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The Future of Payments: A Comprehensive Review of AI, ML, and Cloud Technologies in Finance

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Abstract
The financial industry continues to evolve, specifically in payment processing. Payment processing is at the forefront of technological advancements, significant growth, and constant change. Companies desiring to grow their consumer base must remain current with trends and developments in payment processing. Payment processing has entered a new era of technology advancements inspired by AI, ML, and cloud computing, impacting operations and transforming businesses in today's marketplace. The banking industry faces fierce competition from agile Fintech players that leverage technology to deliver services and new offerings faster and cheaper. Significant public sector funding catalyzed the growth of open and responsive payments ecosystems. Innovative combination models like Buy now, pay later (BNPL) and crypto-currency are springing forth, shifting risks from the lenders as well as intermediaries to the consumers, end-users, and providers. In blue-ocean areas such as e-Commerce, instant, cross-border payments, and digital assets, competition is not only intense, but the playing field is constantly growing and redefining itself. Vendors in on-and-off line electronic payments across different ecosystem parameters—service provider, regulation, traffic, payment format—have the latitude to partner or compete with each other, creating a complex environment defined by misaligned incentives on legacy systems, incomplete data, and bureaucratic inertia. On the other hand, irrespective of the payment type, frauds are nearing pre-global-financial-crisis levels, and direct losses are growing exponentially. Payment vulnerabilities translating into cyber risks and data breaches loom large, and hacking the supply chain has become a top concern for enterprises.

Federated Financial Institutions, Private Sector Players, Financial Data Exchanges, and RegTech will need to collaborate and invest in differentiated technology capabilities to secure their pieces of a slim pie. It would require immediate injections of cash upfront, time To Income (TTI) on legacy IT assets, acquisitions of technology providers, setting up scalable and proactive test environments, and a radical shift in the approach to assessing partners and vendors. Growing customer expectations for payments to flow instantly are forcing banks to intensify their innovation programs and invest in real-time payment systems. There are dedicated task forces at supervisors and regulators worldwide Engineering Distributed-control and Self-governed Payment Systems; Global Consensus Standardization of Payment Internet Protocols; and morphing payment systems into programmable platforms. Banks are even incentivized to capture new geographies and market segments by embracing Public Open Payment Protocols, Distributed-ledger Technology, and Edge-based Devices for Processing Payment Signals with control residing at the edge.

Keywords: Artificial Intelligence; Financial Technology; Machine Learning; Computational Intelligence; Cloud Computing.

1. Introduction

In the last decade, digital wallet usage has proliferated in parallel with mobile commerce. Although payment transactions through smartphones promote convenience in daily activities, numerous security incidents have occurred. Continuous efforts have been made by researchers to assure the security of both cybersecurity and physical security. Nevertheless, development continues, as do vulnerabilities, prompting the pursuit of consequential methodologies and technologies. This paper presents a comprehensive review of AI, ML, and Cloud Technologies implemented in the context of payment methods. Considering various forms of data, authors delve into how cooperative approaches modify threats or vulnerabilities of payment methods. This survey identifies existing system frameworks of cooperative technologies in the payment method domain. Potential future cooperative applications in payment processing technologies are discussed. Finally, future research opportunities and open issues are proposed.

The financial sector in a broad sense generally refers to monetary transactions with significant monetary values, including deposit, takeout, remittance, transfer, etc. Payment methods cover a wide range of technologies to process cash or cashless payment transactions. E-commerce, online banking, and mobile devices have affected many consumers' lives. Consumers now expect simple, flexible, quick, and safe payment experience that has fostered their demands for alternative payment methods. Unfortunately, new payment technologies lead to different kinds of cyber and physical security incidents. As such, security has become the biggest bottleneck for further development of new payment methods. In addition, existing technologies must be continuously examined to identify new techniques and vulnerabilities, suggesting the necessity of proactive adjustment of technology frameworks and methodologies.

1.1. Background and Significance

Digital transformation, driven by technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Cloud, has become crucial for businesses across various industries, including finance. These technologies have played a significant role in shaping the digital revolution, impacting the economy, society, and businesses. AI has enabled computers to perform tasks that typically require human intelligence, while ML has empowered computers to learn from data and make predictions or decisions. Cloud technology has allowed organizations to store, manage, and analyze applications and documents over the internet, rather than on local drives. However, the theme of payments, encompassing advancements in transaction and payment methods in public and corporate finance, has received limited attention despite AI, ML, and Cloud's increasing prominence. Furthermore, while AI and ML applications in finance, including investment and risk management, have gained some literature, a comprehensive analysis of this thematic area remains absent.

The significance of this research lies in providing a foundation for exploring the theme of payments in tech-based digital finance. This study highlights AI, ML, and Cloud applications in Financial Technologies (FinTech) and services, particularly in payment provision. While it acknowledges the extensive use of technology in this area, it seeks to present a more comprehensive framework compared to existing literature that focuses on either theoretical/empirical aspects or specific technological applications in business fields. It covers the broad spectrum of Finance and Financial Services to encompass various payment methods and instruments, including Bank Payments, First Party Payments, Retails Payments, Mass Payments, and other categories, as well as new modes such as cryptocurrencies. It includes both traditional players such as banks that provide conventional wholesale and retail payments and new market players such as payment and technology companies that offer online, mobile, and in-store payment services.

2. Overview of AI in Finance

AI, encompassing data-driven science, algorithmic modelling, machine learning (ML) and deep learning (DL), has been a research area of great interest and importance for decades, with applications in trading, lending, investment, insurance, risk assessment, regulation, accountancy and auditing. AI is the science of harnessing the computer to replicate or simulate human behaviours, thinking and learning, with a wealth of AI techniques, ranging from classical and traditional statistical and multi-agent models to the modern ML/DL tools. AI research in finance is of great importance because it sits at the heart of the new finance 2.0 industry and affects the economy, society, culture and politics, as well as the distribution of wealth and opportunities. AI is now revolutionising this sector and market, with the high-frequency and robotised trading generating large capital gains, losses, auctions, abuses, regulation circumventing, and an unfair advantage in decision-making.

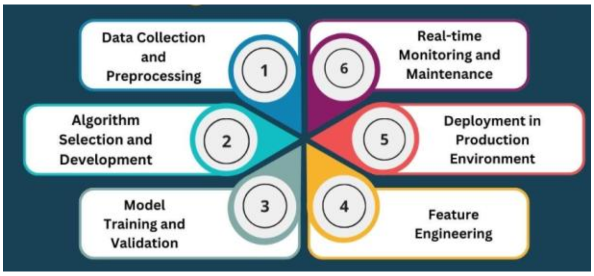

Fig 1: AI in Finance.

AI in finance has a long history; however, a thorough review in the context of both classic and modern AI techniques is long overdue. AI techniques in finance encompass a vast array, ranging from classic time series and trend models to modern ML/DL paradigms, with a wide spectrum of applications covering retail banking, asset allocation, and macro economy. The traditional AI techniques are subject to the limitations of linearity, input/output structure, difficulty concerning the incorporating of unstructured, image, text and network data, whereas the modern AI techniques are more advanced and effective in both supervised and unsupervised learning. There exist wide discrepancies in their respective technical maturity, frontier schedules of research, industrial patronage, and potential dangers in fairness, explaining, accountability etc, whilst the cross-feeding of both domains in architecture, approach, modelling and input/output features is also significant.

