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Developing End-to-End Intelligent Finance Solutions Through AI and Cloud Integration

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Abstract: ***In 2020, artificial intelligence (AI) will be one of the most popular topics across all industries, which either leads to changes of industrial trees and business strategies or accelerates their developments. Apart from consumers who care about their products and corresponding prices, financial intermediaries, who serve as a bridge between financial institutions and multi-capitalists, hedge funds or individual investors, extract fees from this information asymmetry. In the past few decades, however, machine learning techniques have gradually gotten rid of most of the hurdles that existed in analyzing high dimensional features and thereby observed billions of data transactions. As a result, great potential is presented for financial agents to beat their opponents. AI, modeling the decision-making process in a general context of automation, is one approach of intelligence powered by computational processes. It is in turn usually categorized based on knowledge types, computational paradigms, or input data types. Originally leveraging econometric theories and assumptions regarding human behaviors, rational expectations and market equilibrium were traditionally employed to describe asset price movements and forecast their trends. All kinds of methodologies from simple regression models to complex stochastic differential equations are applied on price trajectories or order states to extract timing or directional signals. In the current dynamic market, however, growingly complex data limiting traditional econometric approaches prompt the rise of prediction-based methods involving nonlinear and nontraditional answers, which have never been considered before in the financial context. Quantifying the exogeneity of data sources, recent empirical studies on supply-demand imbalance point out rich sectors' power in driving asset price movements. As such, projects regarding order outbreak clusters' trend or intention forecasting are developed on representing the rise-of-knife stylized fact and trying to conquer methodological hurdles like label noise and nonstationarity. For the vertical aspects, revealing how much a supply-demand imbalance shock affects asset vectors is a recently extending but rather challenging topic. Different from handling snapshots of the system, event-based and causal inference approaches have been proposed to quantitatively handle endogenous price movements and their corresponding feedback. Furthermore, a faster and more accurate model exploiting temporal convolutions has been designed to facilitate the advancement of multi-agent models and incorporate recent methodological improvements.***

Keywords: AI in Finance, Cloud Computing, Financial Automation, End-to-End Solutions, Machine Learning Models, Data-Driven Insights, Predictive Analytics, Financial Forecasting, Real-Time Data Processing, Cloud Integration, Smart Finance Platforms, Risk Management Automation, Intelligent Financial Systems, AI-Powered Decision Making, Digital Transformation in Finance.

1. Introduction

Intelligent Finance Solutions refer to the services in various scenarios provided by companies or institutes that focus on the integration of artificial intelligence and finance such as wealth management, credit assessment, quantitative trading, insured technology. Financial intelligence demonstrates a fast and accurate machine learning capability to handle complex data. But there are still many challenges for intelligent finance solutions such as data quality issues, product complexity, knowledge explosion, and interpretability of black-box models.

Artificial Intelligence is the core technology of technological revolution and industrial transformation. A new wave of technological revolution led by AI is reshaping the world. AI-related technology is widely used in agriculture, manufacturing, transportation, finance, medical diagnosis, education, national defense, service industry, and other fields. The finance industry is the pillar industry of modern economies, and it is becoming increasingly important. AI-driven financial technology is the engine for the rapid development of various financial markets. AI technology has been widely applied in various financial scenarios during the past decade such as wealth management, credit assessment, quantitative trading, insured technology, and other financial technologies.

With mobile internet development, financial service providers are faced with booming business opportunities. However, it becomes a great challenge to handle so many business opportunities in so many complex scenarios. Enhanced business opportunities correspond to enhanced business complexity, which leads to a huge workload, heavily relying on product logic, and poor user experience. In this context, intelligent finance solutions provide a great opportunity to alleviate the problems of booming business opportunities and enhancing business complexity.

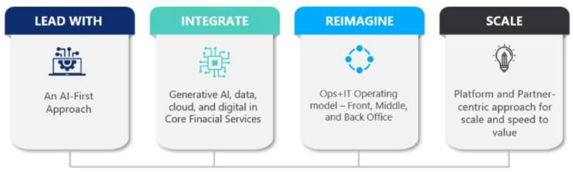

Figure 1: Finance Solutions Through AI and Cloud Integration

1.1 Background And Significance

Artificial intelligence (AI) has become an important driving force for technological revolution and industrial transformation. As the core technology of the next generation of information technology, it integrates advanced theories and technologies of smart perception, smart computing, and smart decision-making. Likewise, AI is a key enabler and catalyst for future innovations in financial services and applications.

Cloud technology enables convenient and quick rental usage of IT resources through a network. Cloud computing, big data, and blockchain technologies are vital enabling technologies of fintech. Cloud AI integrates AI technology and cloud computing technology, providing artificial intelligence services and products to end users based on cloud computing infrastructure.

Equ 1: Intelligent Financial Decision Equation

$$D = f(AI, DQ, CI)$$

Where:

- D = Financial decision output
- AI = Artificial Intelligence model (e.g., ML/LLM)
- DQ = Data quality and volume
- CI = Cloud infrastructure (scalability, latency)

2. The Role of AI in Finance

Artificial Intelligence (AI) has grown into an arguable phenomenon in the financial industry. Driven by the emergence of FinTechs and online finance firms, AI has garnered fervent interest among practitioners and researchers in the economics and finance communities for its usage to bridge, enrich, and improve investing, portfolio allocation, trading, tax-sheltered account management, banking, asset-liability and multi-team cash flow management, equity research, crowd-funding, small and micro credit lending, smart payment, financial accumulation matching, and insure-tailoring solutions. The finance community has hosted or organized increasing forum-styled events and talks on "AI in Finance" both online and offline, with a particular focus on FinTech, smart payments, blockchain, and Internet finance. Finance academics have been presenting seminal research and cutting-edge studies tackling blocks, questions, techniques, and algorithms in relation to the Finance-AI nexus at major international conferences, workshops, and forum events or for journal publications.

Many AI researchers have been innovative in deploying AI as a supplementary tool to best explain, simulate, and understand the why, how, and where questions of EcoFin phenomena in economic and finance science inquiries, leading to another explosive boost of interest and endeavor toward Finance-AI interactions from an EcoFin perspective. Massive FinTechs across geographic territories coupled with tailor-made smart finance solutions have gradually sprouted to address unbanked experiences and an unprecedented pool of overshared financial data, with increased types of ways to produce value out of "big data" in finance. There is a discernible trend toward an ever-stronger interest in broader, newer, deeper, and smarter FinTechs in response to the driving curve of today's data economy. Meeting this rapidly growing demand is key to assuring the maximal value future of AI in finance.

2.1 Machine Learning Applications

Over the last few years, the evolution of artificial intelligence (AI) and its growing importance in the financial sector have drawn great interest from various researchers, such as. The financial sector is trending toward a more automated intelligent platform to facilitate marketing, risk management, and operations. Since AI technology is still maturing, the banking sector is beginning to study how to leverage it. Especially, in the era of AI, building an intelligent finance-oriented ecosystem becomes essential for the finance industry. AI and cloud-based solutions offer banks the opportunity to grow digitally. Firstly, banks should explore the duality of business and technology architecture to clarify its application in the end-to-end intelligent finance ecosystem. Moreover, AI governance and biotechnology risks should be studied in detail.

