IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

Cloud-Enabled AI Architectures for Personalized Financial Services and Payment Solutions

Jai Kiran Reddy Burugulla

Senior Engineer, ORCID ID: 0009-0002-4189-025X

Abstract: The financial industry includes a number of different sub-sectors, including revenue sources for financial instruments, organizations that broker transactions, payment systems, and fintech companies that offer consumer services. Firms using or developing these technologies compete with financial services companies, and established firms are developing in-house capabilities and making acquisitions. The recent proliferation of financial technologies is in part a consequence of mobile technologies allowing small retailers to accept payments via smartphone, and asset management firms either established their own trading and exchange businesses, or became early investors in other companies' developing liquidity technology.

By making central bank redemption clear, straightforward, and secure, a CBDC would foster trust in its own value as currency, which a commercial bank does not typically have. It would blunt the transfer of deposits from a central bank to a commercial bank, preventing bank "runs" as in the Great Depression. Beneficiaries of bank runs are often suspected of taking their banking elsewhere, curbed by a national currency impossible to avoid. If CBDC accounts contain nontransferable monetary balances, then an injection of CBDC would be of higher quality than redistributing existing confederal public debt to fight a liquidity crisis because it would not remove deposits from banks. Restrictions would also contain the more poisonous possibility of nontransferable CBDC accounts.

The proposed architecture allows banks and payment service providers to offer different types of financial services integrated with various cloud-enabled AI architectures based on their size, originality, use case, and customer needs. As efforts are made to commercialize a much wider range of financial services integrated with different payment mechanisms, this framework of schemes will contribute significantly to models and cloud-enabled big data architectures with AI capabilities for the growing middle and lower income segments of countries worldwide in Africa, South America, East Asia and the subcontinents.

Keywords: Cloud-Based AI Platforms, Personalized Financial Services, AI-Driven Payment Solutions, Financial Technology (FinTech), Cloud-Native Infrastructure, Real-Time Customer Insights, AI Personalization Engines, Hybrid Cloud Architecture, Machine Learning in Finance, Cloud Scalability in Banking, Secure AI Transactions, Intelligent Payment Routing, API-Driven Financial Services, Cloud Computing in FinTech, AI-as-a-Service (AIaaS).

I. INTRODUCTION

Endorsed by the European objectives to promote the financial exchanges between the Euro members, new regulatory directives such as the Revised Payment Service Directive (PSD2) promote more control, more transparency and more competition while trying to reduce the contagion risk in a financial crisis. In consequence, the notion of competition has been radically changed. In particular, the financial services such as Personal Finance Management (PFM) are no longer the exclusive privilege of the retail banks. According to the PSD2 directive, it allows anyone with a bank account to use a PFM from a third-party provider. Specifically, this directive obligates the banks to provide access via specific Application Programme Interfaces (API) to the clients' financial data containing the account balance, the last transactions, statements, etc. In reaction, the banks may compete to attract new clients by proposing new forms of credit or financial solutions that don't necessarily involve traditional services. Retail banks can use their clients' digital information to develop one-or-another type of recommender engines in order to target the offer of financial products to clients' personal needs. Such recommendations may be explicitly targeted to particular clients or extracted from a general topic model and sent to the population in a (semi)non-targeted way. However, the financial products such as insurances (especially for young clients), stocks, deposits or loans are not totally comparable with the web items in recommender systems. The financial actions of the clients contain an extensive variety of information entailing various personal features usually unknown to the banks. By analyzing and predicting these financial actions a bank may gain a sizable knowledge on these features allowing clients' interests to be categorized and new products to be proposed to fit their personal needs.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

1.1. Background and Significance

The European economy is an area of focus for both the European Commission and the European Central Bank, thus triggering initiatives to create a truly efficient and integrated payments market. This is already a sector undergoing significant change due to the advent of new technologies and new forms of mobile-based payment services. Yet, even as research has examined this change, it has mainly done so at the level of technology without exploring the economic and societal side effects. This paper thus studies the change in payments spurred by two elements. The first element is a regulatory framework that separates the provision of accounts from the processing and offers new entrants new access to the data and infrastructure. It encourages more competition and the entry of FinTechs, including so-called third-party providers (TPP), into the payments sector. These can provide new services competing directly upon incumbent banks. The second element is the emergence of new mobile-based payment services that rely on these new regulatory conditions and new technologies and that alter consumer behavior. More specifically, it studies how these changes in providers and forms of payments affect the management of consumer data and the competitive position of the players involved.

Fig 1: AI in cloud computing.

The Financial Sector - Banks, Payments, Data, and New Competition. The changing landscape of payment services in Europe and implications for economic entities, users of services, and regulators. The payments ecosystem has multiple players, positions, and roles regarding data, data handling, and underlying technologies. It refers to the current state of payment transactions in Europe, in which competition is growing between banks and third-party service suppliers such as FinTechs. These providers vary in nature but have one element in common: They are fresh competitors that either enable European consumers and businesses to execute their payment transactions differently or provide new, additional services based on transaction data. They compete with traditional and household banks to obtain access to business, leading to significantly altered competitive positions and profit pools.

New Regulation: PSD, P2D, and EU as a Catalyst for Change. From a regulatory standpoint, developments are at the heart of a growing competitive market for payment services. The Revised Payment Services Directive (PSD2) allows all European banks to supply their account holders with Application Programme Interfaces (APIs) so that these customers can become the users of a chosen financial service. The market is opening up, enabling account holders to choose a TPP to manage or insert their financial data into other applications, instead of managing everything solely through a single banking app. This processing may involve cheapening cheaper PISP and AISP offerings or enhancing financial insights as with new FinTech entrants.

II. OVERVIEW OF CLOUD COMPUTING

Cloud computing is a kind of distributed computing, and a new computer network model. Referring to the network 'cloud', computation processes of a huge amount of data, storage, and program, which originally need to execute in local servers, are uniformly assembled on cloud server, and transformed into countless small programs operating in different servers to be parallel calculated and processed. Each small program gets through networking and is distributed by the internet to deal with specific data residence. With cloud computing, several terminals are united to form into a computing network, and various data processing program creation and supply to obtain several services. In addition to passive data storage, cloud computing gradually develops into another virtual computation place, and more active services computing network level by level seeing from an external user's perspective.

Cloud computing is a pay-per-use model, where users can obtain network, server, storage, application and other resources from the configurable computing resource-sharing pool whenever and wherever needed. Using pay-per-use mode, users can approach required computing resources through various terminals without massive investments in hardware and infrastructure. The emergence of cloud computing has reduced the capital load, and further enhanced enterprise flexibility, scalability, and adaptability, rapidly developing it into a mainstay technology for enterprise information construction.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

After 10 years of development, cloud services have become an important part of the financial industry's information technology toolbox, and proliferated in banks, insurance companies, security companies, and other sectors. Financial service institutions have applied cloud computing technologies to excess data storage, back-office service processes outsourcing, and data analysis services purchasing, remitting a series of favorable technological and operational effects. Cloud services also bring several new problems, risks, and concerns for financial institutions, among which are key problems on business risks and compliance risks. Supervisory authorities have raised concerns over the potential concentration risks posed by cloud services.

