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Integrating Big Data, AI, and Financial Modeling in Cloud-Based Insurance and Banking Ecosystems

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Abstract: The trend toward big data (BD) in the financial technology (FinTech) sector has recently gained momentum [1]. By utilizing cloud-based services and advanced algorithms, insurers, banks, credit unions, and other players in the finance ecosystem can efficiently gather and analyze vast amounts of data. Behavioral data (Big Data) gathered through the web and mobile channels is essential to proactively assess risks and opportunities for financial institutions. Here, it is postulated that Cloud-based architecture, aided with big data analytics and AI, augments precise financial modeling in the insurance and banking ecosystems. The paper constructs a hierarchically-structured smart architecture with a four-tier cloud databank, and data mining integrated with AI. It discusses intelligent big data services and cloud-based data markets for financial modeling. The significance and pressing need for the research are highlighted.

Integrated cloud-based architecture as intelligent big data analytic services for financial modeling. New cloud-based financial big data technologies and smart buildings. Intelligent big data services for financial modeling: benefits and challenges. A cloud-based insurance ecosystem was proposed. A comparison of cloud-based insurance systems was also examined. Integrating financial modeling: Services and challenges. Intelligent performance benchmarking-architecture of competitive insurance and banking systems. Financial modeling of insurance, banks, and others. A summated proposal for the integration of AI into the systems was made. The broadest observations were also uncovered.

Keywords: Big Data, Artificial Intelligence, Financial Modeling, Cloud Computing, Predictive Analytics, Risk Assessment, Customer Segmentation, Real-Time Processing, Machine Learning, Data Lakes, Insurtech, Fintech, API Integration, Regulatory Compliance, Data Security, Scalable Infrastructure, Decision Automation, Fraud Detection, Digital Transformation, Personalized Services

I. INTRODUCTION

Financial technologies (fintechs) aim to improve and automate the delivery and use of financial services. Despite its earliest business models being significantly based on big data (bd), artificial intelligence (ai), and cloud computing (cc), a coherent research agenda of blending these facets (bd, ai, cc) in comprehensive financial modeling (fm) has not yet been put forth, specifically in the context of insurance and banking. So, the purpose of this article is thus to find out the unexplored and dynamic interlinkages among the bd, ai, and cc ecosystem in fintech within a holistic fm modeling framework. In so doing, three methodological reviews are tri-dimensionally conducted. First, protocol data analysis is utilized to perform an academically validated bibliometric analysis to explore the need-gap-research agenda linkages among bd, ai, and cc in fintech domain. A deductive interview method is then employed to provide a deep dive, domain knowledge-based action-based exploration of the above ecosystem. Finally, rigorous conceptual and normative modeling is rendered to develop fintech ecosystems framework-based significantly interconnected research agenda maps and model prototypes. The academic, managerial, and regulatory implications of the study have also been provided [1]. It is aimed to draw brainstorming ideas among accounting, fintech, and finance studies regarding the theory, design, and implementation of complex systematic and comprehensive finance, insurance, and banking industry-wide models (spatial and temporal) in a big-data-cloud-artificial-intelligent-connected world.

A systematic review of integrating bd-ai-cloud-based fm for fintechs encourages and guides innovators of commercial fintechs in automating and improving real-time analytics and transactions of money, banking, loans, investment, and insurance-related services in the interconnected clouded world. Proper utilization of the ecosystem of bd-cc-ai prohibits misuse of justifiably accessible user data and excessive trust in user-feeding intelligent algorithms in risky and protective financial matters. To tackle the scourge of putting forth user-feeding intelligent algorithms, mitigative measures focus on aspects of poising, transparency, regulation, explainability, and cross-border cooperation.

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II. OVERVIEW OF BIG DATA IN FINANCIAL SERVICES

Technological developments especially cloud computing have encouraged the explosion of data in recent years. Concurrently, many industries particularly financial services organizations have shifted toward a digital economy where they have become something like data factories. Financial services organizations utilize this new economic asset-called big data-to gain a competitive advantage over their rivals. Big data analytics has turned into a must-have capability for financial services organizations. It aims to extract valuable insights from data and help decision-making. Alongside, in the digital era, many financial services organizations have turned to fintech where they offer their products or services using the internet. They aim to cut costs, enhance services efficiency/updating, and access new customers through their current channels such as a bank's website, a bank's mobile app [1]. There are various types of fintech in the insurance and banking ecosystems including digital lending, cryptocurrency and blockchain, peer-to-peer lending, payment service providers, neobanks, robotic process automation, and automated accounting

Fig : 1 Big Data Explosion.