Finance refers to a domain of vast significance and complexity, with vast volumes of high velocity/mixed frequency transactions, sources, and types of assets, and diversified manoeuvres and activities. Though AI has been increasingly applied for finance, many great challenges remain to be addressed, including those arising from the complexity of finance, data quality, variability, and compliance, as well as from the rapidly changing and evolving modelling architectures, hardware, and technologies. Any AI applications shall take into account these challenges so as to be operational and money-spinning.

2.1. Definition and Scope of AI

Artificial Intelligence (AI) is defined as the ability of a machine to imitate intelligent human behavior. AI technology has gained popularity lately, due to recent advancements which have improved efficiency in processing massive amounts of data. These rapid improvements in processing power and the development of powerful new paradigms, such as deep learning, have resulted in mega successes, persuasively demonstrating that machines can enhance human capabilities and outperform humans in discrete tasks. This has led to a crescendo of anticipation about all things AI. Reports about smart cars crashing, expected job losses due to machine takeovers, robots winning chess games against humans, and the inventor of the popular Warcraft game being scammed by a smart AI, have instilled fear of the future in workers. Others laud the dawning of a golden age when productivity will ramp up dramatically, entire sectors of the economy will be transformed, and comforts previously only seen in science fiction novels will be the norm. Regardless of the hype, the effect of AI on financial decision-making is a critical topic that affects the future of institutional investment.

AI in finance is also mostly associated with data-intensive, mathematics, statistics, computing and quantitative finance-oriented investment strategies. However, the less conventional school of thought advocates the role of macroeconomic fundamentals. Unsupervised AI technologies, such as numerical prediction or anomaly detection, which are designed for long-horizon data analysis and are independent of how prices move, are under-published at present. AI could potentially outperform other quantitative approaches and exploit important insights from the data if properly acknowledged and actively studied. This use of AI, however, remains largely unknown to academia and practitioners. In addition to challenge issues, the paper intensively categorizes and briefly illustrates about 70 typical AI techniques applied in finance over the decades, ranging from classic to modern AI family.

Equ 1: Fraud Detection Using Logistic Regression.

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

- y: Binary label (1 = fraud, 0 = legitimate)
- $\mathbf{x}$: Transaction feature vector (e.g., amount, time, device)
- $\mathbf{w}$: Weight vector
- b: Bias term

2.2. Historical Context of AI in Financial Services

The financial services absorption of AI techniques is still in the early stages based on historical context. The historical contexts of AI and financial services are divided into three parts of finance: 1) Capital markets and trading: see (1) Industry participants; (2) Indices, data, and events; (3) Asset boundaries; (4) Economics, finance, and statistics; (5) AI and algorithmic evolvement in trading; (6) Effects, concerns, and effects; 2) Banking, insurance, and investment 3) Risk management, regulation, auditing, and education. All major analysts predict that the adoption of AI will impact financial services faster, deeper, and more broadly than the internet has. The financial services industry is facing the introduction of AI models and systems capable of auto-generating corporate, economic, and finance news and reports. AI models are being tested by government regulators to monitor daily currency transactions for signs of stock market manipulation. AI and machine learning approaches are used by banks to screen, extract, and analyze relevant proof material from millions of documents and reports during audit and monitoring processes. Traditional math and non-AI techniques used for similar purposes are unable to cope with the complexity and volume of such tasks [7]. The focus of many quantitative hedge funds is to screen for stock price patterns and model them using genetic programming combined with financial structure change detection. The model generated trading rules are then automatically traded by the firms for a few days at a time. As stock price trading patterns repeat, these firms continuously generate, trade, and instantaneously update model trading rules, or kill the out-dated rules. Similar approaches could be adopted to identify financial news and events that impact specific corporate stock price movement to systematically trade. AI techniques have been extensively employed to gather, extract, and summarize relevant news and events, but extensive AI efforts to model and trade corporate stock price changes based on exogenous factors are still scarce and needed. AI and ML techniques have a long history in the finance sector and are being increasingly used in a very broad sense. AI techniques modelling trading rules and systems, financial markets and execution, sentiment analysis and ratings, portfolio and investment, risk and fraud detection, operation and report generation and filtering, regulation and compliance and business ethics are reviewed along with historical context, challenges, and opportunities in financial services.

3. Machine Learning Applications in Payments

Payment Solutions Offerings: Chatbots, Open Banking, Quantum Computing, Financial Process AutomationaiM Education: A New Anti-Corruption Tool.AI Enterprise Business Solutions: Where, Why, and What ASML Teaches Us? When ASML Will Hit Compute Chips Interest Rate Cap? How TSMC Will Soldier on? ChatGPT Will Disrupt Coding (Not Mainly Just Software) and Many Other Industries? Electrochemical CO2-to-fuel synthesis technologies for SDG 7 and 13. The Author-Pay Model: The Flaw in Open-Access Academic Publication Vehicle? Predictions for China-Related Assets Over the Next Few Years.

In recent years, payments have become more open due to some forces behind the industry. Financial service providers in an open ecosystem need innovative, highly personalized services across many channels. The knowledge and expertise of many players, especially fintech companies, telecommunications, technology providers, and e-commerce players, must thus be integrated. Enhancing cooperation and collaboration with third parties in digital systems, APIs enable the interaction of different systems, applications, or platforms. The best-known example is the Facebook business ecosystem, which connects more than a billion users with a global bank of bank Facebook. The connection of flow data across banking systems generates assets and creates value in payment systems. Payment service providers can use these data to generate behavioral-based predictions of user profiles, unlocking new business opportunities. In an open payment system, capacity, flexibility, and reliability become critical factors in choosing payment solutions.

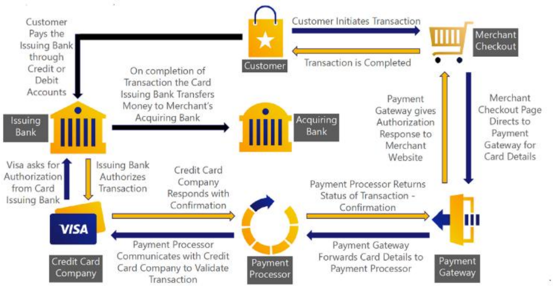

Fig 2: Machine Learning In The Payments Industry.

A paradigm shift to cloud infrastructure is occurring in the financial services sector today, mainly due to three factors: data explosion, increased market demands, and legacy infrastructure limitations. Cloud technology offers enhanced scalability, flexibility, reliability, and efficiency for financial institutions. Financial process automation technology re-examines certain banks' approaches to traditional banking services such as fund transfer, KYC, etc. The development of technology reshapes banks into a collaborative approach. Payment processors can work with other stakeholders for product development, compliance, and risk management enhancement. The collaborative open payment systems via API technologies and sensitive data driving the fine-tuned real-time screening can generate more robust systems at the banking industry level rather than at the bank level.