2.1. Definition and Characteristics

Cloud-enabled artificial intelligence (AI) architecture is a hybrid architecture that is based on a cloud-native concept, and presents containerized, open-source AI engines, such as a deep learning framework. AI user applications can run on the GCP or edge of the cloud and employ frameworks such as TensorFlow or PyTorch to design/train machine/deep learning models. The trained models will be pushed to GCP, in which the platform is built to dockerize and deploy deep learning models and serve-user prediction apps via RESTful APIs, the communication method of microservices in a distributed architecture. Such a platform provides a serverless and low-entry AI service solution, which enables developers to create and provide machine learning services without server and deployment management. Moreover, users can access computation and storage resources with minimal effort. The collective industry trends towards cloud-based AI infrastructure, services, and research in finance indicate that the finance domain has entered the era of cloud-enabled AI innovation.

Similarly to cloud computing, cloud-enabled AI or AIaaS is an emerging way of converting traditional on-premise, AI-based products and applications into public cloud-based, service-oriented, and pay-per-use providers. Cloud-enabled AI-powered seamless augment decisions, enhance contextual understandings, reduce bias, and discover and track new profitable opportunities. It is also a platform that enables organizations to conduct machine learning without server and deployment management. As the aviation industry is changing from internal operational teams to cloud-leasing industry players and service-oriented business models, many cloud enablement, machine/deep learning platforms and service providers are emerging. Platforms such as GCP, AWS, Azure, Alibaba, Baidu, and IBM have enabled machine learning engines such as TensorFlow and Keras to adapt the business context of different domains.

Equ 1: Payment Fraud Detection Using Binary Cross-Entropy Loss.

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

- y_i: True label (fraud or not)
- $\hat{y}_i$: Predicted probability
- N: Number of samples

2.2. Benefits of Cloud Computing in Financial Services

Cloud computing has emerged as a viable solution to provide IT functionalities among organizations with the minimum above-up cost and its complexity. With the advancements in technology, IT has become one of the main enablers/partners of global competition today. The pressure in justifying expenditures has heavily increased on CIOs and as a result, cost-effective solutions have turned into a hot topic. The philosophy behind cloud computing is to benefit from IT as an enabler without worrying about the infrastructure since this is the task of the provider. To understand cloud computing, its benefits, drawbacks, and architecture, first, definitions associated with the cloud are discussed. The cloud is by definition a "versatile, scalable, and elastic IT infrastructure shared with many organizations". This inherent flexibility and versatility create financial and technical differentials which is an enabler of taking the cost/coverage advantage over the pure in-house provision of the service. Yet, what these benefits are became a central question in cloud computing. Using third-party cloud computing offers benefits in two main headings, income management, and outgoing management. Looking at the developments in the academic side, the growing number of publications in the area of cloud computing is observed. Cloud computing can be defined as getting applications (software) and services (hardware) delivered through the internet as a service.

With the development of increasing volumes of digitized information, rising complexity of information storage and access compliance, growing needs for sophisticated and intelligent analysis of financial information, and rapid computing capabilities have posed significant challenges to traditional information technology architectures. Cloud-computing models offer tremendous advantages compared to traditional IT architectures in terms of affordable engagement of

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

computer resources, high scalability of computation, unlimited data storage and management capabilities, and maximizing data processing intelligence. Financial institutions are now facing unprecedented challenges in data processing due to severe information overloading.

While security and privacy risks are inherently attached to outsourcing key services to third-party cloud providers, the intersection of cloud computing and the financial information processing industry is still a major trend. To this end, existing research to the intersection of financial information processing and clouds are reviewed. Concepts, architectures, and operations of cloud computing are first explained. Then a comprehensive analysis of risk classification, evaluation, and prevention and intelligent forecasting and evaluation on cloud computing are presented.

III. ARTIFICIAL INTELLIGENCE IN FINANCIAL SERVICES

Artificial intelligence (AI) is transforming global banking and financial systems and developing new automated AI solutions with sophisticated learning, adaptation, and autonomous decision-making. These solutions are geared to reduce risk, enhance speed and efficiency, provide better financial insights, and offer improved customer services. Overall, the emergence of AI-enabled services and service capabilities leads to the automated alteration of the human-based financial services landscape and the innovation of financial (dis)intermediation processes. The existing academic literature categorizes banking AI-based research into five major interconnected domains, including the possible impacts of AI on banking systems and institutions. AI brings opportunities and challenges, as well as ethical issues, for banks and their stakeholders.

Fig 2: Artificial Intelligence in Financial Services.

AI enables automated insights from complex information content stored in varied cloud-based repositories and systems. Automated insights help banks better assess creditworthiness, reduce exposure to default risk, and improve the efficiency of their loan approval processes. AI enables the creation of services that serve multiple stakeholders, including augmented/mixed reality services. Such services aim to improve the ability of financial services to meet the requirements of diverse banking end-users and stakeholders. AI enables the scaling of multi-stakeholder financial services in terms of their human, software, data, and technology capability requirements. In line with ancillary and supplementary services, diverse multi-stakeholder financial services are automatically created and delivered based on the input and attribute analysis of the multi-stakeholder who wants a financial service. Such AI-enabled financial services target diverse financial user groups with use-case targeted context, process simplification, low-cost alternatives, and relevant auxiliary services.

3.1. AI Techniques and Applications

Artificial intelligence (AI) is important for the finance sector due to the massive amounts of structured and unstructured data it generates. The benefits of AI include greater efficiency in assessing risks, detecting fraud, processing mortgage applications, automating adherence to regulations, and informing loan offers on online trading platforms. Technological advances, such as data streams, cloud computing, and improved computing power, can be exploited to save time and costs. AI techniques, such as supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning, are used to deal with data. AI is gaining great popularity in the economics and finance communities, and many forums and events devoted to AI in finance and FinTech are being organized. One of the latest ones was held in Sydney, Australia. The applications typically focus on simple AI techniques in finance and economics for more powerful financial explanations.

Alternatively, AI is used as a complementary tool to understand economics and finance (EcoFin) phenomena that are primarily dependent on EcoFin theories. Most AI applications in finance are notions that have long been rationalized and insisted in the EcoFin communities. AI is an interest-augmenting technique and is less involved with a deep knowledge of AI techniques used or required for quantitative analyses in EcoFin questions. AI has been successfully applied in

DOI: 10.17148/IJIREEICE.2022.101219

finance and is receiving more and more interest with a focus on newer and smarter FinTech. Conversely, AI-driven innovation in finance is still very limited with a focus on novel AI methods or applications in finance. Turing always had a dream of creating intelligent machines, similar to the dreaming of EcoFin communities in rationally understanding EcoFin phenomena, such as personal and collective investment and trading choices.

With a multi-modal, bi-level, and deep framework, diverse AI techniques can be implemented and integrated for analyzing sophisticated EcoFin systems at different layers of granularity or levels of abstraction and with diverse types of data of diverse financial types. As interpretations are always dependent on analyses based on methods, AI techniques, once integrated with finance theories and models for understanding EcoFin phenomena at the most fundamental level, will reveal the innateness of EcoFin systems and provide new insights into EcoFin for both academia and industry [9]. Driven by trade-offs between approximation and interpretability, informative and useful results obtained with the right models can enhance understanding of high-dimensional and intricate EcoFin systems, generating new theories, models, and methods for both finance and AI domains. Successful applications of AI techniques in finance rely on well-understood EcoFin models, theories, and phenomenological explorations. The initial applications typically focus on pure AI methods to illustrate their applicability to finance.