To this end, a range of proven approaches investigated by finance players globally and various innovative solutions well-aligned with the above. Secondly, as a key enabler of the intelligent finance ecosystem, cloud services should be further fine-tuned to fully unlock their benefits. Extensive case studies from leading banking cloud solution service providers and initial steps for banks to facilitate their cloud migration journey. Additionally, the role of emerging technologies has been expounded, with a view to pointing out further research opportunities. Creating an intelligent finance ecosystem is crucial for banks to navigate the increasingly competitive landscape. End-to-end intelligent ecosystems require banks to reevaluate their existing business-focused digitalization programs and build more technology-inclusive AI-powered cloud-based solutions. This requires a good understanding of both business transformation and accessible technology enablers.

For banks, many of the technologies presented in the broader literature are still immature or too costly to deploy. Focusing on which behaviors to reengineer can yield faster and greater return on investment. Banks need to understand the duality of asymmetric business and technology architecture and explore how their banks can respond to the implications originated from the duality. Preparation, orchestrating, and integrating cloud and AI solutions to operationalize a focus on transforming an end-to-end intelligent ecosystem are discussed. The importance of governance, technology sourcing, and adoption readiness stresses the point that as technology adoption becomes broader, the biotechnological risk is magnified. It is crucial to have AI governance integrated into the enterprise-wide risk management framework.

2.2 Natural Language Processing in Financial Services

Natural language processing tools are reshaping the financial services industry. The financial services industry generates volumes of potential analysis insights, requiring advanced Natural Language Processing (NLP) tools to process vast amounts of financial news in real-time. Financial professionals need to make investment decisions based on complex information from outlets such as news articles, analyst reports, and enterprise briefings. This challenge is compounded by the fact that financial opinions are connected

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with different nuances compared to generic language and contain different excess terms and phrases. Nevertheless, current solutions are both limited and challenging in terms of offering integrated end-to-end solutions. Thus, the objective of this paper is to propose a more general framework for designing intelligent finance solutions through transformer networks. Additionally, from a business perspective, the main focus is on providing end-to-end solutions to six application areas: information extraction, comparison and sentiment analysis, recommendation and translation, and question and answering of financial information. Ignited by the immense growth in digital information, sentiment analysis has become a well-studied subject of Natural Language Processing (NLP). Opinions and feeling expressions, known as sentiments, are essential sources of information that express people's assessments about topics and events or experiences regarding products, brands, and entities. The goal of this process is to identify and extract subjective information from texts to determine whether the expressed opinion is positive, negative, or neutral. The insights into the sentiments held by individuals are valuable to organisations and companies. Traditionally, these insights have been analysed using manual techniques, which are time-consuming and labor-intensive. Consequently, there is a prerequisite to develop automation and machine learning systems in order to help analysts efficiently analyse the sentiments of opinions expressed in reviews, comments, or discussions of products, brands, or entities. Sentiment analysis is one of the most common use cases of NLP. The immense growth in information and the necessity of sentiment analysis tools to discover valuable insights from information have led third-party service providers to develop a large variety of semi professional and professional sentiment analysis solutions for industries such as finance, tourism, and insurance. The financial sector, which is one of the most important industries shaping economies, cannot be ignored by sentiment analysis. On occasion of the 2008 financial crisis, an increasing interest in the significance of sentiment in finance has acquired the attention of academics in the turbulent field of financial market analysis and prediction. Success has been achieved by developing NLP-based state-of-the-art sentiment analysis systems.

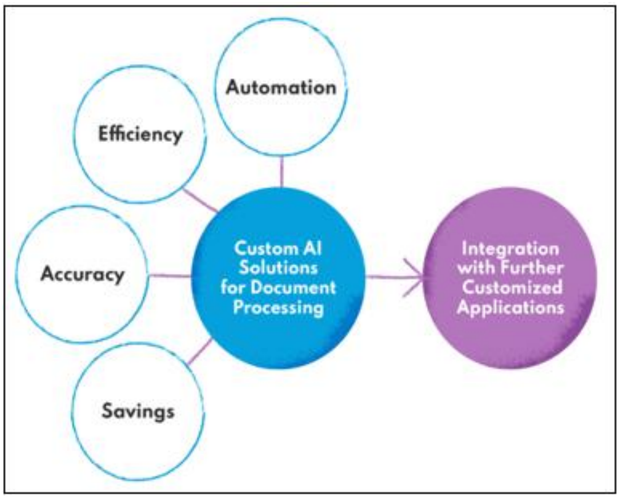

Figure 2: Natural Language Processing

3. Cloud Computing Fundamentals

In this section, the focused concepts related to the evolving field of cloud computing in market finance will be discussed. In the modern world, the networking technology development, computer application technology, and information development technology popularization have transformed the process of data information acquisition in financial institutions. The financial industry has increasingly demanded diverse and large-scale data, with the requirement of the fastest speed, and the overall design of data acquisition, storage, and processing must be considered. Successful financial institutions require fast, accurate, and up-to-date information, and it is in this area that large financial firms, through mergers and acquisitions of specialized firms or a major internal effort, try to make investments in this area. In addition, in terms of risk control, prediction, natural language processing (NLP), assessing customer credit, fraud identification, financial market price movement forecasting, and prediction of retail sales are some main topics of the application. Cloud computing, which provides the fastest orientation to the user and on demand, is one of the most important new technology applications, and other financial institutions are looking for a cloud computing platform in the hope of lowering the entry threshold regarding hardware and software. In the cloud computing model, the networking environment, where data can be distributed, stored and processed, raises new challenges for the financial information risk prediction. The inherent vulnerabilities of an information technology service platform are accepted and preserved by the allot of related enterprises under the implied management agencies, and in this context, the financial institutions will face risks. Intelligence in the earlier sense, as an intelligence quotient, refers to the ability to comprehend new ideas, and think rationally. In this report, the concept of intelligence in EER is proposed through the integration of knowledge and data, and intelligence quotient is represented as the degree of intelligence of a process using the cloud computing platform. Artificial intelligence, which means melioristic skill able to complete tasks in mobile or uncertain settings, was defined, and it is newer than the intelligent systems used before.

3.1 Types of Cloud Services

Cloud computing is a model that makes it easy to access a common set of configurable computing resources (for example, networks, servers, storage, applications, and services) that can be quickly provisioned, and that can be developed and available over a network, with minimum management effort and interaction with service suppliers. The cloud computing service models fall into four types: private cloud, public cloud, hybrid cloud and multi-cloud. The cloud computing deployment modes fall into three types: Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). From the perspective of on-cloud users (financial institutions), IaaS refers to the resource layer and is usually the lowest layer. Long-term self-built data centers with low asset and management efficiency result in high fixed shorten financial resources. The resource pooling offered by the cloud service suppliers lowers the pressure on IT resource management and has been adopted by many industries. Compared with IaaS, PaaS provides a platform to deploy applications to make data

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or results accessible. It has been freely adopted by numerous FinTech start-ups while contributing to concentration. SaaS is cloud products available for leasing by using a convenient online or API-based approach; however, the product complexity or holdup caused by low quanta switching costs has led to partial unwillingness.

3.2 Benefits of Cloud Integration

As the financial industry undergoes rapid transformation driven by the digital economy and the adoption of artificial intelligence (AI), changes are being witnessed in finance products and online finance scenarios. Traditional online finance is being disrupted, leading to the emergence of an End-to-End (E2E) intelligent finance solution. A range of technologies, including cloud, big data, and AI, are enabling financial institutions to build smart risk-control products and services. This focuses on intelligent finance technology integration and offers a comprehensive view of End-to-End (E2E) intelligent finance solutions and intelligent finance technology integration scenarios.