Cloud computing plays an indispensable role in the viability of big data and fintech in financial services. On the one hand, it provides big data mechanism-supporting infrastructures such as cloud storage, cloud database, cloud server which can take almost any amount of data and prevent data silos by allowing the spread of data throughout an organization by virtue of easily sharing data across departments using cloud services. On the other hand, it allows fintechs to be constructed, run, and exploited efficiently, reliably, and effectively anywhere across the world regardless of the organizational sizes with low initial and operating costs. In short, cloud computing creates prosperous ecosystems for big data, fintechs, and financial services. However, existing big data, fintech, and financial modeling literature chiefly operates only in either the banking or insurance sectors resulting in the overlapping aspect of existing ecosystems. Therefore, what will the new insurance and banking ecosystems based upon integrative big data, fintech, and financial modeling in a cloud environment-produce? What new values if any-will it create for current and potential insurers/banks and their end customers? These alluring yet rarely investigated questions swift the core purpose of this study to inspect the integration of big data, fintech, and financial modeling in the cloud within insurance and banking ecosystems.

III. ARTIFICIAL INTELLIGENCE: TRANSFORMING FINANCIAL MODELING

In the financial sector, AI is acutely changing operating paradigms, information production, and consumption. In recent years, great efforts have been surrounding the big data-enabled technical infrastructure for AI. This broad framing includes the adoption of high-performance computing clusters, databases in the cloud, information acquisition and cleansing systems, and R&D and production code that are crucial for the quantification of the dramatically growing amounts of structured and unstructured data in the big data era. AI is a running choice, choosing AI methods or techniques translates to different assumptions about the data generation process and how information is used to make predictions. To account for the generality of black-box AI models, great efforts have been devoted to understanding their success, i.e., interpretability, and justifying results, i.e., reliability. If the model cannot be relevant across data-generating processes or changing regimes, it is less useful. This literature studies whether AI can reproduce using conventional models'

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predictions or LOL?'. LOL indicates non-finite values of features when interpreting models. AI can lead to unrealistic blind or binary predictions and exacerbate prediction errors in overly simplistic use [2].

Currently, experimental designs aim to rigorously assess the true contribution of AI techniques to predictions. Interpretable heuristics and methods are proposed to provide more realistic models and rigorous criteria to evaluate the robustness of machine-learning forecasts. It quantitatively studies the competitive fits and forecasts of machine-learning and conventional models in the overall and persistent price-return series. AI models made forecasts about directional returns or price levels. Despite the impressive predictions results after hyper-parameter tuning, they do not efficiently reproduce the mechanism of the conventional models. AI techniques tended to hastier categorized or shifted more price levels over a longer forecasting horizon. Non-executed fits and regressions are used to disentangle the price mode examined and to propose cautionary steps. There are heterogeneous groups of competitor models to be explored for more precise forecasting. This review article studies theoretical and empirical advances on explainable AI prediction in finance and opens up avenues for future research and implementations.

IV. CLOUD COMPUTING IN BANKING AND INSURANCE

Gone are the days of rioting in bank queues to get a passbook updated or attending cash counters for notes exchange. Today’s world finds cash payment system gradually fading away globally, leading to digitalization of everything. Be it online banking, mobile banking, net banking, social banking, internet banking, and use of plastic money (credit/debit cards), banking has become much easier and comfortable along with service-oriented changes in all sectors. Similar is the case with Insurance – one of the most difficult tasks for a human-being today is calculating the expenses and risk factors of insuring different products like automobiles, properties, etc. In a Flash, things have changed drastically because of the advent of Big Data and Cloud Computing. Today be it a Financial crises, Earthquake, Floods or Tsunami Insurance companies are able to record and analyze innumerable factors efficiently. Cloud computing allows Financial companies to store larger amounts of real-valued decimal attributes (e.g. lat-long of the asset). On the other hand, the advancement in programming has made the cloud storage smart (Disaster Management, Real-time Assessment, etc.). New generation AI machines can access and analyze the data collected exceptionally and generate efficient Financial Modeling to keep things in control. This is something that was not present a decade ago [3].