3.2. Challenges of AI Implementation

Over the past few decades, the financial services industry has adopted AI technology to extend to a wide range of applications, including algorithmic trading, robo-advisors, credit scoring, customer engagement, and risk assessment. However, recent developments, such as the democratization of AI toolkits, increasing volumes of data availability, and accelerated cloud adoption, have leveled the playing field, allowing a wider range of companies, including FinTechs, to compete with traditional financial institutions. As a result, AI systems have been increasingly deployed in a more automated fashion, free from manual intervention. With this unprecedented increase in AI complexity and integration into the financial services industry, it is essential to regulate such self-learning AI systems to ensure they are trustworthy, accountable, robust, and compliant.

In financial services, firms are under strict regulations, which leads to the emergence of model validation and governance practices that aim to understand, test, mitigate, and communicate the model risk, data risk, challenge, and control of traditional machine learning models. The adoption of AI technology often brings the need for more informal model testing, monitoring, and governance, as off-the-shelf ML packages for Data Science empowerment may not be the most suitable approaches.

However, there are some challenges in implementing the above AI governance suggestions. First, the process of incorporating automated monitoring and feedback loops into self-learning AI systems would be a massive cross-functional effort. In addition to modeling teams, business analysts, production engineers, and data engineers are all stakeholders in developing new test and monitoring processes. Prioritizing those efforts would help build a higher level of confidence in the self-learning AI solutions and therefore mitigate the regulatory concerns. Scanning for model governance gaps in the current process would also help identify other areas where one's process may not be robust enough in light of the adoption of AI.

IV. PERSONALIZATION IN FINANCIAL SERVICES

Considering the mass of availability data, AI-enabled personalized systems use a wide variety of data analysis techniques, including collaborative filtering, content-based filtering, and many other hybrid approaches . In light of the current conditions, wide data analysis is considered the most reliable approach in an information system perspective rather than normal highly heterogeneous datasets.

The concept of personalization is related to how the wide variety of data analysis techniques can be handled with the associated datasets. Based on the major events of the processing of available information like privacy-related issues regulations, many companies looked for solutions on how to provide personalized services without the collection of massive quantities of data. Zero-party data is such a term on how service personalization should happen. As an illustration of the significant potential of personalized payments systems, a closed-loop payment system is designed that utilizes chosen digital herbicide software on top of a natural interface human language order receipt processing approach. The approved orders' data are then extracted without data relay as zero-party data secure fine-grained personalization. Therefore smart contracts with measured operation and resource consumptions are automatically designed in personalized payment transactions. Finally, the brain completes the transitive property of smart contract approvals through mass storage network trust negotiation liquidity protocol.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

Fig 3: Personalized Banking.

4.1. Understanding Customer Needs

The first stage in the development of personalized services is understanding customers, their needs, and their behavior. With the financial world opening up and banks losing control over their customers through Payment Service Directive 2 (PSD2), opportunities arise to build intelligent services on top of the open networks and datasets offered by technology firms and third-party payment service providers. Every detail of consumer behavior in purchases and financial management can now be retrieved and analyzed to understand customers better. But how is this done? And how can those insights into consumer behavior be converted into personalized services that help customers manage their finances better? Much lower credit scores as calculated by existing scoring models in the financial industry indicate that current services are not tailored enough to consumer needs.

To guide the development of a data-driven consumer insight service for the payment industry, an exploratory review of the associated work is presented. Literature from the domains of statistical analysis, business intelligence, and PSD2 is reviewed to build a conceptual service with a focus on scoring models and implications. Using machine learning techniques, the capacity of transactions to predict credit scores is assessed. Case studies on how to apply them at important times in a consumer's life cycle are provided. The research provides theoretical contributions by integrating three domains of literature into the disciplines of consumer intelligence and consumer understanding in finance. The research also provides a conceptual and practical base for a data-driven consumer insight service in the payments industry to be developed in future research.

4.2. Data-Driven Personalization Strategies

Banks have long understood that understanding customers and their needs is critical in a highly competitive landscape, driving a strong focus on segmentation efforts. Customer segmentation is therefore an important area of application in retail banking, as banks employ methods and analysis techniques to improve their levels of personalization. The most viable approach to customer segmentation is micro-segmentation, or fine-grained customer classification, as this provides a much finer classification of customers for future personalizing purposes, thus enhancing its potential to serve both banks and customers in higher personalization quality. This topic is important because customer personalization is crucial for successful financial services. Proper customer segmentation enables banks to tailor products and services for target markets, which is one of the few means of gaining a competitive advantage. Personalization provides a much higher level of service as customers receive what is most beneficial to them specifically. Higher levels of personalization promote fairness as well and have been proven to augment overall satisfaction and customer retention. Despite its considerable advantages, this scientific topic research field has remained eerily quiet concerning the finance sector.

As artificial intelligence is becoming more and more prevalent, its applications in the finance sector are also on the rise. In particular, representation learning in deep learning achieved favorable results for customer micro-segmentation, which consists of deeper representations of customers. However, sensitive industries such as finance face legal and ethical obligations regarding the conducted AI. Utilization of AI in responsible means is and must be prioritized in such sensitive industries. Hence, explainability (i.e., the why), interpretability (i.e., the how), and trustworthiness/effectiveness assessable properties of AI in an understandable and correct manner, especially the former two, take up paramount importance in responsible AI. Prior works regarding these considerations are yet to be addressed adequately in finance. As a contribution to these works-in-progress, this study intends to address both responsible AI aspects in the context of customer micro-segmentation with further emphasis on interpretation and explainability, as these are emphasized as being the more difficult research paths.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

V. CLOUD ARCHITECTURE FOR FINANCIAL SERVICES

Understanding users' habits allows providers of financial services, insurance and payment systems to personalize their offers. Financial technology companies are filling the gap left by old players such as banks, insurance companies, payers or credit card networks. Device connectivity and IoT have the potential to improve the situation of condition-based insurance, fraud reduction, etc. A cloud architecture enabling compliant financial services within this paradigm is proposed. Customer privacy and sensitive payment and financial information are preserved using functional encryption techniques. Upon trusted initialization, devices can connect and subscribe to information flow services without disclosing their IDs to the cloud, which cannot assign and keep track of pseudonyms. Although it is known that technically sound information systems with appropriate privacy cannot be built, the solution to the personal data protection problem is to provide their owners with more control on them. Compelling approaches, offered by technology providers, rely on both a formalization of privacy and control settings and on cloud-computing technology. Accessible, performant and cost-effective devices engineer a plethora of services collecting and processing information about users' lives. Conventionally, services only depend on a single data provider. The vision beyond this one-dimensional perspective is to provide services interoperable with datastores across different crosses. On the one hand, datastores that do not share data with queries respecting their policies can adopt a trusted router. Such an approach would allow services to seamlessly access previously unavailable data while enforcing privacy and regulatory conditions. Also, service providers could cooperate to cross-sell services, empowering users with their knowledge over a broader set of domains. The result is more satisfactory for users. They can better quote their policy amount, check their credit worthiness, finely tune their budget, etc. Data dissolves only the business and regulation trouble to comply with. Half the expenses may be re-deployed to entice new services by competing against incumbents. On the other hand, unseen, growingly powerful parties, and not users, can acquire qualitative pro-surveillance enforcement. Data protection poses the more daunting challenge: by preventing control, provide incentives to monopoly as a hurdle to entry into competition. Devised services cannot be legally and technically dependent on the availability of personal data. Breaking data by encrypting is technically sound and privacy preserving, but a source of possible fraud.