The integration of AI, cloud, big data, and blockchain technologies is stimulating the rapid transformation of the finance industry and is promoting the development of the intelligent finance industry. A comprehensive understanding of the concept and meaning of intelligent finance is the prerequisite for the study of intelligent finance problems. Therefore, the finance technology system architecture design method and classification and research of intelligent finance scenarios research are proposed for full analysis of intelligent finance technology types and transformation paths. As a new generation of information technology, AI has great effects in many fields and is leading to the fourth industrial revolution. The financial industry is also undergoing profound changes driven by the new digital economy and the adoption of AI. With the advent of the Internet era, the price discovery and risk avoidance ability of finance products depend on market and trading volume and speed.

The cloud computing industry is now in a pivotal period of migration and transformation. The intensified competition in the financial service industry and an urgent demand to support a restructuring around the new value network, innovative business models, and applications are facilitating the transition. Traditional financial institutions, such as banks, asset management companies, and insurance enterprises face many cloud computing challenges and the acceleration of transition is difficult. As financial institutions gradually migrate business to the cloud, they are confronting various unprecedented risks. In addition, the cloud computing risk observation intensity and extensiveness of the financial industry is a key stretch for information risk anarchy from higher-rank to lower-rank financial services. More systematic, diverse, and exhaustive forms are used by regulators to monitor technology risk, and traditional upfront docility and compliance regimes are under scrutiny.

4. AI and Cloud Integration Strategies

Financial institutions are facing pressure to improve efficiency and reduce costs. Customer-facing applications of AI and Cloud are, more often than not, developed by systems integrators and ad hoc cloud vendors. Well-known bank acquisition and merger cases show that successful integration of middle and back offices is difficult due to large amounts of data and high complexity. Formerly separate applications and backend systems need to communicate with and transfer data to each other, raising a number of business and non-business issues that require cross-disciplinary solutions. Nowadays, to develop end-to-end intelligent finance solutions combining AI and Cloud, banks need to keep track of both areas and find how these are implemented elsewhere. This requires changes in a number of aspects. First, there has to be enough cross-disciplinary competence available in-house or access to it. This includes business and non-business knowledge of the banks, systems analysts, domain experts, and means to deploy the chosen solution into the infrastructure. Second, banks have to find means to stay compliant with the evolving regulation, somehow fitting AI and cloud into the existing regulatory framework or launching a regulatory offensive to avoid being clip-winged by it.

Figure 3: Cloud Strategy

Third, keeping track of AI and cloud developments is a daunting task. In established banks with many legacy applications that are hard to integrate, the market can go in contrary directions regarding the use of AI and Cloud. Last but not least, there are a number of ethical issues between the image of a bank as a trustful partner and the practices of devising predictive approaches to document such trust, often by means of AI. Keeping track of both market trends and omens in these areas can help banks spot winning bets. In the meantime, the cross-disciplinary nature of developing end-to-end intelligent finance solutions requires a way of working that allows for different ways of reasoning, degree of formality, and institution specialized literacies. The gap between the business and the system aspects of an intelligent finance solution is difficult, if possible at all, to bridge. The gap between the cloud and AI domains is also a thing to consider. During design, analysis, and deployment, development in one domain impacts the artifacts in the other, calling for a way of iteratively and consistently capturing these blueprints.

4.1 Data Management and Storage Solutions

With the proliferation of new big opportunities and technologies during the last few decades, the finance domain has undergone significant transformation. Due to the arrival of AI technologies, the amount of data collected by financial organizations throughout the world has dramatically increased. This data, which is now widely dispersed due to the rise of clouds, has led many finance organizations to rethink their business strategy in order to develop novel commodity strategies, maintain users' trust, and preserve daily profitability. Such a change means that all financial institutions are transforming from conventional sales to science-based trading with transaction prices determined via science. Commodities originally traded using physical exchanges are now transformed to soft currencies. Experts in mathematics and future trading have been hired from top banks and universities with a challenge to develop trading functions or reconnect loose trade opportunities, aiming to speed up the trade connection. In order to mine the physics behind trading decisions, parallel and stream processing of large amounts of time-based data is investigated. The finance domain is thus still at the stage of rethinking how to take advantage of the new wealth of data. Focusing on the streaming data generated during trading, a completely new end-to-end approach is proposed to online ingest time-based data, develop models using these data, and trade by using the decisions made by these models. As have already been addressed in various science domains, the proposed new approach is model-agnostic: models can be quickly built based on self-desired features/targets and the need for model freshness. Complicated, fancy, and exorbitant models are not desired here. Decisions made by models can simply be post-processed using probabilistic or game theory methods for trading. In this new architecture, each individual component can be quickly migrated to new underlying technologies. New models can be additively developed without redoing the whole architecture. Against this backdrop, a cloud-based architecture is proposed as a complete solution for small to medium finance organizations. The constituent components are all off-the-shelf services fully managed by MS Azure, thus ensuring a bright innovative future. Some routine house-keeping work is illustrated, covering state management, feature generation, and training. Open approaches and packages are modularly designed to enable on-going contributions, generational updates of models and services, and the usage of other models.

4.2 Scalability and Flexibility in Deployment

The growth of the data storage and processing markets has led to the rise of diverse cloud providers and products. In order to increase a knowledge-based service's shareability, reusability, and interoperability, it should be governed by open standards at different levels of abstraction, including data and metadata representations and exchange formats, and exchange protocols. Such standards should be supported by application-independent service proxies that form a programmable layer on top of knowledge-based services in the cloud to provide a unified API. Cloud providers and platforms should negotiate with the scientific community and relevant standard organizations to engage them in the above efforts. Future research should address advanced topics, such as regulatory issues in the cloud with respect to privacy, confidentiality, and intellectual property rights, and federated, meta-, and hybrid cloud systems. Recent advances in service-oriented computing make it possible to deploy knowledge-based services as web services either on the cloud or in hybrid settings—partly on the cloud and partly on local servers.

Rapid machine learning (ML) service deployment can realize application solutions to novel problems, as the needed technology may already be available. In order to catch and keep pace with the quickly changing needs in the application domain, rapid deployment of cloud services is crucial. Service deployment and configuration are usually application dependent. The cloud platform offered by cloud service providers provides generic deployment options encapsulated in an abstract form, while on-premise nature of the knowledge-based services may not facilitate automatic deployment. Domain knowledge about the knowledge-based systems and their cloud counterparts should be taken into account to provide on-line deployment solutions adaptable to rapid changes in data characteristics, user activities, and cloud virtualization products [7]. To this end, cloud management services are essentially necessary for runtime deployment.

5. End-to-End Solutions in Finance

Intelligent finance aims to provide inclusive financial services to meet the financial needs of ordinary people. This goal, promised by AI technology combined with big data, can integrate long-tail markets and mitigate information asymmetry to improve fund allocation efficiency and enhance financial risk management. With the development of AI technology, information beyond human perception has been generated. Combining such information with identity recognition and natural language processing technology, machines can replace laborers, realize all-around perception that exceeds human perception, and provide interactive services for customers. By combining financial intelligence with the new generation of AI, knowledge graphs can be constructed, which depict relationships and flows between metadata; an effective intrusion-detection system can be constructed with the help of machine learning, a pioneer intelligence that exhibits a combination of human-like judgment and machine efficiency; and the 'financial brain' can be constructed to provide inclusive financial services to meet the financial needs of ordinary people.

