversely, it may be sensible for some innovative firms to "park Funds" with a payments partner to allow for a brief moment of review. On the enterprise side, a firm's anti-money laundering and know your customer compliance views of, e.g., transactions, vendors, and employees may need to be instigated in consideration of RTPs. Digitized breaches of trust in these channels must also have a better methodology for foiling crooks than the traditional working back in time.

4.5. Technological Framework for Integration

The convergence of RP and AI calls for a systematic conceptualization of AI’s (in)effectiveness fluctuating over time, which can be achieved through the introduction of the AI pyramid. AI-based TP is considered on three levels of AI advancement for RP systems: (i) no evidence of AI implementation, (ii) evidence of AI implementation but indirect implementation, and (iii) evidence of AI implementation that directly and substantially enhances TP in RP systems. The introduction and application of AI across the AI pyramid will similarly add value to RP systems on three levels of TP enhancement: (i) no evidence of enhancement or strictly disabled enhancement, (ii) knowledge-based enhancement that is less reliable but an easy fix, and (iii) knowledge-

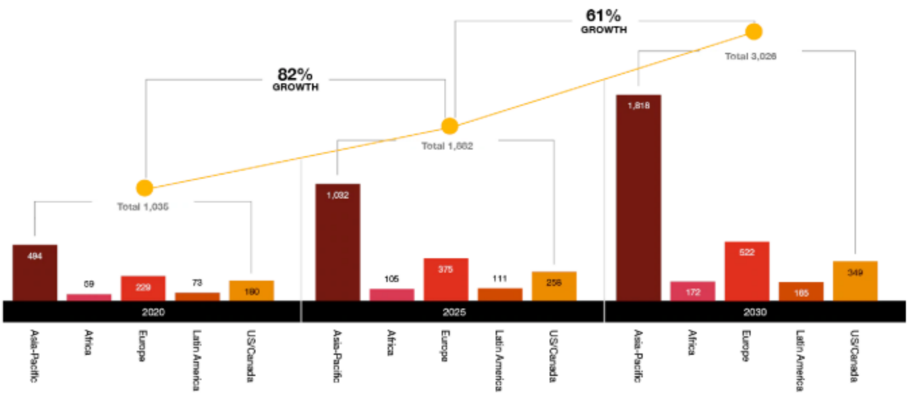

Fig : Payments 2025 & beyond

and process-based enhancement that is more reliable but seemingly complicated. In addition to the software and data engineering concerns, the convergence of RP and AI introduces three more complex concerns on three levels of AI (de)-enhancement. The AI pyramid creates the simplest conceptualization of the fluctuating effectiveness of AI-based TP, enabling meaningful future investigation and applications. The conceptual framework delineates future research possibilities for AI and RP convergence in the spam avoidance subprocess, using responsibility-oriented multi-agent nouns as examples. The three levels of RTP and AI's fluctuating effectiveness across the future applications of the AI pyramid enable precise research subject and objective formulation and thus generate scientific outputs. Future studies will enhance the understanding of the applicability and acceptance of AI in TP. Furthermore, the proposed pyramid also helps practitioners implement AI and RP enhancements that are consistent with their business environment and user base, contributing to a win-win cooperative advantage for all parties involved. Through systematically investigating the two feasible convergence paths, this study adds value to both AI and RP research fields. Artificial Intelligence (AI) and Real-Time Payments (RP) are today's two most actively adopted innovations in FinTech, yet the convergence of these two companies would result in unexpected consequences that are still irrelevant.

4.5.1. Architecture of Real-Time Payment Systems

A real-time payment (RTP) system is a payment method that enables the instantaneous transfer of funds regardless of the payment channel. These transactions can occur between two different banks, banks of the same family, and within the same bank through different payment networks. The transaction entails the immediate transfer of payment and reconciliation messages that are conveyed between the payer and payee banks, facilitating the crediting of the respective payment accounts. This change in legacy payment channels has engendered the need for destination banks to implement an RTP system with crediting arrangements. Thus, the RTP processor is of paramount importance in determining the system design, processing the transactions to ensure compliance with the payment channel, and colluding with partner regulators to assess the system's robustness. From the perspective of the destination banks, the RTP gateway is the system that ensures the safe exchange of messages with the RTP processor. The banks refer to regulations set forth by the central bank in implementing payment channels. Such regulations define clearly under which circumstances the transactions must be accepted, the maximum amount for the payment message, and the operation of refunds.

On the basis of the payment channel, the message format must adhere to standards defined by the clearing network. These define the structure of the payment messages and clearly stipulate the contents (message type, validity period, remitter information, etc.). It also refers to certain information that helps the payment channel to comply with scenarios defined by the central bank (payment redirection number, unique transaction reference number, etc.). From the regulations viewpoint, the RTP systems must provide a KYC mechanism that consists of business rules against fraud and compliance. A typical setup can allocate a score for each special type, such as an abnormal payment amount. If this score exceeds the threshold, the transaction will be rejected with the reason code and additional information such as a reference number. Since RTP messages are processed in a near real-time fashion, fine-tuning of these rules and thresholds is desirable so as not to cause too many false positives. As a remedy, the central bank, being a central bank for many commercial banks, can develop and foster modules based on a prepared rule set, the record of businesses in RTP systems, and information about customers from each bank.