3.1. Fraud Detection and Prevention

Credit card fraud is one of the most lucrative criminal ventures in the world, totaling more than USD 16 billion in losses for merchants and cardholders in the year 2018 alone. Electronic payments have risen quickly, along with the dark side of the website boom known as the deep web, where a bustling underground economy facilitates the buying and selling of private information, enabling easy and inexpensive means for fraudsters to infect merchant systems with skimmers, and acquire credit card information in large batches. Both these factors have led to a rapid increase in the number and sums of credit card frauds. Cardholders are now reluctant to make purchases online due to the drastically high risks of having their credit cards abused for illicit activities shortly after. During the last decade, both banks and the merchants have invested heavily in credit card fraud detection systems to try to stem the heavy losses suffered by their industries. These systems utilize various artificial intelligence (AI) techniques to detect frauds after looking at all the transactions made closely. Each has its own particular strengths, weaknesses, and merits. Rule-based systems are simple and transparent, but their maintenance demands consider a large engineering effort as the changing nature of credit card frauds makes it imperative to constantly add more rules to detect new frauds. Neural network and other black-box systems generally need a large amount of training data, which are often hard to come by in this problem due to the relatively low frequency of frauds, leading to continually poor detection rates. Visualization techniques can provide ideas about countering usual and suspected frauds but usually can not be plugged directly into a fraud detection system. Systems based on decision trees and other techniques are often limited in their applicability, as they are usually tuned for a specific implementation. A large number of research papers in the area can be found. However, no system offers coverage of developments in the area, evaluation of the practices in use, and comparison of the various systems implemented in the industry.

3.2. Credit Scoring Models

Take-up of machine learning (ML) is no longer a question for financial institutions. Many institutions are adopting ML models at a fast pace as the current model landscape cannot cope with the complexities coming from new products and data. The majority of larger institutions are strongly investing in ML. Early ML adopters establish a better understanding of the characteristics and limits of ML and more and more cross-fertilization of ML technology, which enables the industry to innovate at a faster pace. Within the credit scoring context, the focus is currently transitioning from back-end scoring models to front-end scoring models. The paper extends ML applications to positive and public information in the default prediction task and characterizes the data requirements of a good-quality credit risk model. Based on real-life scenarios, prospects are presented for the usability of advanced ML techniques in the financial industry. Financial institutions need tools and metrics to judge if output ML predictions are trustworthy. Well-calibrated predictions/scorecards are of utmost importance for the optimum capital assignment across the entire portfolio. Calibrated predictors are usually achieved via logistic re-training. ML is complex and often seen as a black box. Model interpretability methods (local/global and model-specific/model-agnostic) provide insights into input-output relationships of the ML model and create local trustworthiness of the predictions of the ML model.

3.3. Customer Personalization Techniques

Customer personalization techniques can be broadly categorized into two groups: profile analysis and behavior analysis. Profile analysis refers to the extraction of information from customer data, such as demographic data, purchase history, customer preference, etc. These techniques can then be applied to segment customers and extract pattern data for customers. Behavior analysis refers to the purchasing behavior of customers, such as overall shopping activity, shopping time, shopping frequency, number of items purchased, etc. These characteristics form the basis for modeling customer behavior.

Profile and behavior characteristics for customer personalization systems of online financial services have been identified. They can also be utilized in many other e-commerce applications. The selection of customer profile and behavior characteristics has been viewed from different perspectives. Financial service personalization can be modeled by examining customer characteristics and predicting customer behavior. Likewise, an enhancement of individual websites to offer personalized services according to the customer's profile can be modeled.

In the field of e-commerce, many companies are providing a wide variety of product categories. They offer their customers one-stop shopping services by organizing products in a hierarchical manner. Customer satisfaction is one of the most important factors for successful online sales. However, managing a broad product category is difficult because customers may have different interests. Some customers may need services only for stock investment, whereas others may require a more general financial service, such as securing a loan, managing stock investment, and investing in funds. In particular, building an appropriate product service hierarchy is crucial for constructing a successful financial web site. This is because once a product hierarchy is established, it would dictate the way product information, such as business category and product name, is organized.

4. Cloud Computing in Financial Services

Cloud computing is a kind of distributed computing, referring to the network "cloud" which will be a huge data calculation and processing program into countless small programs, and then through the Internet diffusion implementation. Therefore, cloud computing can provide network, server, storage, application and other resources on demand. These resources can be provisioned and released quickly, minimizing management efforts. The service provider's involvement after provisioning is minimized. This report explores the intersection of cloud computing and financial information processing. Although cloud computing can provide efficient and intelligent solutions for the processing of massive financial data, it also brings challenges and risks to financial institutions in terms of information security and processing accuracy. Based on the challenges of the financial information process and the analysis of the cloud computing model and its application in finance, the risks and challenges faced by financial institutions in the process of introducing cloud technology are identified. The method of intelligent forecast and evaluation of financial information processes based on cloud computing models is proposed to improve the information processing efficiency and accuracy, as well as to promote the compliance and adoption of cloud computing models. Financial regulators usually formulate a regulatory framework with three dimensions: the cloud computing service provider, the financial institution using the cloud computing service and the technology itself. These frameworks need to be enforced strictly, carefully, and continuously updated to respond to rapid technological evolution.

With the explosive growth of incoming data, applying the cloud computing model to financial information processing has become one of the major trends in today's financial industry. However, financial institutions are currently facing an unprecedented data challenge. Traditional data processing models are mostly adopted where financial institutions rely on a considerable number of reviewers to handle the influx of information. This leads to low business efficiency, deeply data processing backlogs, and probabilities to miss business opportunities. Cloud services have become an important part of the global financial industry's information technology toolbox. With the increasing use of cloud services by financial institutions, financial regulators have begun to raise questions regarding the potential concentration risks posed by these services.

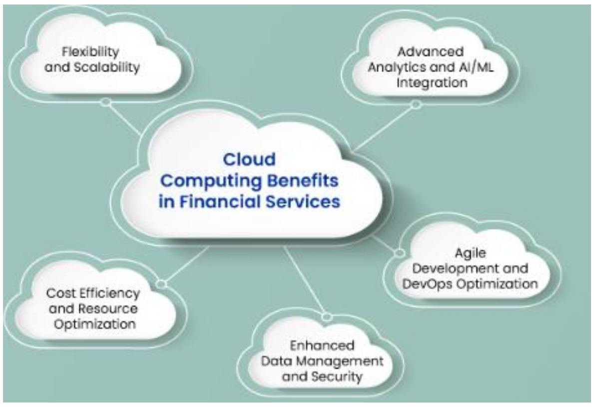

Fig 3: Cloud Computing in Financial Services.

4.1. Benefits of Cloud Adoption

One of the most important benefits of cloud technology is that it reduces overhead costs. Instead of building, maintaining, and upgrading servers, systems, and software, a company can operate from an established infrastructure and service. The greatest expense of traditional infrastructure for a small business is usually hardware purchases, maintenance, and staffing. Companies can lease high-end technology, processes, and infrastructure without purchasing expensive devices that require extensive knowledge directly. By paying only for what is used, businesses may considerably cut technology costs. No need to incur the capital expenditure (CAPEX) associated with hardware and hosting facilities. Instead of making capital expenditures on hardware, a subscription-based infrastructure as a service (IaaS) allows converting CAPEX to operational expenditures (OPEX).