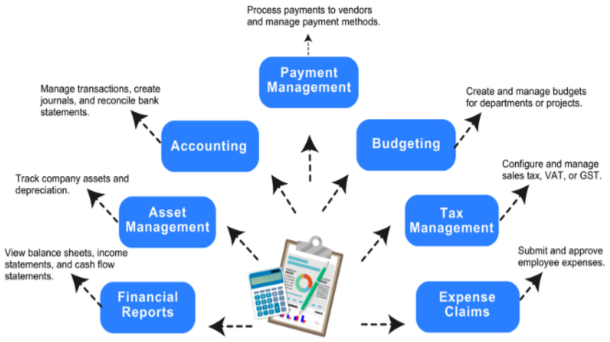

Figure 4: End-to-End Solutions in Finance

Traditional professional financial services, such as investment banking, securities, hedge funds, and accounting, are regarded as widely acknowledged lucrative fields. However, these services usually have a high threshold. Investors require a certain amount of wealth and a level of financial knowledge to obtain professional financial services. A lack of required wealth and knowledge may lead to less information during investment, resulting in either huge wealth loss or excessive risk-averse behavior. Meanwhile, the financial needs of these ordinary people are not well met.

Financial threshold has been defined as the highest cost-benefit ratio of finance, which indicates that individuals must possess a combination of certain factors to enjoy professional financial services. The emergence of new technologies and proliferation of information in the Internet and IoT era have dramatically reduced the effective cost of credit assessment technology from hundreds of billions to millions. Financial services with a financial threshold lower than this boundary can target a larger client base while being sufficiently profitable to sustain its operation. On the other hand, the wealth-management service industry, once only available for the rich, is now blossoming with product diversity. To mitigate risks associated with rising new clients, firms are willing to invest in technology to maintain good customer experience and avoid dramas similar to Didi or Alipay.

5.1 Customer Onboarding Processes

At present, the financial sector is evolving from isolated to integrated platforms, and from data-based decision-making to AI-based intelligent decision-making in the direction of end-to-end intelligent finance. An integrated and automated marketing platform for the marketing management of departments, front, middle and back office risk management integrated platform, and the fully automated intelligent operation center should be built, that is, the marketing and management decision-making based on big data module, the risk decision-making based on big data, AI and DL algorithms, and the operation automatic decision-making based on big data. Recently, DL has been in the spotlight as a big data equivalent. Even Tesla's camera version autopilot can be implemented based on the end-to-end deep learning algorithm. Its function will evolve gradually over time according to the amount of data. Bank money transactions and stock market trading will not be able to be automated by DL technology in a very short term, but marketing, risk (including financial and operations), and operation supervision all have precedential experience in this aspect, and thus will be investigated and realized through DL technology first. With the in-depth development of big data and artificial intelligence (AI) technology, the commercial bank business mode is undergoing complex and profound changes. The board of directors' charges into customers' service experience and the technological arm of grasping clients' bottom line brings both risks and challenges to banks. Banks which are used to employing such classic and simple marketing modes as sales, advertisement, telephone, and so on face ever-increasing challenges from well-prepared Internet banking and third-party payment. Of the features of the high-value marketing hypothesis, it is necessary to discover first-class clients efficiently. The marketing model based on big data and AI is suitable. The BGNN-GFT for understanding graph structured data is designed, and the connection management is fully integrated into the structure optimization. The experimental advances in the application fields verify the advantages of the approach in dealing with graph structured problems from different aspects including accuracy, execution time and energy saving.

5.2 Risk Assessment and Management

The continued rise in economic globalization has made anti-money laundering (AML) and counter-terrorist financing (CTF) measures more imperative than ever for the financial industry. Anti-money laundering (AML) is a procedure and set of techniques used to prevent, monitor, and disclose suspicious activity or fraud related to money laundering and maintain the behavior of new types of money laundering and terrorist financing. As the social economy has advanced, the modes and methods of fund laundering have changed subtly. This poses higher and more severe challenges for banks' AML measures. Additionally, both domestic and foreign regulatory authorities have introduced a new batch of procedures, mechanisms, and regulations to strengthen the compliance of the financial industry, increasing the penalty for violations.

At present, AML systems mainly rely on some carefully selected rules to screen customer transactions for money laundering tips. However, the rules are generally static and often fail to keep up with the changing trend of fund laundries. As a result, thousands of false alarms will occur every day due to complex rules and huge transaction amounts in the bank. Human analysts can only check dozens of screened transactions in a day, and the rapidly rising false alarm and rapidly rising workload of analysts have caused huge economic losses to the bank. The development and increasing complexity of financial institutions and products, as well as the continued globalization of money laundering methods, pose serious challenges for the existing AML rules and systems. On the one hand, as a quasi-policing anti-money laundering task, AML accepts supervision from the financial management department. On the other hand, the bank has to also comply with anti-money laundering supervision from the central bank. The huge fine for non-compliance and the penalty cost such as customer loss have caused banks to pour huge manpower and material resources into anti-money laundering work. For example, thousands of compliance analysts are employed in large banks, and the annual maintenance costs of small-scale anti-money laundering systems range from millions to dollars.

5.3 Fraud Detection Mechanisms

In the era of digital banking, the security and integrity of financial activities have become paramount concerns for banking institutions and users alike. Financial frauds posed in online banking and credit card transactions, commonly referred to as financial fraud, are amongst the severe and prevailing threats that, on a yearly basis, account for billions of dollars lost due to fraud, drawing significant concern to the global economy, the trustworthiness of banking institutions, and the financial well-being of individuals. Overall, billions of dollars are lost annually as a result of fraudulent activities. This growing concern has resulted in financial institutions conducting rigorous research in an attempt to combat and identify fraud. Amongst the financially related frauds that are the subject of extensive research by the scientific community and financial institutions, one prevalent domain is bank-related fraud.

Bank account fraud is a type of financial deception that employs methods, impacts, and resulting detection challenges that differ from other types of financial fraud. Unlike traditional fraud methods that may be immediately apparent, bank account fraud can often be a subtler endeavor, involving unauthorized funds transfers, or even identity theft. Thus, understanding the nature of these threats and how to mitigate them requires thorough research, which hinges on a rich and diverse dataset of normal and fraudulent bank account transactions. Machine Learning (ML) is a term often used to refer to a class of intelligence developing systems that use statistical inference to detect hidden patterns in data. In fact, illustrations with datasets of bank account transactions have been utilized extensively to demonstrate the capacity of ML approaches to detect bank account fraud.

Nonetheless, these datasets hold confidential data, and as bank account fraud is rare in practice, they exhibit an imbalance, where legitimate transactions are far more common than fraudulent transactions. As a result, banks use their proprietary data to train different ML models to detect customers with a higher probability of being involved in fraudulent activity. However, because different banks often suffer from different types of fraudulent endeavors, detection models that are trained using data from one bank could be ineffective in discovering new potentially fraudulent behavior in another bank. One potential solution is Federated Learning (FL), a novel privacy-preserving approach to decentralized machine learning. In general, FL enables two parties to jointly train a machine learning model without revealing their datasets to each other, where instead of sharing data across institutions, the machine learning model is trained on local devices with only aggregated updates being shared. In this context, FL is presented as a collaborative and confidential countermeasure against fraudulent schemes. Stated differently, instead of heavy data being shared across institutions, only model updates would be sent, ensuring customer data would not be compromised.