This is the era of Cloud computing. Every task under the sky is done by running a piece of software either on the Mobile/Web/Console. Replacing birth-time Infrastructure with On-Demand Infrastructure is really a paradigm shift in Computing and Networking. The Financial domain is the biggest beneficiary of this cost-effective structure. Performance on-demand computing enables the financial sector to explore new areas of research and applications that are not possible before. Also, it has given rise to some computation-intensive new generation problems that are being solved with parallelization of the algorithms [4]. It is high time to harness the Cloud computing in any domain for better data handling, and classification and to save the planet from disasters at minimum cost.

V. THE ROLE OF DATA ANALYTICS

A large volume of transactions is produced daily from the interplay between insurance companies and stakeholders through a series of policies and competition between various stakeholders in the cloud-based banking and insurance ecosystem. The role of data analytics to fully understand trend analysis and anomaly detection in the cloud upsurge. The collection of data has the scope of product recommendations and forecasting future claims for different insurance policies. Predictive analysis of historical accident data and claim ratios from a specific location can happen with the help of big data analytics. The insurance companies highly rely on data analytics and modeling of risks since it cannot be claimed on something does not have the data set. Generally, data sets from the cloud have fair use regulations in terms of ownership and privacy as a part of shared data-oriented architecture.

For the cloud-based banking and insurance ecosystem, integrating payment systems using mobile Number, QR code, or UPI-IDs can instant share transaction amount or purchasing products with ease. The data can concern from an online payment gateway, ecommerce, and the bank payment due amount with respect to transaction identification details. Saving account transaction can be tracked through loss of documents or misplacement of saves can verify the amount with this data. This will drive to improve fairness determination. The fraud detection systems can use this data to verify both transactions from policyholders or claimants having discrepancy.

Cloud-based Banking Ecosystem Event Data Structure or bank technology event data structure bring the perspective of transactions that can happen in the marketplace for different configurations holding on the belief of price amount foundation. 1. Insurance Marketplace Event Structure – The change in the configuration of the cloud-based Insurance

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Ecosystem can be determined by trading of policies that classified as the purchase or cancellation of policies at trading instance with respect to insurance offer generating cloud-based applications. if the instance of trading policies is added possibly when there is change in the cloud-based insurance ecosystem such so the whole selling process of policies online. 2. Bank Trade Event Structure – The events of bank trade model only communicate active banks searching for a loan. If there is bank granting a loan of town then the banks budget in concern to amount will be decreased whereas loaning repository instance will be added consequently.

5.1. Predictive Analytics

Predictive analytics involves the retrospective exploration of data to create and assess the accuracy of models based on patterns in historical data. It entails the combination of sophisticated statistical techniques with tools that allow the transformation of data into information [5]. It also involves wildlife telemetry studies that collect behavioral data at higher dimensionality and complexity and have inherently spatial component explored at greater detail. In recent years, the advent of more proficient recording devices has been paralleled by a dramatic increase in the potential for the intelligent processing and comprehension of images. And thus major technological developments that facilitate the processing of coded data. The application of predictive pixel analysis techniques to wildlife telemetry studies is illustrated, for example, through the development of several publically available tools executed on free and open-source software packages. Novel applications, including the tracking of animal/eco-system networks using classic image analysis techniques, are described in open source innovation that shifts animal handling methods to more ethical protocols with positive knock-on public engagement potential. As wild environments change faster than they can be tracked by anecdotally collated reviews, the continual development of more versatile, customizable coding routines with open availability is called for. Systems used to code the retrievable analysis of coded data types into simple tools that can be adapted and presented for various users.