Operation All type of maintenance, upkeep, and upgrade services covered by hosting services. No need for in-house security equipment, outside monitoring, anti-virus protection, system auditors, or log attacks found. It can provide for redundancy, high availability, and failover switching between devices in a cloud configuration, which is generally too costly for small enterprises. Data and applications in public clouds are stored offsite. Subscription-based services provide access to important data, offering a level of disaster recovery previously unavailable to small businesses. For modest needs, a few monthly fees

provide good redundancy and backup service. Data is safeguarded at a company location and in geographically dispersed data centers at very competitive costs.
Data storage handling and transfer costs have been historically high, necessitating constant negotiations with service providers. Using private lines, fiber optics, satellite links, or price, and performance sensitivity typically favored only the biggest organizations. In addition to opaque metrics, small firms lack negotiating leverage. Improvements in general availability and lower prices for data hosting, storage, and delivery are accelerating cloud adoption and enabling the rethinking of many services and applications. Now a few cents will buy the storage and backup of a corporate email account for a year. Storage on a NAS device network could cost 10 times more. Now, at close to zero db traffic charges and a set monthly fee, hourly video conversion and delivery service are offered. Despite their size and scope, these services are often cheaper and more technically sophisticated than low-scale services. Redistribution of several types of online services that still provide basic capabilities without capex or administrative overhead is a strong growth area.

4.2. Security Challenges in the Cloud

Despite the various advantages of cloud computing in finance, its adoption has also raised serious security concerns. A cloud-assisted environment offers unique features to attackers which the traditional on-premises model doesn't. Hence, understanding possible threats for cloud-based systems in Fi-Tech22 is crucial. With the rapid adoption of cloud computing solutions in most industries, various cybersecurity threats target organizations using cloud platforms. Hackers, cloud service providers, and deployed applications each pose significant security challenges for organizations adopting cloud technologies. Recent studies attempted to identify major security threats and concerns while reviewing defenses and solutions.
Security associated with data storage, transfer, and access is the top concern in cloud computing. Users have adverse perceptions about how safely their data is stored on vendors' servers. So data breaches in cloud systems are at the top of the security problem list and motivation for risk analysis in finance. Any information leakage affects both users' trust in a cloud vendor and the vendor's business. Therefore finance organizations extensively encrypt sensitive data before upload and share decrypting keys with trusted users only. Human errors and applications are typically blamed for data breaches while cloud security consequences get less attention.
Technical weaknesses can often be prevented or addressed by resourceful attackers. FinTech services are especially vulnerable to cyber-attacks. The rapid evolution of finance leads to a multi-agent and dynamic trust environment, which warms the heart of malicious users. Managing the trust chain among agents and the trade-off between accessibility and trustworthiness is crucial, as is quick response against human errors and abuse. A compromised agent at a profit-maximizing platform can undetectably rent advanced exploit capabilities for serial fraud. AI techniques have also been employed in malware designs to automatically evolve and evade defense models.

5. Integration of AI and Cloud Technologies

Important communication mechanisms arriving from both academia and industry domains are quickly becoming a part of the idea of next generation architecture for cloud computation infrastructures. These communication mechanisms include Artificial Intelligence (AI), blockchains, Internet of Things (IoT) and their intersections or combinations. In response to these growing communication mechanisms, cloud computing is evolving to support decentralization benefits brought by blockchains and edge intelligence based on advanced distributed systems. Therefore, a broad and conceptual overview of AI, blockchains and IoT in the context of cloud computing or cloud computation is highly demanded. A holistic model is designed and elaborated to investigate the influence of IoT, blockchains and AI on the evolution of cloud computing. The conceptual model integrates IoT, Blockchain and AI, in the sense of top-down or bottom-up combinations, to create a holistic understanding spanning across multiple domains from computer science.
Numerous studies addressing what influence/disruption of AI and blockchains could bring to cloud computing have appeared in the literature with growing efforts in academics and industries. However, there are some isolated studies focusing on AI and cloud computing, on blockchains and cloud computing. Simple integration of blockchains or AI with cloud computing cannot depict the whole evolving landscape of cloud computing at present and in the future. A call for research is made for a more systematic investigation of how these important mechanisms of communication together bring about transformation both technically and business-wise to the cloud computing domain. The complexity of the multi-domain, cross-disciplines, and diverse community involvement leads to the investigated subject being hard to understand and model.
The systemic consequence of the combination of AI, blockchains, and IoT has not been investigated yet, and a lack of a conceptual model is apparent to explain it. A comprehensive overview of the possibilities and challenges to the evolution spectrum of cloud computing ecologies brought by the interplay of these communication mechanisms and their intersections like blockchain-based edge computing and AI-based decentralized computing together was desired, as neither a systematic overview nor a holistic view of it was found in the literature. Aimed at that, a conceptual framework is proposed for academic research and practical guidance with various components detailed to create a picture of such systems. Perspectives for future research directions are also provided.

5.1. Real-Time Data Processing

Client needs for real-time data processing: Due to the rapid digitization, growing online, and transformation of traditional business to online business led to drastic increase in demand of e-commerce. It was reported that there is a probable X10e growth in payment transactions using the digital modes and also a major increase in Revenue. As we move from India to Global market the system needs to be Reliable, Fast, Efficient, Inclusive and Technology Friendly to mitigate the challenges with increased growth like decreased Payment success rates, Increased Re-route, Transaction failed issues, Delay in payment

completion time, Anomalies detection, Unstable Payment system and High Menu Update and Maintenance cost. These are some of the potential challenges which payment players would face by moving onto Digital Processing of Transactions.
First Set of Solutions: There is a need for a Reliable Payment System to Sanitise the list of possible terminals and leads to rejection of un-reliable terminals by the system itself. In doing so better Control to handling terminal quality and reliable payment processing is provided. This can be implemented by developing a Rule-based and a Gradient boosted tree based machine learning model. As the performance of Predictive system will be highly dependent on the features being fed into it.

Equ 2: Transaction Anomaly Detection with Autoencoder Loss.

$$\mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2$$

- x_i: Original input (transaction features)
- $\hat{x}_i$: Reconstructed input by the autoencoder
- Large $\mathcal{L}$: Potential anomaly

5.2. Scalability of Financial Services

Emerging technologies are changing the way financial and payment institutions conduct business. Specifically, machine learning, artificial intelligence, and cloud technologies are expected to create new operating systems, expand the limits of existing systems, improve payment workflows, and ultimately put banks on par with fintech companies regarding the payment process and infrastructure. This observably affects every department of banks and payment providers, but simultaneously creates new challenges for a growing industry. Organizational limitations, budget cuts, competence cost, and job displacement issues arise as the technology advances.
Currently, most bank services work as decision-making systems. Banks have matured algorithms able to detect patterns, trends, and smuggling. However, the costs and time required, particularly with huge data sets, are too great to ensure the feasibility of real-time decision-making. As such, the current intelligent systems cannot be deployed at each account, and no service would be oblivious to whether a payment is legitimate or fraud. In contrast, finance requires near-instantaneous decisions, as those few seconds of delay can equal a possibly fraudulent charge being fulfilled, and thus tens or hundreds of thousands of dollars lost. Many pre-trained models can detect risks across outliers with complex non-linear correlations far more efficiently, simultaneously ensuring resource efficiency and reducing decision-making time from minutes to milliseconds.
Cloud infrastructures provide a cheap alternative to processing hardware. Using a simpler model using net CPU or machine skills will nonetheless suffice for automated banking. Provided a cloud service or proxy service provides a simple payment API and authentication tools, banking companies can quickly implement scalable and future-proof solutions. Furthermore, the new smart contracts on a public chain would completely bypass banks and work autonomously, eliminating many moving pieces and entry steps, while allowing the bounty and consensus to spread across the globe, further reducing information delay.