Equ 2: Real-time Risk Assessment

$$R_t = \frac{\sum_{i=1}^{n} w_i \cdot M_i(x)}{T_{latency}}$$

Where:

- R_t = Real-time risk score
- w_i = Weight of model i
- $M_i(x)$ = Risk output from model i given input x
- $T_{latency}$ = Processing latency (optimized via cloud)

6. Case Studies of Intelligent Finance Solutions

The finance sector has faced great challenges in technology in recent years. It was difficult for financial institutions to keep up with this technical revolution. The rapid development of information technology, especially the third wave of technology represented by big data, AI and deep learning, cloud computing, mobile ecosystems, social networks, etc., has brought both opportunities and challenges to financial innovation. Financial institutions need to adapt to the new environment through cultural and technical changes, building educational platforms, reforming the staffing structure, and establishing new promotion mechanisms. The best strategy to regulate the financial sector is to establish an integrated and automated intelligent finance platform for marketing, risk management, assessment, and other areas. Therefore, an in-depth investigation of not only back-end AI technology for regression, non-linear mapping and classification but also cutting-edge DL technology that processes structure and non-structure data is required. Since its establishment, One Connect has utilized the well-known DL algorithm and the earlier traditional methods to address a myriad of financial concerns. Big data and AI technology have been combined into business procedures to create an integrated marketing scheme, minimizing the customer attrition in service, and motivated by reasons to increase the revenue stream to cope with fierce competition in the finance management area. A brand-new intelligent marketing method was explored. This new marketing method can conquer the drawbacks brought by traditional marketing mode, improve the marketing effectiveness in the financial sector, and further boost the work productivity, market competitiveness, and satisfaction of customers. Intelligent marketing is established by the behavior data of customers. Clients are assessed based on interests, and then the targeted marketing programs will be generated iteratively. Connected messages will be employed to enhance the conversion of the value and the introduction of new products. To dig the hidden optical flaw and supplement the hard, numerical limitation of presently available nifty random reflective worlds, the review model of the margins of qualified retail clients will be further examined. This huge model is established on manual crafting with responsible deed data which discarded both data quality probability interpretations and dynamic actions, but these are the small-tail triggers of unfolding the macro-turbulence in the modern financial marketplace. Backed by the control of central bank and AI technology, a validation chamber is proposed to prevent despicable and preventable catastrophes, and regulatory-commercial integrations in the digital silence selling position. Deep dive BLSTM is proposed to quantify difficulty within an intricate multi-delivery approach that considers the performance, quality, and risk simultaneously. The technology demonstrated acuity in gauging the calibration of individual models, guiding them to sufficiently exploit orthogonal information, curtail over-finessing, and heighten the antirust efficacy.

6.1 Successful Implementations

Intelligent Financing of Financial Business Through AI and Cloud Integration is an innovative and effective approach. It not only integrates multiple businesses, but also combines intelligent software with finance cloud. Artificial intelligence is ushering in an unprecedented wave of technological advancement in the financial sector, and its capabilities have made it one of the most significant innovations in the past 20 years. Beginning in 2016, the People's Bank of China designated "FinTech" as the spotlight for innovation in the financial sector, as well as development and growth in itself. AI has caused a paradigm shift in software R&D technology, allowing the financial sector to undergo a quantitative leap, and accelerating the move from traditional finance to "smart finance. " By adopting this design, a complete cycle of enterprise cloud migration has been established to ensure that the solution can be implemented and operated in a short span of time. The solution can generate data analysis reports and various types of data visualization reports through automated batch reports, analysis, and visualization at set times. AI-modified data is uploaded and inserted into the cloud through intelligent bots. The implementation of financing has been constructed by devising prudent deployment based on engineering expertise and custom-developed best practices. Solutions were delivered jointly by domestic first-tier and second-tier vendors, which included on-site and remote resource deployment adjusted based on needs, application and integrated tests based on the defined success criteria, end-to-end delivery management, and creation of a knowledge sharing and nurturing working environment. The end-to-end intelligent finance solutions implemented at a Chinese banking giant were introduced in depth. The solutions supported both traditional finance business and FinTech business types, while providing multiple products such as intelligent customer traffic analysis and smart factory project management that integrated multi-industry capabilities. The cloud-native intelligent products successfully served the core digital transformation needs of a Chinese banking giant's numerous domestic branches.

6.2 Lessons Learned from Failures

A review of the literature on the failures of AI-based systems reveals that they can be classified broadly into four classes: conceptual failures, design failures, deployment failures, and hardware failures. These classifications are mutually exclusive and jointly exhaustive when taken individually but can overlap in cases where a failure simply cannot be assigned exclusively to one classification alone. Design failures, defined as structural flaws in the architecture and algorithms of an AI-based system that lead to the malfunctioning of that system, can themselves be further sub-classified into a number of concrete categories based on how the fault translates into an erroneous response. Class 1 failures occur when an AI system is unable to draw on a pre-configured recourse to handle a situation it has encountered under live conditions at its deployment site. Class 2 failures arise when an AI system is unable to act on a known piece of information because of a failure to process the information appropriately. These failures typically originate in the pre-processing stage of translating features to represent ‘frames’ or ‘ticks. ’ Class 3 failures occur when an AI system cannot sufficiently adapt to variations in the nature and scope of an expected scenario. Class 4 failures arise when an AI system takes an inappropriate action either because of a flawed design in its cognitive architecture or intention module.

As noted, deployment failures, when systems with known design flaws cannot be redeployed owing to unforeseen obstacles, do not translate effectively into actionable countermeasures. However, learning from a well-publicized deployment failure may prevent the repetition of similar mistakes. There are many broadly famed deployment failures across different domains such as speech recognition, language translation, and facial recognition, some examples of which have been described. Training a voice interface to recognize only ‘phrase watch’ greatly simplifies the task, but when deployed it can only capture the attention of users rich vis-à-vis the AI deployment platform. Deep sentiment analysis based on net-popularity thresholding is not computed on reviews on the understanding that these reviews are seldom co-opted. However, no low-scoring reviews are assigned to the ‘devoid’ class owing to the lack of training data which can cause frustration to a user attempting to search for a negative review as absolute five-star ratings are uniformly reported in all instances.

7. Regulatory Considerations in AI-Driven Finance

The design, deployment, and use of AI technologies in finance must be carefully regulated to manage risks, ensure that fairness goals are met, and increase consumers’ and stakeholders’ trust in institutions. This entails increased attention to transparency, explainability, and interpretability of AI technologies; treatment of bias, equity, ethical, and fairness risks; and ongoing scrutiny of AI outputs and decisions. Regulators need help from AI developers to ensure that regulation captures state-of-the-art methods and their societal consequences. Regulators must work closely with financial institutions to gain knowledge on an iterative basis. Institutional approaches to compliance must be participatory, grounded in transparency and explainability, and achieve ongoing regulatory oversight from the beginning. Patterns of AI non-compliance and regulatory evasion will, however, emerge in time, necessitating the need for regulatory intervention on a higher level.

A long list of AI governance challenges motivates the need for new solution approaches. These include how to assess solutions regarding financial incentives for compliance and evade-proofness against financial incentive-based regulatory evasion, especially if financial institutions become aware of the regulatory requirements that AI systems need to comply with. The latter technical concerns further rely on encouraging AI self-analysis and human-in-the-loop regulatory oversight. These foundational contributions are implemented through a modular AI system framework that is flexible enough to accommodate various AI techniques, solution types, and risk scenarios, aimed at both financial institutions and regulatory agencies. This setup provides insight into important mechanical design challenges, including the effective representation of regulatory requirements and compliance risks, which have yet to be studied in this broader context. Several important research directions lie at this intersection.