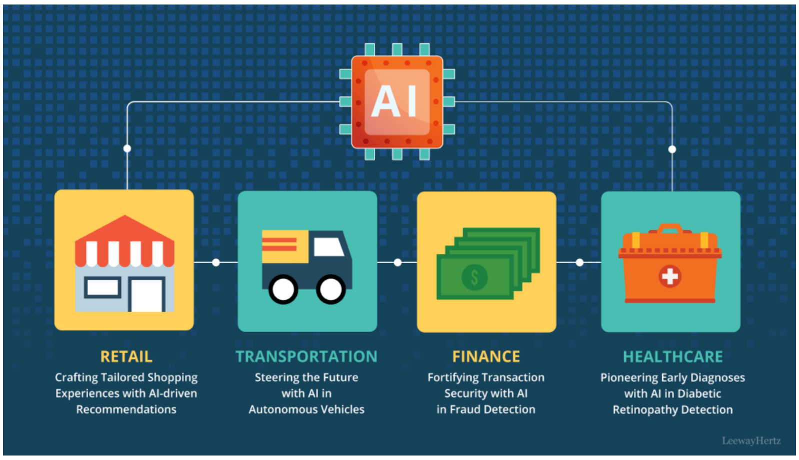

Fig : 2 AI integration

Provides an intuitive interface that incorporates user outputs such as graphs and statistics, and can issue finely implemented interactive procedures for web-based distribution. Such applications usually involve visualizations with different tagging and evaluation output types that have applications in image, sound, and text media, ultimately improving engagement potential with a broad audience base. The programming language packages freely available powerful routines that allow flexible handling and processing of coded data types including raster data, time series analysis, geographic information systems, etc., and facilities for their censorship in animation from near real time video streams across hundreds of independent cameras. Object-source routines for an expanding array of coded media are constantly developed in packages, lending to animals and their environments immeasurable return on investment (ROI) for equity based citizen science.

5.2. Descriptive Analytics

Descriptive statistics aim at summarizing the main characteristics of a dataset, with graphical representations. Descriptive analytics can help businesses identify trends and patterns in their data through visualization tools. Dashboards can be created on top of data marts containing datasets from multiple sources being restructured into a dimensional schema suitable for OLAP. Effective dashboards rely on UI design principles and help companies aggregate, slice-and-dice, and drill down data to identify serviceability, product performance, or anomaly clusters that need investigation. Descriptive statistics and analytics answer the question “what happened?” based on historical data that is assumed to be valid.

Descriptive statistics comprise indicators that summarize basic numerical characteristics of the dataset. Basic numerical statistics include proportions across categories, avg, min, max, percentiles, and bins for numerical variables. Counting-of-non-blank rows stats can identify missing values. They also include visualizations like histograms or box-plots for numerical variables or bar-charts for categorical variables. Descriptive analytics summarizes facts extracted from historical data with reports and dashboards that help answer the question "what happened?". Reports may aggregate, filter, group, slice, dice, or pivot basic statistics, while dashboards summarize key metrics or KPIs across segments. Time-series statistics may indicate performance trends, while point-in-time snapshots may indicate serviceability or inventory. Graphical representations can also help identify trends and patterns in large complex datasets. Many statistical visualization techniques exist, yet few of them are intuitive and effective in analyzing large and complex datasets. Visual analytics tools combine visual powerful representation with interactive exploration capabilities and rely on new displays that enhance human perception of complex data. Dashboards are interfaces that gather information from multiple sources, consolidate it into an appropriate model, taxonomize it, discretize it as rows and columns of figures, and classify it according to user needs.

5.3. Prescriptive Analytics

Prescriptive analytics approaches optimize the decisions in line with the goals of the models. Well-established prescriptive analytics approaches, such as linear programming (LP) and its non-linear and integer variants, regional econometric models, and simulation approaches, are widely used in the industry. However, they require numerical models to be defined, which are complicated in the financial sector due to the complexity of the problems and the lack of data [6]. As a result, development of robust modeling frameworks for prescriptive analytics in financial services is also underexposed. Classical optimization methods require mathematical formulations to be specified in the decision support systems. On the contrary, modeling with the proposed data-driven methods requires only data which are recorded in the form of tables. This cuts developments time considerably, lowers the barriers for development of prescriptive analytics tools in banks, insurance companies and industries. Lack of data, which is an obstacle key for using machine learning and big data approaches in modeling of predictive analytics, is not an issue for the proposed framework, as these learning-by-examples methods inherently require only the recorded data. To provide operating guidelines on why and how an optimization problem should be solved, the associated bottom-line consequences of the suggested actions should be estimated. Unlike forecast-driven prescriptive systems, which guess the best decision option(s) based on predicted models of the laws governing the financial process and an uncertain plan of the future (the so-called look-forward methodology), scenarios-driven prescriptive systems predict back the optimum sequence of events, on the condition that some specific events will occur next on the timeline (the so-called look-back methodology). The lack of goals, which are often an obstacle for using forward-looking optimization approaches, is not a problem for calculating prescriptions with the proposed scenario-driven systems, as the modeled goals correspond to the changes of the mock-up scenarios only (the motivation).