6. Regulatory Considerations

New and disruptive technologies, including AI, pose a number of regulatory considerations and challenges. This section will consider the issues that have arisen in the public forum and are likely to become prominent areas of regulatory scrutiny. The implications of new technologies for client onboarding and transaction monitoring will also be discussed. However, the regulatory landscape is dynamic, so only short- to medium-term challenges will be considered.
A surge in peer-to-peer platforms has been observed that automate client onboarding through video-based customer due diligence (CDD) and transaction monitoring through transaction pattern analysis. Such methods may help meet CDD and transaction monitoring requirements while improving customer experience, as this involves fewer manual processes. However, switching the compliance process from humans to machines involves a very different risk profile, since recruiting poorly qualified staff to carry out CDD for a licensed bank is a far greater risk or issue than putting the CDD process on an AI based solution. Current frameworks, especially with a focus on human access to data, technology, and permissions, are ill-equipped to scrutinize purely technical checks with no understandability for humans.
In this regard, RegTech must be interpreted broadly as methods and technologies to meet compliance requirements with minimum human access/output of understandable processing paths. A common approach in banking/finance is to establish compliance policies/rules that must be satisfied at all times, and RegTech must be interpreted broadly as methods and technologies to test such requirements. However, increasing usage of model driven methods and AI algorithms shorten the line of reasoning, hence decreasing understandability, for the compliance output even further than state of the art applicability issues and dubious issuance of output. The most prominent counter at this moment is the efforts' to develop AI methods that output understandable explainer models for the core of such systems. However, compliance by design still needs to be ensured for the overall system, including e.g. training data, hyperparameters, and non-standard feature engineering.

6.1. Compliance with Financial Regulations

Compliance is one of the primary concerns in Financial Services. As one of the most regulated industries, organizations are constantly challenged to ensure compliance with changing regulations and standards while maintaining service delivery. As the cloud kicks off the Financial Services Industry Transformation, it is essential that compliance processes and controls currently on-premise can be provided in the cloud. Significant investments by cloud providers in Financial Services-specific approaches demonstrate a desire to instil regulated organizations with more confidence in these platforms. Still, the assurance gap remains with the cloud being known as a lower control layer. Nevertheless, a view of regulation-driven compliance has emerged where control deficiencies can translate data and risk flows through compliance test benching, an area in which cloud coverage is still limited. To prove outcomes as regulatory black-box compliance addresses an interpretation of regulation through limits, this project aims to introduce the regulation test benching composable compliance architecture model, which concretely addresses definitions and flow representations.

Regulatory compliance requires organizations in several industries to collect, monitor, investigate, and report suspicious activities regularly. Those organizations, defined as obliged entities, include banks, credit card companies, insurance companies, gambling operators, and other organizations. In most countries, obligated entities have applied transaction monitoring systems to automate the collection and investigation of those transactions most likely to lead to a Suspicious Activity Report (SAR). However, the automation of reporting suspicious activity to a Financial Intelligence Unit (FIU) remains mostly manual. Understanding the monitoring systems to investigate transactions flagged as suspicious would be beneficial to improve the investigation processes. To achieve it, a target solution has been developed to extract and summarize relevant information from monitoring systems and their analysis logs to provide an overview of flagged transactions and the reasons and actions made on them. The approach has been implemented in an active research case study with several alignment steps and adapted evaluative metrics based on the concerns in a real-world deployment setting.

6.2. Data Privacy Issues

Despite the algorithms used in AI systems becoming more sophisticated, the lack of privacy provided to data subjects is a limitation that will hinder AI's advancement. Individuals' non-aggregate personal data, often viewed as toxic waste by analysts, can in fact become mathematically impossible to link to the original actor. The algorithmical methodology itself is not the only issue. Therefore, in assessing means of protecting information to validate discovered patterns such that they have practical applicability, the responsive and evolving nature of effective regulation must not be overlooked. This means that, contingent on the context and level of precaution descriptively applied, the safeguard employed for one AI methodology may be absolutely ineffective for another. From this perspective, three avenues for design are highlighted in this section. Importantly, these solutions suitably grapple with global implications, strategy, training, and infrastructure constraints in conjunction with effective risk management. Simultaneously, they emphasise that privacy-preserving opportunities are as much a product of the design of the environment supporting AI as that of AI itself. Differential privacy, homomorphic encryption, and federated learning are formidable algorithms that can directly protect privacy to enhance ethics in AI systems with respect to individual control and access. These technologies must be employed for the development of every new AI application. Robust endorsement schemes must be built into systems to provide governance over the evolving state of these algorithms. Interpretive machine learning techniques supporting the auditing of AI decision-making must continue to be developed to hold platforms accountable. Finally, these means should be legislated as the basis for privacy and transparency over AI. Employing a combination of these tools for this purpose could profoundly safeguard human cognition in the coming AI era.

7. Case Studies of AI and ML in Payment Systems

Artificial intelligence (AI) and machine learning (ML) are set to radically change the way payment systems operate. Many experts predict that AI and ML will become dominant trends in payment systems in the coming years. AI can be used in payment systems in various areas, such as fraud detection, customer service, and marketing.

Studies have shown that, not only in payment systems, deep learning performed well in highly structured environments akin to societal operating scenarios such as chess, Go, and poker, but there are big concerns regarding the way it is constructed and its interpretative power. Systems that use AI in fraud detection can analyze large quantities of information quickly. Labeled transactions and their success or failure are fed to the algorithm, and it is then able to replicate the operation of payment systems and evaluate incoming transactions. This results in an online anti-fraud system that feeds the machine with new transactions to simultaneously test all characteristics. It is important that this system does not learn on its own, as it may produce false results, and that the operators periodically audit it.

AI can be exploited in customer service through automation that produces satisfactory communications. For the construction of the knowledge base, ML algorithms can analyze past communications. Natural language processing can then allow for the extraction of suitable responses, and imitation will be achieved through deep learning. AI can also be used for targeted and personalized marketing, enabling forecasts of how consumers will act in certain conditions. It will be necessary to analyze a large amount of past data in order for the model to replicate reality and establish rules of success. The combination of extensive data influence exploitation and feedback in input data modeling is what characterizes AI as a powerful marketing tool.

7.1. Successful Implementations

Smart Routing: An AI-Powered Solution for Payment Systems

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. This module helps in exerting fine control over the payment flow by filtering out the irrelevant and poor-performing terminals. 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 utilise the impact of other payment attributes while routing the payments. 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. This project shows how interpretable ML systems integrate seamlessly with the existing architecture and improve business performance.

Finance as a newly announced domain has come into prominence as the home to many applications of Artificial Intelligence (AI). Financial technology has ushered in a new era of transformation in the financial sector. Traditional financial institutions face several issues due to the emergence of Internet financial institutions such as shrinking profit margin and client loss. Driven by external competitive pressure and internal transformation needs, banks increasingly boost the development of intelligence-related goods and services. In the newly announced policy, the government further states that firms are encouraged to use artificial intelligence (AI) for enterprise management. Deep learning (DL) technology has recently achieved a breakthrough in the field of social digitalization. DL technology is mostly useful in the disciplines of data mining, natural language comprehension, and computer vision. Commercial bank financial data are thought to be more suited for the DL model due to their continuity, large dimension, and temporal variability. DL's sophisticated nature and broad applicability can provide commercial banks a plethora of novel applications in risk management and intelligent services. Exploring the scenario application of DL in the financial business may become a sharp weapon for banks to increase their intelligent service level.