Equ 3: Cost Optimization in Cloud-AI Finance Operations

$$C_{opt} = C_{AI} + C_{Cloud} - S$$

Where:

- C_{opt} = Optimized total cost
- C_{AI} = Cost of AI training/inference
- C_{Cloud} = Cloud infrastructure cost
- S = Savings from automation and improved efficiency

7.1 Compliance Challenges

Over the last two decades, banking systems have witnessed incredible progress through the emergence of business process automation, shift from legacy systems to component-

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based architectures, continuous evolution of digitization, and utilization of cloud technology. As a further step in the financial and insurance industries, this chapter proposes end-to-end intelligent finance solutions for the digital transformation of partner organizations and long-term collaboration through open platforms by an industrial case. Intelligence encompasses the aspects of AI and human-like characteristics. Finance solutions involve the application of the banking ecosystem by any enterprises. Constraints and challenges inherent in the banking ecosystem using data aggregation are addressed first. Then, a detailed use case of end-to-end intelligent finance solutions with multiple components is derived. In consideration of data and model privacy concerns, the architecture and decision support system using privacy-preserving and modularization technologies are introduced. Finally, on top of benefiting from automatic personnel allocation and AI decision support, business model transformation options to embrace the large language model (LLM) era are discussed, consisting of a significantly improved banking ecosystem, a conceptual content generation and auditing assistant, and transformable business models for instant lending and brand establishment.

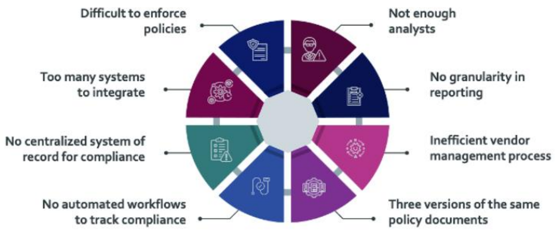

Figure 5: Major Compliance Management Challenges and Their Solutions

Compliance departments in financial institutions (FIs) are faced with challenges from the lack of automation, the need to increase performance while facing more requests, and the constantly evolving regulatory landscape. In order to deal with these challenges, automated compliance systems are gaining attention in both the public and private sectors. They have the potential to change how financial regulation, surveillance, and compliance are conducted in the future. Displayed regulatory monitoring technology feeds information to compliance that may affect the rules they're responsible for enforcing. Compliance tasks performed in-house and outside of the organization, augmented technology, and the AI transition are mapped into technology groups. Expectations regarding the future of automated compliance systems are matched to concrete developments that take place at the same time. Automated compliance systems are more limited than is claimed in academia and the media. Greater awareness of their potential and limitations may prevent future problems while capitalizing on opportunities. A multi-level system for an automated regulation compliance framework in financial services countries is proposed.

Many financial services organizations uncritically implement AI models that are sometimes not properly understood or adopted, which raises various governance challenges. Unconscious exposure to discrimination and blind reliance on opaque models are cited as two examples of AI governance failures that have been observed in practice. Well-documented and relatively easy to interpret, AI models can also yield dramatically unequal outcomes. In Europe, core regulations on AI model governance are already adopted or scheduled to enter into force soon. Obsolescence of existing governance frameworks is a side effect of the rapid advancement of AI technologies. Moreover, enforcement of existing governance frameworks becomes a challenge because of the complexity of AI technologies, particularly in financial services where performance is paramount.

7.2 Data Privacy Regulations

Privacy has proven a pressing issue due to technology and society's everlasting development. The need has arisen for more systems to help protect users' privacy. European citizens worry about their data missing or stolen. A prime example is Romania, where a recent scandal uncovered that insurance for work accidents was a public service handed over to an enterprise. A lack of management led to privacy breaches as a private firm had access to personnel data. How could such an unthinkable scenario occur in an EU country? This is the question that sparked the development of an architecture in compliance with the General Data Protection Regulation (GDPR). With the new laws, collecting, processing, and storing user data without explicit consent becomes a punishable offense. But monitoring such possible breaches is an administrative nightmare. More so, health institutions in Romania still rely on paper and pen for file analysis, leading to countless dirt paths through which numerous public employees can access private information. With the new regulation, there is a need for cloud service providers to either improve their frameworks or change their business models. The discussed medical insurance system has a massive data breach risk. A distributed system is proposed to automate this process, offering the same services while sheltering user privacy. The system is centered on a user’s anonymized identity, leaving it to the cloud to automate this indexing system while everything remains on-premises. Only issues that require running untrusted code and untrusted data will be stored off-premises. Since it must foresee data breaches and integrate confidentiality in its components from the beginning, the design must adhere to the Privacy by Design principles. It is still in its infancy, as, although replica systems such as CryptDB exist, they require heavy computation time to be secure. However, potential kids’ games provided by academic institutions impose no such restriction.

8. Future Trends in Intelligent Finance

Artificial Intelligence (AI) offers financial institutions new opportunities to improve the customer experience through long-due process optimizations and to make informed decisions at unprecedented speeds and scales. However, to successfully leverage AI’s benefits, financial institutions must first understand how to integrate AI into their environment and what tools to use. More generally, financial institutions are facing new challenges when it comes to digitalization and technology adoption. The magnitude of the problems institutions face clashes with their typical approach to technology adoption. Different from the tech-first, data-driven approach adopted by wholly new industry entrants, financially-established organizations need to prioritize change management and adoption because many existing tech stacks are cumbersome or lack data.

Software-as-a-Service (SaaS) vendors aggregate data, reduce labor costs by eliminating manual processes, and reduce carbon footprints through AI and cloud-based services. For example, a hedge-fund firm can possess more than 20 years of trade data across multiple custodians. Aggregating this data is a yearlong, costly task. With the advent of SaaS solutions, a hedge-fund firm can point to new data fees and painlessly get insights over 20 years' worth of trades. However, while acquiring SaaS solutions may work for smaller institutions, larger firms or banks experience major pushback because it undermines existing employees and departments whose main focuses have always been on managing vendor risk and technology integration.

Many buy-side firms' tech salaries are tied to revenues from basis points. If a firm's revenue is $100 million at 35 basis points, it can pay 180 tech employees $50k a year. If a firm's strategy creates a net loss, other lines of business will not pay for these tech resources. This is unlike other industries such as eBay or Amazon, which were able to focus solely on talent and quickly outscale incumbents. The opposite is true for sell-side firms, half of which purchased a trading system 15 years ago but have never seen it go live. For these firms, minor manual upgrades are preferred since recession-proof budgets allow employees to maintain their jobs.

8.1 Emerging Technologies

According to the Bank of England, financial stability is of prime importance. In agenda, the Bank of England is engaging with FinTech companies to better understand the emerging financial stability risks as traditional banking is being reshaped by technology. Many large and medium-sized banks are starting to integrate FinTech into their own services. The Financial Technology Partnership is not intended as a forum for discussion around the technology itself. But comments on the implications of the technology should help begin to assess the potential impact on the traditional banking sector. Customers want more choices, more options, more flexibility, and more control over where and how they bank. As an industry, banking must respond to these demands. If traditional banks don't meet these challenges head on, they will be excluded from the most profitable parts of a rapidly growing market. The part of FinTech starting to be looked into is AI. AI is a branch of FinTech that is now a hot topic across all industries but with its vast ability to change what an industry is all about, is seen as a more riskier and competitive area than any of its cousins in the FinTech family. It's perhaps because of this factor that the financial sector is being looked at here firstly as an area where FinTech, and more specifically AI, can offer significant improvement in efficiency and costs. Despite this, the applications of AI in the retail banking sector have not yet been thoroughly explored or discussed. The benefit and challenges of utilizing AI in retail banking has not been well investigated and understood so far. The deployment of AI is widespread in the financial sector. In the UK, banks are now rolling out banking applications that make use of voice recognition. In a similar vein, HSBC has successfully tried an AI engine intended to predict the promotional behavior of small and medium-sized businesses. Standard Chartered Bank has in place a recommender system that cross-sells non-mortgage, retail loans to existing mortgage customers based on neural networks. Artificial intelligence (AI) refers to intelligence exhibited by machines. It is an interdisciplinary science with multiple approaches that aims to mimic and mimic human behavior. AI technologies such as machine learning and natural language processing enable machines to perform tasks that require human intelligence.