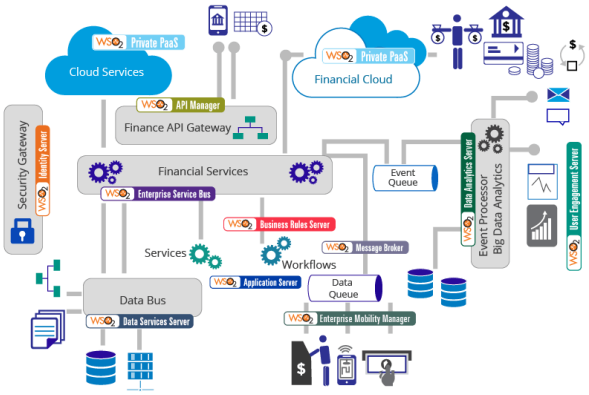

Fig 4: Cloud Architecture for Financial Services.

5.1. Key Components of Cloud Architecture

With its advancements and integration into various industries, cloud technology is enabling new opportunities in the finance sector. Financial Institutions are finding it easier to accumulate and analyze massive data pools with affordable vertical and horizontal scalability. The cloud's cost optimization aspects, including variable pay-as-you-go spending and low capex, are attractive to start-ups and new entrants in the finance space, resulting in a competitive landscape for established Financial Institutions. This section identifies the key components of cloud architecture.

The cloud architecture model contains various design systems and components. The cloud architecture refers to the systems that comprise the cloud, including the cloud components, which work together to perform a particular task on the cloud to support payment services. It refers to the computer-based services made available to the users on demand, such as storage, application development, and infrastructure. The two primary components of cloud architecture are front end and back end. Together, they establish a communication channel through the web. The end-users and hosts comprise the front-end, whereas the data and client will reside in the back end, including the database and servers. In between lies the Cloud for communication between the two ends, consisting of numerous servers and data centers.

The front-end structure includes clients or end-users of cloud computing service and the application required to support the interaction with the cloud. The front-end applications may include web browsers, email clients, that end-users use to

DOI: 10.17148/IJIREEICE.2022.101219

store and access information and perform necessary tasks. At the same time, front-end structure includes the application needed to support the front-end or user-side component of the cloud architecture. These components may include a web server, application server, database server, security server, and transaction server.

The essential components include hardware and service models that support the cloud infrastructure. The hardware component may vary. The essential components include hardware and service models that support the cloud infrastructure. The hardware component may vary with different tiers of service ranging from common-grade hardware in the consumer market for infrastructure-as-a-service to highly customized service-specific devices and hardware switches of proprietary designs for Software-as-a-Service or Application-as-a-Service. The service models and components of the Cloud related to the service delivery process to the clients may vary based on the three-tier model of service delivery in cloud computing.

5.2. Scalability and Flexibility

Scaling and Flexibility are key challenges for the use of Cloud-Enabled AI architectures in financial services and payment solutions. Scalability often relates to the ability of an application or a solution to perform well when front-end and server are both increased in the number of instances, while flexibility tackles the amount of effort needed to extend an existing application to support new requirements or needs. Answering the mass adoption and great interest of AI and Data analysis in the financial sector, Automatic Portfolio Optimization platforms, Digital Wealth Management applications, Credit Scoring algorithms or Credit Approval/chat-bots have all been the subject of Cloud-Enabled AI architectures.

However, scaling and flexibility of such solutions are not thoroughly discussed in the public domain. Indeed, while some Data-Science platforms provide evaluation of machine-learning models for the Financial Sector, the path from the Machine Learning model to the production AI system is rarely addressed. Consequently, some advocates of AI applications in financial services adjoining several tens of thousands of words, Cloud, Efficient Cloud Computing, Big Data and or the Cloud-Enabled AI were all admitted as the hard core of these solutions. In the presented work, how to address the above-mentioned challenges for the deployment of production-ready Cloud-Enabled AI solutions for the financial sector is discussed. How to implement scalable and flexible Cloud-Enabled AI architectures is demonstrated. These solutions protect investments by presenting the implementation framework of such solutions. Continuous training, which is an essential property of AI systems to adapt to new market conditions, is often neglected in public domain discussions of such systems; how to make production AI models reusable to jointly serve historical needs, make-make analysis and production-ready models are presented. The applicability of the conceptual ideas around scalability and flexibility are demonstrated providing an easily adaptable solution for others against a production financial service already in use by an international Bank.

VI. AI MODELS FOR PAYMENT SOLUTIONS

In an increasingly digital economy with the advancement of FinTechs, payment solutions are versatile fiscal solutions provided cloud-enabled services. As a layer above cloud service providers (CSPs), payment solution service providers (PSSPs) are multi-tenant to better explore computational resources, big data, and lower service price. Leaning on fraud detection, transaction prices, and loan payment evaluations, AI models could produce personalized payment solutions with accurate detection, anomaly explanation, and payment forecasts. Residing in multiparty payment services, AI models enhance personalized payment solutions founded on cloud services. However, the prediction of state-of-the-art AI models is susceptible to malicious perturbation, affecting the quality and compliance of payment solutions.

In the financial era of digitization, platform-based payment solutions have become versatile fiscal solutions with the prevalence of FinTechs. On process initiation, cloud service providers (CSPs) afford basic service modules for infrastructure and platform service layers, including resource allocation and hidden input population. As a service layer above CSPs, payment solution service providers (PSSPs) efficiently integrate default modules. To better exploit the computational resource, big data, and lower service price, collaborative and multi-tenant PSSPs emerged. Aggressive FinTechs conduct AI-enabled and personalized payment solutions for user transactions.

AI models in PSSPs produce fraud detection, transaction price predicting, and loan payment evaluating features for payment solutions . However, owned or collaborated AI models are occluded for PSSPs. Payment solutions are high-stakes products, with breaches threatening business loss and even social turmoil. Payment service providers must comply with data privacy regulations. Conventional encryption schemes defeat personalization. Exploring AI model performance in a multiparty setting helps truly adopt powerful AI models, while challenges arise.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

AI models in PSSPs enhance multi-tenancy with federated training and cloud deployment. Federated training improves model performance with high privacy. Existing federated AI models inherently keep PSSPs away from products and users regarding payment solutions. Far comparable to accuracy, loss precision detects frauds, discovers anomaly transactions, and explains prices whose equivolutions between vertical distributions are addressable. However, trade-off compression achieves almost zero-bit communication, which harms traceability and compliance. Benefiting from data shareability, PSSPs could rigorously monitor cloud services with uploaded payment transactions. Compliant explanations guarantee fraud investigation with baseline transactions or acknowledge signals curtailing payment residuals. Privacy exposure pessimistically leaks transaction details, identity, and model parameters that harm compliance and user trust.