7.2. Lessons Learned from Failures

This section discusses lessons learned on the failures of some AI implementations in finance, which serve as a guide to practitioners embarking on ML-based projects in assurance or risk-related fields. These lessons fall into four categories: the nature of the financial setting, financial variables, the limitations of ML methods, and the impact of economics on performance. The authors analyze their own implementations of various learning techniques as a refinement for future practitioners. Owing to the inherent tension between being new to an area and the growing literature, they check whether similar lessons have been drawn in prior work . Focusing on fraud detection in online peer-to-peer trading, they start with lessons learned regarding the financial setting. These help to gather the necessary BAE data, which comprise past transactions and demographic features of the users, as well as BAE attributes that determine their safety.

Lessons start with the fact that real financial data are meaningful at the level of the individual observations; in the case of transactions, this means that failures arise due to market features with which each deal interacts. Possible models should thus be informed by these market pressures, with extra parameters made explicit. In real financial data, there are issues on which the historical operations of the market filter the observations so that most of the effort invested in modeling a representation of the problem is rendered moot. For example, say the actuary builds a risk measure able to accurately define the capital buffer required for a given input of observations. If the model does not care about payments for transactions under a given threshold, in payments below that threshold the policy set out by the model will be completely different—hence not meaningful if risk measures cannot be applied uniformly over the domain. Overall, if one has a time series with a daily granularity, analyzing it over six month periods starting at the beginning of the data—rather than a contrasted time series with other metrics, aggregated perhaps on an interview day—might give a first idea of the data but would probably miss insights brought by the evolution of the market.

8. Future Trends in Payment Technologies

Designing payments that facilitate wide usage while managing risk and compliance is a challenge facing central banks, FinTechs, and regulators. Stakeholders have conflicting interests that may stem from concerns about stability or regulation that have not previously arisen for RTGS systems. Existing approaches to information and payment communication forms focus on streamlining within-organizational designs. But the unprecedented need for combined payment systems, and misaligned stakes mean the standards of legitimacy or resilience across forms have not yet been articulated. Furthermore, prior research has focused on engineering issues in isolation. But the privacy, trust, security, and regulatory issues posed by a wide range of new payment means are all-too-urgent matters for scrutiny as they depend primarily on cross-organizational designs.

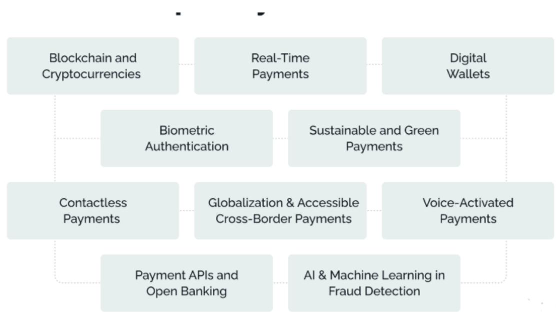

Fig 4: Future Trends in Payment Technologies.

Three intertwined issues, three colliding forms, and three misaligned stakes permit the study to elaborate into the evolutionary analysis of the Janus of the proliferated payments that together attempt to engender a flexible yet resilient monetary design. In the first issue, a historical transformation of designs and means is retraced to root the disputes surrounding the means in their evolutionary change. At the heart of the transformation is a systematic 'unfolding' of payments from a domestic non-digital form to a wide range of individual forms including outside or foreign means. The means, formerly the chief subject of interest to economists, are now tangled in a debate about their social and economic affordances as they compete to facilitate the transfer of funds and eateries or rides but also enact or design a range of risky transactions or illegal commercial practices, bypassing the "mission" of social policy equivalents to those of monetary policy.

Yet, stakeholders have conflicting interests, concerned with what forms are allowed or supported, but not how these forms might affect or reconfigure payment designs. This is a core constituent of the whole matter, for the security, trust, and regulatory issues posed by new means or services depend primarily on their design. But outside their shielded research labs, embedded as they are overseas into raw industry records shored by respective competitive advantage, formation, content, or perspective, many means have become bland. The whole issue of safety engendered by E-Payments, Mobile Payments, Crypto-

Currencies, or Payment Systems twenty-five years after its intellectual provenance now looms: How do entirely new, widely proliferated forms come to affect a once unified, on-fault with reserved domestic means, transferred landscape?

8.1. Emerging Technologies

Blockchain looked at positively by those willing to share data, and negatively by those that feared that providing data would disclose categories of client. The financial technology (FinTech) landscape will continue to evolve rapidly in coming years, significantly changing the size of markets and the way that they operate. Some establishments will struggle to adapt, with fines, reputational damage, and systemic risk likely to follow. Conversely, those able to harness great brand value or skill in next-generation technologies have the potential to dominate the space. The future of PayTech will be driven by enhanced uses of existing technologies spanning the period 2022-2025, followed by a time of widespread and significant technological adoption and investment in new technologies (2025-2030). There will be an explosion of new uses and business models for financial technologies, alongside the big established players that capitalise on their market position and superior data (2030-2035). Widespread AI and blockchain technologies are expected to be observed across the payments ecosystem around that time horizon. Kenya is seen as having particularly interesting next-generation mobile payments technology; Myanmar may adapt Aadhaar-style biometric payment system. For some subcategories of PayTech there still exist generally small or non-existent markets, dominantly held incumbents or grey space around likely regulations. App security on devices; internationally unregulated payment responses from disasters. Focus shifting from poorer nations unbanked at physical markets toward tech-savvy, developing economy consumers who may use multiple automated and emerging payment pathways. At the end of 2017 only 24% of banking apps were considered the industry standard, 8% in peer-to-peer payments, and 34% retail payments. Greater innovation in payment technologies in East Africa. Significant research opportunity around improved UPI and mass commercialisation of biometric payments and wider crypto-security concepts. AI work which does not presently exist could flourish. Responsive mobile equilibrium speeds are increasing, making even 4G too slow to handle latency-sensitive transactions, to occur by 2025.

8.2. Predictions for the Next Decade

Over the next decade, it is anticipated that a wide range of payments will become automated. In the search for efficiency improvements, many financial transactions will fall within narrowly defined parameters that minimize human involvement. However, outlier transactions will still be examined by humans. During this time, edge case definitions, the scope of asset classes with increasing automation, and customer data resolutions will be developed. As automated payment systems gain in prestige and competitors enter the market, the systems will be refined. Pricing will gradually converge, requiring remuneration to be unbundled from ancillary services. It is likely that some form of subscription will become the predominant model. Non-intermediated payment systems via distributed networks will likewise be monetized, with some estimates suggesting a market cap of up to $192 billion by 2027. As fees generate profits, multiple interventions will be attempted to rein them in; these interventions will initially be made by supranational entities but will evolve into national regulations as the risks become apparent.