8.2 Predictions for AI and Cloud Integration

AI and cloud integration will result in a fundamental transformation in the finance industry. The first trend is improving the adaptation of AI in finance and finance in AI. The development of AI technology has progressed from the statistics and algorithms of the school of thought to the big data of machine learning and to the new world of computing power, architecture, and fast moving toward the natural intelligence enhanced human intelligence, the AI finance-centered world. Finance could use the natural language generation tool and AI models to code the accounting and business rules in the code-free world only needing data. It can drink more clouds and benefit workers in the home office by a more relaxed structuring regulation on business and financial rules. It can try quantum experiments using simulated quantum finance at the edge of tomorrow's finance. The finance-tech model can be more visible, interpretable and audible, more landscape and mobile orientated to like a GPS real-time directive guiding engine. The ethics on AI's talkable smart assets and biases produced from training data skewness could be better designed and executed. Chat-GPT, big shots of finance, news, label data and rules may even propose the required rules and propose the amendments through design thinking, boot storytellers creating benefits. Engineering a systematic change is of fundamental importance, the AI design and coding business could be shifted to the co-creation by regard a user's effective preferences sampled by its management and crowd.

The second trend is turning the finance management sustainable by autonomous and consortium clouds and AI-Inside AIOps. The corporate management will not depend upon one or two top accountants who keep the instrument of analytic excellence, the consumption and returning of knowledge but auto receive and utilize knowledge service. To best stimulate the healthy active and self-organizing of a consortium, the chance of business best practices and prominent designs can be rotated quantum-like among smart assets and suppliers. Steer digital twins might supply simulations of risk and corresponding return knowledge for intelligence agents. Transparency provides more mutual guarantees and promotes the credit control, IQ-Environmental, social, and corporate governance (ESG) disclosure will gradually asset chance and financing cost separately, and the charges about incentivizing AI-outside data could be transparent.

9. Challenges in Implementation

Although AI finance solutions and cloud integration provide many advantages to organizations, there are numerous implementation concerns that firms must confront. Traditional risk frameworks, particularly those related to data protection policy, information security, and corporate ethics, may not be appropriate for a cloud-based environment. The provision of cloud services introduces many potential new risks that cannot be remedied by controlling the risks that arise from on-premise hosting. The financial service industry must start to develop a paradigm for risk and compliance that embraces cloud technology. To truly assess the vendor's competence in terms of maturity, compliance, and security, regulatory agencies need to think about transforming business practices. Only firms that are prepared to rethink and innovate with today's markets in mind will be successful. Developing technology must pivot from establishing fundamental capabilities and systems of record to offering integrated and real-time decisioning of events in associated areas. As people favor activities that can be conveniently and instantly conducted on mobile gadgets, transaction velocity is expected to proceed to accelerate. Upstream information ecosystems that unlock real-time data sources can help to close the gap. As a result, a more integrated imperative to view latent information in one place, rather than in data silos, is foreseen. Data nudges, which continuously push models and decisions to the user and utilize information to automatically stimulate improved/alternative behavior, may also aid in decision speed.

With the sudden expiration of the era of low interest rates, banks must pay attention to making sure that the investment bubble won't burst and cause panic. This is a challenging assignment due to the various factors involved. AI risk food chains, which span the entire organization and its outside ecosystem, must help to safeguard a variety of forms of bank sensitivity and redesign governance paradigms. AI super visibility and accountability structures are also vital to assist organizations find improvements in performance, compliance, and identify unforeseen impacts, especially where complex situations and cross-business risks at close velocity are in play.

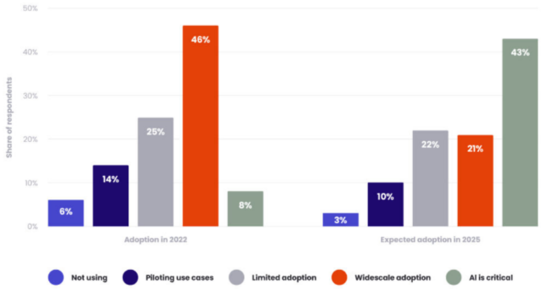

Figure 6: AI in finance

9.1 Technical Barriers

FinTech is an increasing trend in investment banking, but developing FinTech products is still challenging. At present, there is almost no end-to-end intelligent finance solution based on AI and cloud that is applicable in the real world. In this section, a five-level system is introduced based on AI technology, knowledge graph, and cloud technology to challenge traditional investment banking work. Level 1 is about how to collect the public data according to the interests of financial analysts. Level 2 is about how to further process the massive unstructured data and visualize the processed content. Level 3 is about how to analyze the market and extract useful knowledge according to the financial needs. Level 4 is about how to automatically write the financial analysis report utilizing extracted knowledge. Finally, Level 5 is an end-to-end financial analysis solution based on multi-agent architecture and cloud services.

9.2 Cultural Resistance in Organizations

Despite the significant consideration for cultural barriers in the study, organizational culture, employee opposition, conservatism, and cultural resistance knowledge gaps were identified. In the emerging corporate culture involving the use of AI in finance, HR, and other sectors, employees' opposition to AI decisions has been a failure point. Such resistance is borne of cultural dimensions including, but not limited to, uncertainty avoidance, trust, conservatism, and job-oriented vs. people-oriented. AI technology is perceived as uncertain due to useful AI systems' limited availability, initially, which creates fear of being poorly prepared or incapable of coping. Furthermore, individuals in organizations often wish to feel in control (low cultural resistance) and endeavor to trust AI systems. High uncertainty avoidance contributes to a perception that lacks trust in the tech. Openness, in terms of acceptance of innovations, collaboration effort, and relationship, is also a cultural source of resistance. High conservatism is linked to a low level of corporate openness and proactivity, characterized by avoidance of bold innovation, risk aversiveness, and defense of the existing state. Resistance is also based on human versus machine/mathematical expression variables, as the algorithm bias in AI systems may unfairly impact a human opportunity. Hence, even if the AI system is successfully installed and adapted, if the employees are resistant to it, then its effective use will be limited. Natural language processing and generating tools are used for intelligent chatbots to assist financial professionals. Secure cloud computing is developed to fully record and systematically archive auditable and referable materials from online meetings for compliance tasks. AI systems' outcomes must be explainable to facilitate trust building, requiring full model understanding. AI and human collaboration is fostered with enhancement systems to help employees mitigate difficulties associated with the AI so that errors are avoided. Low resistance technologies may also be integrated to gradually introduce users to a more advanced system over time. Furthermore, employee usage education is needed to curtail uncertainties or to enhance trust. Financial audits have to educate employees about the AI technologies so they know how the tags are generated and why specific documents are collected.