6.1. Machine Learning Algorithms

Machine learning (ML) is making its foray in all financial services including pre-approval, credit underwriting, investments, and a plethora of front-end and back-end activities. Machine Learning is a family of data-centric learning models that augment traditional data processing and reporting techniques by learning from the underlying data through training. The learning process allows machine learning systems to automatically detect non-linearities and interactions in the training data. As a result, machine learning can assist decision-makers with faster and more accurate credit decisions, fraud detection, pricing the risk of products, predicting churn behavior, and other analytics in retail banking that were not feasible previously. Emerging machine learning methods provide the banking institutions with the power and flexibility in building smarter solutions in the highly regulated traditional industry.

However, machine learning has its own set of unique challenges. Foremost among them is the model opacity. Most machine learning models are opaque and hence, difficult to explain. Explainability is of utmost importance since understanding is a critical element needed for establishing a reliable technology. As machine learning-based systems garner the trust of banks and regulators, explainability in turn becomes essential for automated credit risk assessment systems. Recent legislation explicitly requires explanations for credit decisions. This is a critical issue currently faced by every financial services provider in Europe under the auspices of the general data protection regulation (GDPR) and a similar case in the USA.

A portfolio of investment decisions is sought for a US stock basket where the model selects loans that have a high chance of success while adhering to the constraints of a portfolio for a low risk and a high return. The optimization parameters include defining and selecting a model's objective and constraints that consider the return-risk balance of the portfolio. The results of the proposed approach outperform that of the candidates and indicate the preference of the penalty terms. Finally, the potential enhancements and additional explorations related to the model are pointed to.

6.2. Fraud Detection Models

Fraudulent transactions remain a significant problem for financial institutions. In 2020 alone, online fraud cost businesses about $20 billion in losses. This is estimated to rise to $40 billion by 2027. Before the introduction of the Payment Services Directive-2 (PSD2), there were insufficient regulations concerning consumer protections when conducting financial transactions. A surge in fraudulent online transactions has raised the need for advanced fraud detection systems. There are many possible ways for these transactions to be conducted; they can be done through card-not-present online purchases via e-commerce sites, via Automated Clearing House transfers in which money is wired within seconds, or by setting up direct debits. The amount of data generated from these interactions is vast. Because of data privacy laws, sharing customer data to facilitate a higher-performing centralized model is impossible. This is where Federated Learning comes into play.

The regulator's perspective on mitigating the risks of fraud detection systems deployment further complicates the challenge of inverting a sample blinding feature precisely. In finance and payments, design choices in fraud models are influenced by regulations regarding personal data and legal/non-legal requirements pertaining to model explainability, robustness, and confidence. Concerns exist around the operational costs, complexity, and risk of enabling privacy-preserving federated learning solutions.

Equ 2: Real-Time Recommendation Score (Using Cosine Similarity).

$$\text{Similarity}(A, B) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|}$$

- $\mathbf{A}, \mathbf{B}$: Feature vectors of users/products
- Values close to 1 indicate high similarity

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

VII. INTEGRATION OF AI AND CLOUD TECHNOLOGIES

The trends of Industry 4.0, including Artificial Intelligence (AI), Automation, Cloud Computing, Cyber-Physical Systems (CPSs), Digital Twins (DTs), and the Internet of Things (IoT), are mutually reinforcing. During the last decade, their evolution has driven a technological revolution, leading to profound changes in processes, business models, and skills needed by the industry. Smart manufacturing has been recognized as the next industrial revolution, where CPSs are empowered by AI solutions and massive data transfer and storage. Cloud-based AI is a solution known for large model size, high complexity, and high training and prediction time, but data privacy issues may arise. The epistolary COVID-19 pandemic has shown how data transfers can become bottlenecks, hampering prediction time and causing a disastrous loss of time.

Moreover, as more firms understand the importance of data and AI as an asset to maintain their competitiveness, they are growing in-house analytics and prediction capabilities. Responses to such issues include the development of on-premise solutions, Cloud systems partially managed by the firms, or re-deployment of firm-specific models into a public cloud. The definition of "Cloud-Enabled Intelligence" and of an AI model by such a few words means that the needed hardware infrastructure exists on a Cloud provider edge, and can carry out a Data Extraction, Transformation and Rehabilitation (DETR) workflow, and the training and inference of the corresponding AI model.

Recently, the strong push of several AI-based firms and Big Techs in the smart manufacturing market has come with a new level of competition. Such a competition level gives even smaller firms the possibility to swipe off the competitive gap composing complex systems for client firms by consuming pre-Level 1 services, from which they provide for their own Level 1 system integration. The possible break of the components market standardization may break the level of interoperability between stand-alone agents, very often proprietary systems. Such "agent" enablers must be empowered by interoperable, composable, deployable, re-capable cloud-edge AI knowledge graphs, capable of being composed into a full-fledged system generating process and machine control Changes with explainable/interpretative agent reasoning, and providing human-in-the-loop Solving.

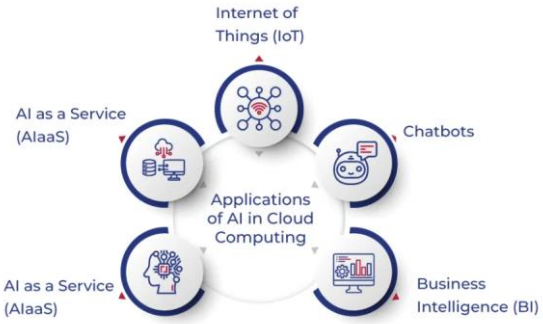

Fig 5: Integration of AI and Cloud Technologies.

7.1. API Management and Integration

One of the key characteristics of the future financial services infrastructure is an extensive acceptance of open integration principles. Providing access via API interfaces has many advantages, as it enables any device in the information and communication technology (ICT) space to integrate and share data. Traditional banks are required to follow the standards, publish APIs, and allow third parties to offer financial services based on the access gained via the APIs. Consequently, anyone can create a third-party app that allows consolidating users' income and expense streams across banks in a single screen. Integration does not only enable tailored product and service offerings but is also crucial to mitigate risk exposure by spreading wealth across multiple banks.

Therefore, user data and transaction data, enabling tailoring of offerings and services, need to be collected, shared, and integrated from multiple banks, payment providers, brokerages, and third-party service providers. Standardized APIs will enable system application integration and correspondingly minimize risks by allowing flexible dependency on multiple parties. Application developers around the world developed payment gateways, billing services, gratuity calculators, income tax calculators, customized rates for users, and monitoring of expected bills, risking human errors and fraud activities. Even after immutability and security are ensured through blockchain, stakeholder attack still needs to be considered. For instance, individual users may deny service utilization and payment. On the other hand, financial service providers need protection from fraud activities.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

7.2. Data Security and Compliance

Cloud computing has become a prominent technological solution for organizations. However, in order to completely use data, especially sensitive or mission-critical ones, in the cloud, organizations must meet regulatory compliance. This means that further implementation of cloud technology needs to satisfy compliance controls imposed by ever-changing regulations. Such compliance management is burdensome due to the complex needs for compliance. In addition to the actual business services to the customers, heavily regulated organizations, such as financial institutions and healthcare companies, have compliance controls with which they need to conform. Regulations are often volatile, while the organizations' compliance posture, the degree to which they satisfy a regulation, can change while the regulation stays unchanged. Thus, organizations usually dedicate a considerable amount of time and effort to audit themselves, prepare compliance reports, and even react to audits more carefully, to prove their compliance with a regulation.