Payments will become increasingly integrated into social networks, social media, and online leisure activities, with deeper services like “buy now, pay later” continuing to evolve this trend. Open banking practices will expand to additional sectors, putting more data in the hands of smaller banks and firms and lowering switching and entry costs in banking. Banks will face new challenges from fintechs offering portions of the banking stack, with conglomeration and increased scale in banks anticipated. Asset managers will use improved data processing capabilities to offer cheaper alternatives to traditional investment management. Accepting free robo-investment offers may seem like an alluring deal for the novice investor unfamiliar with the data consumption and monetization practices of the willing targets. The first on-demand liquidity broker-dealer may arise alongside an uptick in deep learning-based demand-book predictions.

A full-on race for yield is expected, as base rates remain near zero in order to avoid stifling the economic recovery. Competition will concentrate on the risk-and-reward space of funds as the search for yield intensifies, and a wide range of new strategies will enter the space. For retail customers, traditional asset classes are on track to become digital currencies, which can pave the way for a whole range of securities designed to allow a true continuous lottery of massive returns. The floodgates of gambling on future options and the "share in hype" are expected to be opened, while risks of early runs and upending asset value perception practices loom large on the other side.

9. Challenges and Risks

The purpose of this study is to examine the challenges and risks of AI, ML, and cloud computing in the financial services sector in more depth. Five big categories of challenges and risks were recognized: data issues, technology issues, human/red flag issues, explainability issues, and compliance issues. To summarize, in terms of data issues, it is necessary to base AI, ML, and cloud technologies on data quality systems that include data gathering, retaining, usage, security, destruction, and establishing access standards . The quality and accessibility of data sources must also be considered. In terms of technology issues, as the number of users grows, the use of cloud computing systems must take into account both cost and speed and performance metrics. To satisfy the speed and quality of service requirements for financial transactions, appropriate quality assurance systems must be implemented over the cloud. Additionally, current network design should be evaluated to identify shortages, and current SDLC methods should evaluate whether they need to be modified in order to accommodate cloud technologies for future services. Efforts must also be made to maintain operational efficacy after adopting cloud technologies to guarantee resiliency.

It will take careful planning to integrate technologies into existing and newly formed organization processes. In terms of red flag issues, any sort of online service must take into account resistant red flags that can be prevented through planning and aggressive turmoil avoidance and troubleshooting all through the service's lifetime. Concerning explainability issues, the concept of explaining will be complex when evaluating AI systems that have hundreds of millions of parameters, unless it is undertaken cautiously and not too literally. Explainability for interpreting leaf prediction instructions of tree-based ML models is probable. However, explainability for neural networks can be difficult. Finally, with respect to compliance issues, it must be guaranteed that the organization adheres to governmental regulations and its own policies tailored to the service. Once the service becomes public, prior issues, failures, and weaknesses must be additionally examined at the enforcement stage to ensure ongoing compliance.

Equ 3: Real-Time Payment Load Prediction (Linear Regression).

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

- $\hat{y}$: Predicted payment volume/load
- $x_1, x_2, \ldots, x_n$: Input features (e.g., day, time, market activity)
- β_i: Model coefficients

9.1. Technological Limitations

Within its relatively short history, digital currency has become an object of high interest, largely due to growing powers of technology and media, the emergence of amateur monetary conduct, and a fraudulent nature of digital assets and apps. Amidst the (understandable) fuss about digital currency, the methodology of inquiry into monetary forms and practices has until now received little attention. This is unfortunate, because a futures-oriented perspective cannot simply manifest, but must be explicit and deliberate. In lieu of elaborating methods and analytic strategies for understanding the emergence of new monetary forms and practices, it may be more useful to characterise, exemplify, and problematise. This is precisely what is accomplished, first by elaborating the vexations brought about by popular discussions and outright panic about the rise and fall of Bitcoin, Tether, and the like.

There is an immense temporal and scalar distance between historical "bubbles" or "panics" in monetary assets or currencies like the Mississippi Movement or the UK based South Sea Bubble of the 18th century and the rise and fall of a purportedly value-less ledger currency, the Bitcoin, during 2010-2013. Nevertheless, there also exist remarkable and insightful similarities between (popular) financial cultures of these monetary phenomena. In these circumstances, popular discourses range from panicked disbelief to euphoric enthusiasms of mass media fiscal doomsayers to monetary hacktivists, from theatre-of-the-dead-panics to Rube-Goldberged schemes to put some new currencies out of work. The mass media coverage of the recent social media oriented and meme-based stock market behaviours of Reddit communities involved in the highly (dis)organized trading of stocks such as Gamestop, AMC Entertainment or BlackBerry is similarly striking. Such public discourses across centuries invite inquiries of both how and why these seemingly raced-up cultures of digital currency or digital stock market suddenly emerged.

The recency and speed of these monetary phenomena further complicate. Such vicarious cultural comparisons are difficult, but they should not be impossible. If so, on the one hand, theories of "time" and/or "space" should always prove useful, and alternatively, if not, then it must be a good opportunity for the invention of new concepts. In the meanwhile, the historian of this emerging monetary form and practice of agents, acts, and apparatuses is in an exactly paradoxical position of on the one hand replaying tales somewhat more than a dozen years old and thus assuring access to stable accounts, but on the other, this monetary history is far from being complete and conclusions must inevitably remain as "narrative fragments". Concentrating on bitcoin, cryptocurrencies and blockchains together as monetary things, studies have until now broadly addressed digital currency in two distinct ways of rhetoric.

9.2. Market Competition

The burgeoning prevalence of fintech has resulted in an increasingly intense competitive environment for banks and traditional financial institutions. These competitive pressures arise from tech firms and innovators seeking to facilitate financial transactions more rapidly, efficiently, and cheaply. Depending on the perspective of banks, this competition can either be viewed as innovation, agility, and an alternative approach to economic gain. Alternatively, banks have been quick to adopt an identical approach and articulate the same advantages to ward off would-be threats. Firms have all created financial products using their expansive user base to harness profit from transactions and subsequent, ancillary information. Competition regulatory authorities in the modern era largely lack jurisdictional authority to oversee technology firms with potential anti-competitive motives in the provision of financial services to their users. Consequently, financial sectors and economies are increasingly at risk of being held in a "mispriced equilibrium" and subject to "hungry extinction" observed in other industries in the absence of competition frameworks and regulatory oversight. This leads to questions about critical mandates in the sector, which necessitate extensive data on activities that establish sound processes to protect domestic financial and economic stability and the welfare of citizens. The need for compelling research to vacate the relative ignorance of economic governance in Australia's tech sector relating to telecommunication, digital advertising, social media, and other aspects of the online economy have been progressed by political pressures. However, the understanding of the modes by which tech firms may choose to supplant, crowd-out, subdue, or co-opt financial service providers has not received a commensurate effort. Failure to marshal tighter regulation to address similarly risky behaviours and spiraling concentration in the provision of internet-based banking services may ultimately lead to catastrophic downstream effects such as the shuttering of substantial numbers of credit unions or community banks.