10. Measuring Success of Intelligent Finance Solutions

Business clients seek not only traditional financial products, but also sophisticated services and comprehensive assets. A bank's intelligent operation and decision-making capability is a crucial competitive advantage. The intelligent finance solutions of a bank include finance as a service platform, management assistant, business recommendation system, finance + research, etc. Key architecture design goals of the intelligent finance solutions should involve decoupling business application modules from ML model modules, publishing business APIs for internal/external clients, hosting ML model service on a cloud-based AIaaS platform, pushing model prediction result into the data platform for further analysis and visualization, and providing an integrated development platform for enterprise users to develop their own models that are trainable. It is also beneficial to convert existing ML models into Chen effect model and Tensorflow Fold model. In addition, a business API gateway and control panel can help to manage security policies for mainframe interaction APIs and allocate resources for AIaaS effectively. The architecture should separate data storage systems from business application modules, while providing open-source interfaces for secondary development. The design should also consider adopting a sequence of uniform data models (UDMs) to ease the secondary development burden of business application systems and raise the efficiency of data migration and analysis. The UDMs should define important business objects and their attributes in an entity-relationship model and develop corresponding MongoDB collections and concerted documents on this basis. In addition, SMEs of different businesses can build their own basic model to update well-known routines of data cleansing/transformation based on the pattern-based design of data execution. Furthermore, a multi-module optimization method can be used to create a global optimization model by effectively connecting the divide-and-conquer strategy with a set of model linkage together.

10.1 Key Performance Indicators

With the rising acceptance of AI technology, the finance and banking environment is evolving to a more integrated, automated, and intelligent finance platform. Accompanied by the digital transformation of the finance industry, consumer-centered digital financial technology and finance services have begun to become elite. In this review, the architecture design of intelligent finance and the implementation of 16 finance scenarios integrating AI and cloud are discussed. In this evolving environment, intelligent scenarios are covered with both concept diagram and scenario description. Development opportunities and suggestions are also shared to motivate the building of intelligent scenarios in the New Finance paradigm. Fast development and implementation of innovations have already changed the old finance paradigm. Tech-driven innovation is enabling dynamic marketing beyond organizational boundaries and changing customer base, customer relationship, customer anticipation, and customer experience. Traditional finance has been facing the dilemma of fast customer loss while the net profit growth was gradually reducing. On the one hand, new finance platforms were encroaching on customers with more open intelligence means of product push, service awareness, and user experience, resulting in a fast customer loss in traditional banks and insurance etc. On the other hand, the customer base of traditional financial organizations itself was at risk as those newly onboarding were more young and tended to be allocatively upper or lower than the former users. Building up intelligent marketing techniques is discussed as a turn-around for both the customer retention and growth. Challenge along with opportunity is analyzed in detail considering the knowledge reserve of financial organizations, the development stage of deep learning methods, the potential of talents, the investment timeliness, and the change of organization structure. Emerging from a rich oligopoly, intelligent finance is now still composing in a comparative blank stage with defected tools and strategies existing, not to mention the design of finance scenario level. Integration of on-cloud testing and in-field application deployment is crucial.16 intelligent finance scenarios are to date released with implementation results demonstrated covering scenario design, architecture, solution implementation, and practical application.

10.2 Return on Investment Analysis

Return on Investment (ROI) analysis is used to assess the relative cost-effectiveness of investments by comparing expected gains to investment costs. It is a key metric to evaluate the net gain of investment over time as a percentage of total investment costs. The ROI analysis of the baseline AI model and the developed optical character recognition (OCR)-debit card number extraction system for online new account opening (NAO) is presented.

For the AI model, the cost of implementation covers labor, AI model running, maintenance, and storage costs. The usage of self-built server, model interfaces, and storage costs are considered at a calculated annual depreciation time of five years in the cost model. The AI model can cover multiple use cases in retail banking, and the primary use case is selected with the highest expected gain. In 2021 and 2022, the model had been fine-tuned and iterated with a large number of one-off adjustment requests, so the gain is off-scale at the moment. The gain of 2023 is projected based on the reasonable assumption that further use case expansion requests are much less than before. If there is one additional use case on the model customization that consumes resources and thus incur costs, conservatively, one-third of the expected gain of the first complete use case is accounted for.

The ROI for different depreciation times of the AI model is calculated. The annual gains from the AI model were far more than the annual costs at very forecast errors, indicating a strong business case for AI integrated finance solutions. The accuracy on the test dataset was further demonstrated to guarantee a precise ROI calculation by providing an ROI lower bound. For the OCR model, an internal server applying classic server hardware with a lifetime of five years, was used to implement both the AFSA and streaming OCR systems. The assumptions on the expected gains and costs were described in details including amortization/learning phase consideration.

11. Conclusion

Financial departments are adopting the latest technologies and searching for AI, data, and cloud integration. Enterprises need to invest in intelligent finance transformation to improve their unique finance intelligence capabilities. Financial smart engines are needed to increase efficiency. Every department uses tools alone with a siloed approach, resulting in effectiveness reduction. More intelligent business information is required today and in the future. Hence, platform-based financial cloud is needed for services. Financial departments cannot bear huge workloads in intelligent finance transformation and core processes monitoring. Traditional watching tools mainly display dashboard data and alerts without process intelligence. Workload transformation is labor-intensive and time-consuming. Unstructured data democratization is needed for self-service analysis. With data growth, transparency exhaustion exerts challenges on the whole finance industry. Comprehensively prepared WMS tools mainly automate functions. The configured rules cannot handle complex and non-standard behaviors. Semi-structured and unstructured data accounts for over 90% of the world. Hence, the requirement for data intelligence to deal with unstructured data is out of the question. Cloud computing alone cannot solve the problem of tailor-made services. The combination of base and progressed knowledge can solve the problems. The intelligent RPA technique can be used to reduce fact-checking costs and improve efficiency. Independent RPA without intelligence cannot handle unpredicted automation tasks. Text recognition and NLP are needed for attached PDF files to mitigate semi-structured data treatment jobs. Decision trees can be adopted for credit risk avoidance measures. Frameworks without differentiating white-and black-box model choices cannot create attractive explanations to comply with stricter regulations. Analogous development of finance intelligence brings commercial ethical problems, which can destroy financial security and put the industry and globe in jeopardy. More interaction between finance and AI is needed to promote rethinking intelligent finance.

11.1 Future Trends

AI-based intelligent solutions will enable finance practitioners to enhance production efficiency, data management capabilities, system performance, decision support systems, and personalized services in financial supervision, risk management, credit scoring, market prediction, trading strategy, arbitrage opportunities, and wealth management. These AI solutions are time-aware and ingest data from heterogeneous sources, including unstructured text files, images, audio files, and numerical signals from the physical world, allowing for complete situational awareness of risks and opportunities in various applications. Solutions can incorporate more effective AI models to better identify and analyze various financial events, risks, and opportunities.

Cloud native technology provides container orchestration and service orchestration mechanisms for effectively deploying and managing various AI techniques, including micro-services, batch algorithms, real-time models, as well as industrial productivity, customer data management, legacy service migration, and data analysis. In addition, cloud technology enables flexible and elastic resource provisioning to meet the dynamic demands in the financial industry. Wide-spectrum finance practitioners will be able to deploy intelligent solutions in a cost-effective and real-time manner with comprehensive tools and ready-to-use models to substantially alleviate challenges in applications.

Intelligent finance is expected to encounter challenges in the coming years, such as industry standards for business cases or solutions, along with application behavior models and performance indexes. Robust and explainable solutions are also needed. A comprehensive evaluation platform for AI pipelines could automate the production processes of AI solutions, in which various workflow modules are invoked and executed on dynamic resources, and different routines are compared and selected with consideration of performance and data freshness. Such a platform will be useful for both commercial projects and academic research. An open and transparent share of public finance datasets is required to design versatile and robust models. A large-scale and multi-faceted financial dataset is expected for academic research in unsupervised pre-training and autonomous intelligence.

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