However, this effort does not create business value and is extremely tedious and difficult for organizations with limited resources. Thus, too burdensome compliance management hinders the ultimate vision of cloud technology use – rendering it usable to share data freely, regardless of its type and where it is used. Security challenges for cloud or fog computing-based machine learning services have recently risen significantly. Recent accidents show that all of these security concerns can lead to considerable impairments of these AI applications. Securing the underlying cloud or fog services is crucial. Successful attacks against these services can lead to significant impairments. Furthermore, as AI applications' requirements can differ, both fog-based AI applications face different threats. In cloud platforms, the responsibility for security can be divided between different parties. Security deficiencies at a lower layer can cause direct impacts at a higher level where user data is stored. Finally, in contrast to cloud-based networks, fog computing networks need to be secured against physical access to the devices.

VIII. CASE STUDIES OF SUCCESSFUL IMPLEMENTATIONS

A case study of AI dynamic pricing at a certain bank, covering the use of AI to improve banking products' pricing decision-making, the construction of a dynamic pricing model, the implementation of pricing strategies with various channels, and assessment of the effectiveness of a pilot test program. Given the retail deposit product features and the bank pricing ecology, the suggestion of construction pricing rules with a multi-factor approach using transaction data, the consideration of market share and usage of AI methodology to set an initial price is given. While transacted amounts and average deal ticket with prices under should be considered in dynamic pricing, the prices with transaction amounts over ought to be excluded.

provides customers with customized AI credit assessment tools, marketing automation platforms backed by customer insights, leading intelligent customer services, and customer management systems so as to improve advertisements and enhance ROI for advertisers. After digital transformations, has enabled traditional retail banks to improve operational efficiency by 20% and customer transaction processing efficiency by 90%, while cost per acquisition could be reduced by 50%. Its fully automated credit assessment system is based on one-click API integration, which could be implemented within one month, and used to minimize turnover time to 1 second. Complying with relevant regulations, is leveraged to help banks to identify which features should be concerned in model building and avoid discriminatory results.

has been actively involved with leading banks across the globe in the journey to implement AI. The vast and direct impact of its work is crowned by a successfully designed Target Operating Model for AI at one of the four largest banks, which covers the entire AI management spectrum ranging from Use-Case Identification to Technology Enablement. Successful orchestration of this model in the Bank has established an industrial-leading AI capability that will be harnessed to support the Bank's transition to Future Assets. teams have methodological rigor and best practices that accelerate value realization while mitigating AI-associated risks.

8.1. Leading Financial Institutions

At the start step of an AI regulatory block, financial institutions and AI developers/owners have to expose the models in order to be evaluated. This is often a challenging task because only a limited amount of detailed AI models can be provided. The particularities of the industry as well as regulations compel institutions to keep certain information confidential, such as customer information, risk thresholds, business strategies, etc. On the AI side, while deep learning and ensemble methods are generally accepted "black-boxes", financial institutions and insurance companies need to publish lists of risk indicators and cost/pricing structuring techniques. This restricts the type of ML methods to be considered. Additionally, the mathematical formulation of the models is often too intricate to check manually. This motivates for the definition of AI regulatory proxies that are interpretable and a small fraction of the size of the original models.

DOI: 10.17148/IJIREEICE.2022.101219

Model documentation, testing and auditing, or interpretability and explainability measurements, are possible remedies that strongly increase compliance and reduce chances of abuses on the account of prejudiced customers. On the flip side, they can expose model weaknesses, or even worse, types of abuse that might not surface detectable scrutiny over the course of models' lifetime. Therefore they should be handled very carefully and strictly regulated.

Structure	**Description**
Abstraction	Defines an interpretable and significantly smaller proxy of the model to regulate.
Monitoring	Monitors AI model performance w.r.t. the regulated thresholds.
Reasoning	Given a breach in one of the monitored signals, selects one or more regulators to run.
Action	According to the regulators' signaling, triggers actions both on the regulatory and the model levels.

8.2. Innovative Startups

Eight innovative companies that use advanced technologies, particularly in AI, are highlighted. They are split into two groups: innovative start-ups and leading players already in the market.

Q.ai

Q.ai is an AI-driven FinTech start-up that uses machine learning to provide binary outcomes and alerts to its users. The service is available through an app that monitors selected markets for indications that could lead to possible gains or losses. The user can set the time frame desired and the view before starting the search. A graphical chart will show probabilities for the views set. In addition to signals, the app allows the user to conduct trades on certain markets through an embedded trading platform.

Acknowledge AI

Acknowledge AI is a start-up that uses data algorithms to estimate the chances of default of a certain borrower from a bank's portfolio. The application was initially created to offer assistance in risk management to banks, for example, by issuing alerts to the commercial team regarding a counterparty's change in behaviour. The aim was to avoid exposure to large losses by acting quickly. As the project evolved, it became marketing intelligence software that helps banks estimate whether a client is more likely to attend an exhibition or conference than planning a visit to the bank, among other options.

ZestFinance

ZestFinance is a start-up that credibly assesses credit risk without requiring detailed knowledge of the applicant. This means credit can be made available even to those who cannot be classified as "standard". The start-up uses extremely advanced modelling techniques and, thus, massive data from various operators. It is still in the start-up phase but has already accumulated some credibility.

DirectID

DirectID allows users to share their financial data with banks, trading platforms, and other businesses so that they may assess their risk standard using advanced algorithms. The service provides instant feedback on the rationale behind the current estimate and alerts if there are any signs of irregular transactions.

IX. FUTURE TRENDS IN CLOUD AND AI FOR FINANCE

In recent years, the popularity of using cloud services has rapidly increased in a variety of industries. Cloud computing IT architecture is a centralization of computing resources that provides various services over the internet. However, recent research about bitcoin theft, hacking e-commerce transactions, and fraud detection indicates that cloud-enabled services are vulnerable to numerous kinds of attacks. To tackle these issues, there are some research challenges and open problems to solve for improving the security and privacy of cloud computing. These techniques are also well extended for designing secure communication and storing models between cloud clients and cloud service providers. They can be beneficial for user security and privacy on a commercially viable platform. Recently, artificial intelligence has been leveraging many industries such as healthcare, security, smart cities, finance, e-business, and manufacturing to enhance their efficiency, productivity, and competitiveness as well as improve human well-being. Many companies have deployed cloud-enabled AI systems or services to lower setup and management costs, and focus on model training and performance improvement. Cloud-enabled AI services facilitate the provision of data, computation, and model/algorithm over cloud servers. However, the neural model and training data of remote AI services are under the risk of extraction during transmissions and invocations.