The banks can either build system-specific modules or purchase modules from the central bank to further boost the speed of implementation of the RTP system. On the other hand, the privacy of the data is immense, which motivates banks to devise their own modules. A significant difference from message formatting processing is that it is an evolving process. The conducting frauds, the attack vectors they use, and thus the behavior of the customers all change over time. This necessitates a periodic parameter update, inferring better business rules and thresholds tested on a long observation history. However, training an effective model requires enormous datasets, and models usually offer a performance guarantee on a fixed period, i.e., with unlabeled data, the model performance is uncontrollable. In summary, one way to achieve compliance and fraud detection is to prepare modules based on rules with the cooperation of the central bank.

4.5.2. AI Algorithms for Transaction Processing

Transaction processing in the present scenario involves integrating multiple models and sources of information. For payments receiving banks, these models may involve understanding their customer's behavior pattern for legitimate transactions, scoring rules for anti-money-laundering predictions, fund safety heuristics, and so on. For banks sending payments, these sources of information may include routing districts to ensure timely transits, modeling customer behavior (legitimate/local transactions), and limit control. To cater to such overheads for a central bank, transaction processing systems should support integration with all levels of models in an efficient manner. Internally, these systems should support streaming architectures. The stream processor should support continuous operation, where new transactions can be processed as soon as they arrive. They can then use the working knowledge to apply the static (batch) models to this state, updating it, and updating/cleaning the raw data to ease the processing of new inquiries. It is also important to select the relevant regulators for each inquiry (a partitioning step), since there will always be many more interested regulators than the size of the regular comparison.

Two types of transaction processing pipelines that cater to different systems are discussed. The interface can be adapted to support static models for batch queries without overly complicating the implementation. Exploring complex pipelines on the basis of carefully choosing the source models is a major open problem. Case studies on SEBI and the highly deployed 820 transaction systems are demonstrating this architecture. It is also shown how it can practically work on trillions of transactions with seriously constrained data availability. A brief overview of the pipeline design and implementation and current progress on experiments with the Reserve Bank of India are also discussed.

A smart routing solution based on explainable AI and ML models has been designed and built to route payment transactions to terminals for further processing. The 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. The static module is based on rules and simple ML techniques to prune the list of probable terminals for a given payment transaction .

4.6. Conclusion

Real-time payments are fast becoming the standard for transactions, whether it be for purchases in stores, money transfers to friends, or paying bills. Digital transactions are expected to reach USD 2.25 trillion globally by 2024, with growth at a CAGR of 16%–18% [1]. The majority of this transaction volume is expected to occur in e-commerce, and a significant percentage of the global population, especially in developing regions, is expected to shift from cash payments to digital payments. However, the conventional methods via card payments are slow and risky, owing to the need for intermediaries, leading to a demand for alternative payment mechanisms. The banking sector has also emphasized the need for Fast Payment Systems (FPS) as an alternative means for settlement.

Any payment transaction infrastructure connecting multiple Banks/Registered Entities for the exchange of full-service payment instructions for value gross settlement on a real-time basis and allowing 24x7 payment processing is termed an RTGS payment system. This infrastructure must run in four processing modes, viz., normal, emergency, backup, and supervisory mode. Such a transaction processing system for FPS worth an overall amount of INR 50,000 crores was envisaged. This payment transaction processing infrastructure was determined to comprise of two components, i.e., the payment switch intended for routing of payment instructions, and the RPS intended for securitisation and processing of payment instructions received from the payment switch.

Machine Learning (ML) systems, however, require careful design of the features fed to models, which is a non-trivial task. As new terminals are introduced in the live environment, they do not have any historical data to populate the features' information about these terminals. The proposed solution is designed as an ensemble of two modules: static and dynamic. The static module tests certain static rules such as truncation and delays and gives a list of payment terminals to be considered. After implementing the static module, a rule-based initial static feature set is designed to be calculated collectively for a batch of payment terminals. At this time, certain ML models are trained on historical payment data to decide which terminal input to the payment switch for processing. The predicted probabilities are treated as a score to rank the terminals.

4.6.1. Future Trends

The increasingly high number of Electronic Payment Transactions has seen financial transactions losing their bank monopoly. Spurred by recent technological advancements, a wide range of transaction processing systems for different payment instruments have emerged. Transaction processing systems are crucial in protecting payment processors, merchants, and institutions, as they now handle a major portion of the entire transaction lifecycle. Traditionally, transaction processing systems relied on rule-based systems that required human supervision to perform changes or integrate new use cases. As payment processors and Fintech advanced, systems began to handle higher volumes of transaction flows in real-time, processing millions of payments per second. The spike in number, form factor, and volume of financial transactions called for an intelligent, self-supervised, extensible, and robust solution to match the systems' intricacy by accommodating recent ML advancements. Malaysia's TLB, a payment processor for multiple e-wallets and banks worth billions since inception, highlighted the importance of transaction processing systems in real-time payment processing. Its intelligent transaction processing system successfully reduces human supervision by implementing Smart Routing (SR) design patterns in Fintech.

The union of the two domains began over two decades ago, with AI technologies growing remarkably. Personalization and recommendations have shifted to machine learning since the need for adaptability and intelligence rose. Machine learning has pushed rule-based decision-making paradigms to their limits. Accelerating unforeseen anomalies has allowed firms to act in real-time, enhancing profitability, customer satisfaction, and trust. Advances in anomaly detection utilizing real-time network logs and supervised ML trained solutions have demonstrated their generalization in languages similar to Java and PHP. SMEs are also utilizing intelligently programmed chatbots permitted to go outside certain rules. In IoT, ML has dramatically reduced false alarms in intrusion detection with the possibility of self-learning. In FinTech, AI/ML efforts to improve detection systems for money laundering activity have gained traction.

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