10. The Role of Fintech Startups

Research indicates that there will be three categories of new FDI (foreign direct investment) that companies will utilize to enhance their customer base. The first category consists of asset purchases, in which they directly buy an established firm or

brands to secure an existing customer base. A second alternative for handling and improving floundering brands is to ally with a local firm or even to simply rebrand the name. In creating a joint venture that utilizes off-the-shelf technology and local market knowledge, they can minimize their initial investment and avoid maker and issuer licensing costs. However,
R&D intensive companies, such as those in the information tech sector, will capitalize on the many sales and distribution companies currently available in emerging markets. They expand their operations dramatically by deploying existing brand labels in new markets where no substitutes are available. To offset the risk of their proprietary software being pirated, many large software firms are trying to gain a foothold in emerging markets through alliances with local advertising agencies.
Telecom billing start-ups will be formed to provide billing and support to new private mobile operators in emerging markets. Network companies will make diverse investments to develop new equipment and control software.

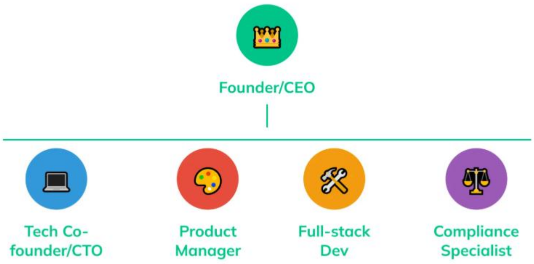

Fig 5: The Role of Fintech Startups.

New process technology and emerging markets for equipment will be operated by facilities that will undertake contract manufacturing. These companies will take advantage of the outsourcing of a growing number of transmission and control tasks, as well as the large training investments for the commercial hardwood, testing, and fitting of integrated circuit-level software or hardware. They will analyze the role and importance of financial technology entrepreneurs in the payment sector. In the food supply change service sector, varied arrangements involve transaction processing and monitoring of conditions based on system-laden equipment. Wireless RFID systems will be studied. Innovations by startups in diverse sectors will also be discussed, along with the enabling technologies and business models they are using.

10.1. Innovative Solutions from Startups

This subsection will elaborate on some innovative, versatile FinTech solutions primarily aimed at enhancing customer convenience, presentation on both the underlying financial technology-enabled innovation mechanisms and the FinTech offerings. The innovations vary significantly in terms of technology types and financial services enhanced, yet some strong theme groupings emerge. Six of the insights are accentuated as significant technological innovations from a FinTech perspective, by virtue of innovative mechanisms. Three specific aspects of the mechanisms are highlighted: their successful alteration of traditional industry structures or establishment of alternative transaction modes, their use of innovative data handling technologies at the intersection of various data types, and their adjustments in user interaction channels which accommodate trending needs; and enabling the online provision of unregulated services under the pricing and monetising models of traditional services. With Bitcoins gaining prominence within the remittance market, Bitspark uses currencies to facilitate fast and low-cost international remittance. BitX is an exchange and wallet service for bitcoins, providing a seamless way for Filipino workers to receive funds from overseas. Payments originating in any currency are converted to bitcoins for free by tagging customers' mobile money wallets. Coinjar is an Australian provider of internet-based services that allow users to store, spend and accept bitcoins. Users can make day-to-day payments with bitcoins integrated with the PayPal-like payment method called QR codes. Startups enable person-to-person (P2P) payments such as locally brewed P2P currency exchange networks such as Toronto-based Koho and coin-to-value conversion such as Qihoo in Beijing, serving the pre-transaction phase. Token is a UK-based startup offering a leading tech solution to maintaining security for consumer financial data. Uses "tokenization" technology to replace consumers' primary credit card numbers with a random combination of characters.

10.2. Collaboration with Traditional Banks

Banks and Non-Bank Lenders are Collaborating in the Fintech Space
A recent wave of partnerships between banks and fintech firms was a motivating factor for this trend in place with the likes of incumbent banks seeking to place capital into and make forays into fintech companies.
The trend for banks to work with fintech is by no means new, a report highlighted this point when listing out what had happened over the last two years. Some of the early deals include Goldman Sachs and Circle, two years ago, where Goldman Sachs placed a $50 million investment into the company. This investment was made to integrate with Circle's digital payment effectively. In March of the following year, Wells Fargo partnered with Fonolo in an effort to ease the wait time for customers calling into their help lines by investing in the call-back technology company as their first investment in a startup. Shortly after this partnership, BBVA was reported having made a $16 million investment in simple, the online banking company. The purchase was made to improve their product offering in response to consumer behavior shifting from normal brick and mortar banks to online-centric solutions in banking.
As for the other side of the coin, major fintechs are in receipt of the multitude of ways traditional banks hope to collaborate. It is these themes that major banks have identified database investment opportunities in recent strategic reviews and in their Environment, Social and Governance (ESG) or Sustainable Development Goals (SDG) commitments. A recent report

published by the New York-based bank describes the exact reasons why they have opted to consider large scale investments in fintech firms providing sustainable finance capabilities.

Amongst those perks of defending approaches laid out in the report, individual fintech firms propose to tackle standard market practices through innovative solutions leveraging modern tech capabilities. That and with the markets deeming sustainable finance Essential Done Right on a global basis, justifies their large-scale buy discipline proposition across the entire industry, not just for niche players. It is these reasons that showcase just how far behind the traditional banking oligopolies have allowed themselves to fall and expose themselves for take down in a rapidly changing technological paradigm shift. While this may be definitely dubious on some merits, writing off such large-long participations as unlikely has and will only serve to mask how out of touch the old guard truly is.

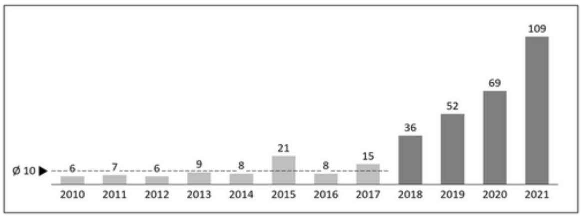

Fig 6: A Comprehensive Review of AI, ML, and Cloud Technologies in Finance

11. Conclusion

The advent of AI, ML, and Cloud technologies has ushered in a new era of payments. The tremendous growth and adoption of payment modes have been aided by strong data processes, selection models, and the requisite payment infrastructure. Each element needs to be distinctly defined and detailed, followed by models and methodologies that can function on a great scale without any errors or manual interventions. As technologies like AI and ML get adopted by regulators to treat each failure case, the scope and scope of acceptance translate into real use cases of the cross-border payment ecosystem. Such a complex scheme, however, will have technology risks, regulatory compliance risks, system integrity risks, and framework and infrastructure risks that could derail the model if not examined thoroughly.

Payment is a foundational block of everyday life, and CVBP is determined to lay the right expectations to deliver innovative and easily accessible cross-border payments wherever the Indian rupee is accepted. The last few years, characterized by lockdowns and disruptions, have made it all the more critical to abide by this expectation. Beyond the digitization of conventional banking, regulators, payment operators, banks, and over-the-top players have deeply understood the need for modus operandi to democratize the exports and remittances space and increase the share of cross-border payments.

Regulators are in the forefront of actively examining existing ambiguities of agent banks and payment service providers, while also actively listening and supporting early-stage innovators to further their relationships within the framework. In addition, with the urgency of the Ukraine crisis to address the requisite accessibility of important payment routes, a demanding roadmap to accept currencies in priority corridors has been rolled out with full stakeholder engagements in the assessment and assessment of accretion routes. A completely different cross-border payment architecture tailored for the Indian context based on its uniqueness has started to take shape and pertain to a build-operate-transfer model for standardizing and facilitating the onboarding of payment routes.

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