With the advent of Industry 4.0, personalized financial services have emerged, allowing for customized services that cater to users' preferences. Personalized financial services refer to proactively recommending financial investment

DOI: 10.17148/IJIREEICE.2022.101219

products tailored for users based on intelligent and flexible data mining and deep learning. A cloud-enabled AI architecture for deploying large-scale personalized financial services is proposed. Intensive work can be conducted by personalized financial services providers to tailor investment recommendations exclusively for cloud users, which helps to cater to customers' preferences in payments and financial investment products. To protect users' privacy, cloud-based analyses and recommendations given would be obscure, meaning that cloud servers could not disclose private information. A cloud-enabled AI architecture is designed for personalized financial services, which consists of two cloud servers managed by the personalized financial services provider. The payment solution search service engine implements a cloud-based, secure, and efficient solution for payment growth predictions. Users' payment pattern analysis is private such that cloud servers do not learn users' records or business details, yet enable local similar solution searches.

9.1. Emerging Technologies

The agenda for inclusion of technological facilitator stems from the increased penetration of information and communication technology, applications of big data analytics in the digital platform economy, and automated algorithmic applications. The consequences of its merger in banking too are significant, where personalized off-the-shelf financial services, personalized pricing for digital goods, integrated extended payment plus value added services, cross-industry product co-creation and digitized switching costs need to be enabled. With the emergence of big tech, income dependence on transaction-led business as well as business model evolution is attempting to be sorted out via the digital finance ecosystem led by tech-fin firms. To thrive against global big tech potential invaders, regional fin-tech firms can better next key digital assets plus personalization-driven signification-enabled platform ecosystems emerge, regulation considerations, and collaborative action among main stakeholders. What is necessary is a clear understanding of the anticipated trajectory of infrastructure and face of the global retail payments market in four phases across two dimensions. To stay competitive amidst fintech onslaught, incumbent banks ought to lever on entrenched advantages by investing on an omni-channel platform, and adopt platformization-based open banking strategy whilst ensuring sound governance of customer data and maintaining regulatory compliance. Over the years, there has been an exponential growth in banking technology, where extensive amounts of funds have been allocated to find solutions for post-crisis regulation. The emergence of the FinTech ecosystem with innovative financial technologies that find application in the acceleration of banking business have also proliferated massively. The extensive deployment of Artificial Intelligence or Machine Learning applications too have gained prominence across the banking ecosystem. Banks have started to adopt AI for enhancing overall productivity. However, in the banking decisions, the transparency of machine learning applications have become a paramount concern, especially among regulators across the globe. The traditional Financial Services industry is now being challenged with adoption of Emerging Technologies rendering it obsolete, insecure, and outdated. The FinTechs are finding richer data and better distributed cloud computing capability, thus introducing stricter regulations and more by-passes.

9.2. Regulatory Considerations

Client-facing AI applications are becoming increasingly crucial across a broad range of sectors for differentiated offerings. However, their complexity also drives up regulatory challenges. Regulatory and supervisory requirements on reasonableness and fairness make totally relying on canned algorithms untenable. The need for explainability is further exacerbated by the increasing complexity of AI. These issues are prevalent and of utmost importance in the context of delivering financial services, making banks a natural place to scout for challenges and solutions. The undue advantage of AI is clearly reflected by the growing divide between big banks and community banks.

Costly deep-learning architectures and high-performance computing infrastructures for big data/AI are only affordable to a few huge banks. That division appears to be ideological as banking dovetails with sheer data, availing innovative products and services for deep-learning architectures. Promising start-ups fall short of developing defensible advantages vis-à-vis established banks. Deep learning's success often depends on a plethora of hidden neurons and long training periods. Yet, early-stage FinTech players are rarely provided datasets large enough to train a newcomer product or service. Governance in complex and competitive environments are oftentimes diffusive rather than elusive, revealing intelligent yet interpretable designs. A(n) AI system comprises data, algorithms, and infrastructure, imbuing an AI model built upon the algorithms with learning, prediction, monitoring, and controlling. Data and model complexity have both continued to grow exponentially, and an AI system's sophistication grows nonlinearly through their interactions. The list of AI governance challenges in financial services is long, including deplorably fortuitous data pricing for inexplicably worse models, unproductively hazardous dynamic coder-taught behavior, inoperability with one competitor's offerings, unexplainable decisions and predictions, and undetected neural net resource exhaustion outputs, leading to uncertainty in capital assessments, impairable regulatory oversight, and risk of distress contagion for the financial system. The provision of financial services entails three generic chains: a human-in-the-loop service chain comprising agents and clients; and an AI-in-the-loop model chain between the agents, models, AI systems, outputs, predictions, inputs, intended behavior, and the firms; and data sourcing.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.12 ⁜ Vol. 10, Issue 12, December 2022

DOI: 10.17148/IJIREEICE.2022.101219

For a given agent and financial service type, generic functionalities can be offered by reusable building blocks. With respect to AI/finance education, knowledgeable labor recruitment, and decisions regarding eligible use cases, there is a nascent industry providing the toolkit to budget-expansively develop governable and interpretable solutions.

Equ 3: Customer Lifetime Value (CLV) Prediction.

$$\mathrm{CLV} = \sum_{t=1}^{T} \frac{R_t \cdot P_t}{(1+d)^t}$$

- R_t: Retention probability at time t
- P_t: Expected profit at time t
- d: Discount rate
- T: Total time horizon

X. CHALLENGES AND RISKS

A growing body of literature on AI governance (or more broadly technology governance) is beginning to populate these missing angles, contending that digital technology development necessitates a refocus on risk governance, legal liability, and technological accountability. While the many dysfunctions of AI introduced in Section 3 show that these are not merely abstract concerns—certain AI systems can be very sexist, racist, and exclusionary—broader governance issues relating to regulation and accountability are less articulated when it comes to AI models. GovTech specialists argue that this can exacerbate issues with legacy platforms, and it is not out of the question to worry about a new generation of AI models amplifying and radically changing the nature of these failings. The hope is that initiatives to govern AI in an upstream manner can close the gate and prevent the worst. This is in addition to nascent initiatives to regulate and understand algorithmic harms more broadly. A feasibility assessment of existing and possible governance policies is conducted. In light of technology development that outstripped regulatory response, IT engineers in the early 2010s began asking how to influence, guide, and curtail the use of technology with tools of technology—paraphrased as "If technology, then control technology," or "Can one program a robot to mince the other one?" As AI systems have matured into trillion dollar components of the financial services industry, this question has become increasingly urgent for the purposes of robustness, compliance, and commercial stability. A case example with a financial prediction model currently used in the industry is drawn on to frame its historic development and some of the dilemmas raised. AI models don't come out of the box reliable; pre-deployment robustness is an issue a priori in any model. But the firms that produce them are not long-standing financial services providers; some came about as a result of seeking outsized profits in the zero interest rate environment post-2008, along with regulation-s optimized hedge funds. This means that the nature of governance oversight straightforwardly potential accidents such as 2008 are less applicable.

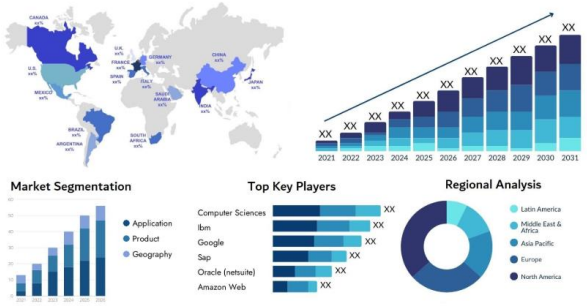

Fig 6: cloud-enabled AI architectures for personalized financial services**.**

10.1. Data Privacy Concerns

Personalization in financial systems is a clear driver for better user experience, increased user engagement, and therefore improved key performance indicators of these systems. However, model training in AI-powered financial systems usually requires a significant amount of sensitive information from multiple parties. As payment card transactions contain sensitive information and may expose personal spending habits, any misuse of this information can severely impact original users or financial companies.

DOI: 10.17148/IJIREEICE.2022.101219

Customer data is often propagated to other services during model training, increasing risks associated with data leakages or stakeholder misalignment. Developing a service without exploding personal information is non-trivial as it adds overhead on model training, predicting, and deploying. Therefore, integrating privacy-preserving AI in classic hierarchical financial networks such as the payment card transaction network is non-trivial due to additional communication, computation issues, and security/privacy concerns. However, the cost/reward of such service architectures is close to being deployable in the near future.

Conducting AI on transaction data in payment card networks needs to follow hierarchical structures and requirements, where financial institutions form a hierarchy as users' transaction information propagates from acquirers to issuers. A flat-structure privacy-preserving service architecture design, where off-chain service input ratios are optimized considering configurations constraints, service operating costs minimization, and a system-wide evaluation metric. Found services provision architecture configurations, query costs vis-à-vis monetary rewards from financial institutions, are expected to be significant as the model-training data increase and/or feature data diversify.

10.2. Technological Barriers

Despite the obvious overabundance of opportunities to state of the art AI technologies in finance, the adoption of cloud-based AI architectures and tools is unfortunately still constrained in various ways. First, as the case of France demonstrates, barriers abound in the law and regulation in the financial sector. To legally process any personal data about clients, a data controller must ensure that all provisions of the GDPR are respected. Similarly, the ruling highlights how previous interpretations of the GDPR provision may impede the adoption of state-of-the-art fine-tuning next-generation cloud-based LLMs which drastically outperform proprietary alternatives. Notably in banking, the access to personal data from clients is strictly limited, and often impossible due to data minimisation requirements. Furthermore, financial institutions cannot disclose sensitive information about clients, including any other sensitive computation required for basic AI algorithms, such as a mortgage loan prediction. Arguably, shortly after the application of first-generation cloud computing platforms by financial firms, regulatory institutions across the world began to scrutinise the complexities behind preventing the possibility of biases in, as well as systematic de facto systemic discrimination by their AI tools. The fears of regulatory authorities' scrutiny prevented many financial institutions from experimenting with AI tools and built a solid friction against the adoption of cloud-based AI modeling spaces.

Second, technical incompatibilities with existing computing systems and firm-specific operating regimes significantly impede the transfer of proprietary assets to third-party cloud architectural premises. Popular open-source stack implementations of state-of-the-art machine learning or AI algorithms often require non-standard yet facilitated data processing schemes that need a steep learning curve to understand. Non-standard data processing and preparation regimes, in conjunction with stricter compliance requirements, result in substantial initial meeting effort and resource requirements. Moreover, training and fine-tuning of the LLM and similar architectures require tens of thousands of GPU hours a day on various cloud platforms. Put differently, deploying fine-tuning of commercial cloud-based AI service platforms is less costly, easier to use with scalable interfacing and closely monitoring of the service health and uninterrupted services perspectives. Third, a well argued and meticulously explained transfer on the problems encountered during the modelling process would enhance the replicability notions across the world.

XI. CONCLUSION

Considerable attention has been paid to analyzing the credit default problem through cloud-enabled Artificial Intelligence (AI)-based Architecture to provide personalized Financial Services and Payment Solutions. With the advent of new cloud-computing environments, various AI-enabled techniques, such as deep learning or ensemble learning, exist for credit risk prediction. However, most of the existing literature lacks widespread acceptance or has been stated outside the banking domain, thus leaving flawed financial service architecture, lending decision recommendations, intelligent customer care, and fraud detection. Attributes of increased credit default prediction accuracy, classification process speed, and fewer biases are required at a global scale. The authors have presented comparative research by considering existing solutions based on industry-accepted performance measures with a wide range of limitations under the same environment. The combination of cloud-enabled AI architectures has been proposed to enhance the prediction quality of an intelligent credit risk analytics module for financial service organizations dealing in predictive credit risk analytics. The novelty of the solution is focused on being the first of its kind to propose a combined solution for volatile financial datasets. The architecture is adaptable enough to be used by other financial institutions to deal with many other kinds of financial prediction problems.

In February 2009, a G20 commitment was made by government leaders to reform the global financial architecture and voluntarily apply the Financial Stability Board's proposals to enhance the regulation, oversight, and governance of the

DOI: 10.17148/IJIREEICE.2022.101219

financial sector. One of the critical regulatory directives is the European Directive on Payment Services API project. As a consequence, new banks (Fintechs) – account information service providers (AISP) – can receive a holistic vision of an account holder's financial situation and offer personalized products. The Financial Services Authority implies that banks can now no longer just be vaults holding deposits. Customers' interest in their financial situation has been enhanced by new relationships with utility providers and the new generation of banks. As a response to this change in control and competition, banks now receive related data from outside which they can store, combine, and exploit.

REFERENCES

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

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

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

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

[5] Pamisetty, A., Sriram, H. K., Malempati, M., Challa, S. R., & Mashetty, S. (2022). AI-Driven Optimization of Intelligent Supply Chains and Payment Systems: Enhancing Security, Tax Compliance, and Audit Efficiency in Financial Operations. Tax Compliance, and Audit Efficiency in Financial Operations (December 15, 2022).

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

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

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

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

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

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

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

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

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

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

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

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

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

DOI: 10.17148/IJIREEICE.2022.101219

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

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

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

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

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

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

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

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

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

[28] Gadi, A. L., Kannan, S., Nanan, B. P., Komaragiri, V. B., & Singireddy, S. (2021). Advanced Computational Technologies in Vehicle Production, Digital Connectivity, and Sustainable Transportation: Innovations in Intelligent Systems, Eco-Friendly Manufacturing, and Financial Optimization. Universal Journal of Finance and Economics, 1(1), 87-100.

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

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

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

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

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

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

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

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

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

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

DOI: 10.17148/IJIREEICE.2022.101219

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

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

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

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

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

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

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

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

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

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

[49] Srinivasa Rao Challa,. (2022). Cloud-Powered Financial Intelligence: Integrating AI and Big Data for Smarter Wealth Management Solutions. Mathematical Statistician and Engineering Applications, 71(4), 16842–16862. Retrieved from https://philstat.org/index.php/MSEA/article/view/2977

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

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

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

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

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

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

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

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

DOI: 10.17148/IJIREEICE.2022.101219

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

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

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

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

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

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

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

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

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

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

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

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