VI. INTEGRATION FRAMEWORKS

The financial services sector is composed of differently regulated industries including banking, asset management, insurance, capital markets, payments, financial market infrastructures, and wealth management. However, new disruptive financial technology trends may enter or impact multiple sub-ecosystems. For example, non-bank financial intermediaries that provide lending of contractual savings or deposit-taking transform from a banking ecosystem into a competitive shadow ecosystem. The boom of cryptocurrency-based payment services may question the validity of fiat money. Additionally, ever-evolving regulatory technologies and policies may disrupt or abolish fiduciary trading businesses. There is significant heterogeneity in the financial math models, components, and Internet technologies employed across the ecosystems. Resolving the heterogeneity and realizing seamless collaboration across the ecosystems is highly valued but remains an unaddressed research problem. All financial institutions, regardless of their types, sizes, and systems, need to follow the same market-driven compliance or regulations imposed by regulators. Since February 2021, the Financial Stability Board has put forth a series of recommendations on enhancing climate-related disclosures under the guidance of the Task Force for Climate-related Financial Disclosures (TCFD).

Eqn.1: Big Data Ingestion & Processing

$$R(t) = \frac{dD(t)}{dt}$$

- $D(t)$ is the cumulative data volume over time.
- $R(t)$ helps model data flow into AI/ML systems in real-time credit scoring or fraud detection.

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Integration frameworks may include suggestions on the interoperability of existing models. Gaps in mega quantitative models have been identified as insurance technologies have been assessed for the subsequent Tsunami. A wide range of integration interfaces is listed in a cloud-based ontology that represents 78 systemic markets selected from the International Monetary Fund's list. Enterprise models for the integrated ecosystems have been constructed and formally expressed using the Business Process Model and Notation diagram rules. Many-financial modeling-based enterprises, modeling types, disciplines, languages, and modeling forms have been specified. The multilingual, multilevel, and multi-illustrative modeling requirements for the integrated ecosystems have been analyzed [7]. Meta-models for the cloud-based ontology, interfaces, and BPMN-based enterprise models have been formally defined using the Meta-Object Facility, which may lead to the full implementation of tools that support the automated construction of the cloud-based modeling and simulation platforms. Mechanisms may include novel enterprise compatibility assessment between the two ecosystems.

6.1. Data Integration Techniques

Data mining techniques are increasingly being applied to various business domains, including banking and insurance, and are evolving into a standardized methodology with terminology (e.g., 'Big Data'). The advances made in the last decades are significant, but there are some important research issues that need to be explored further. Advances in big data storage and management techniques now support the use of the full probabilistic function for a single insured risk with modeled stochastic loss [8]. The key benefit of using this full probabilistic single risk loss distribution is that the insurance policy underwriter can compute any Value-at-Risk (VaR) and Tail-Value-at-Risk (TVaR) type of risk metric. Such tail risk metrics enhance classical underwriting formulas, including premium pricing dependence on tail risk uncertainty. More flexible pricing functions may include an accurate risk loading factor for expected standard deviation of loss and dependence on tail risk. Such capabilities are now in use by a big insurance data user, integrating full probabilistic single-risk loss distributions in (re)insurance premium pricing.

Big-data storage is the first layer of four proposed data layers, where data are stored using conventional RDBMS and specialized NoSQL databases. Data organization objective is to produce interpretative database tables from raw data in data storage. All data layers are provided with SQL- and media-specific dedicated query languages. Data organization tasks use relational technology, which is well researched and documented [6]. Data organization tasks for the third data layer are not well researched. For this layer, it is proposed to use pure scripting languages. Data organization tasks for the fourth layer, which interprets big-data into decision-making metrics, are also becoming an engaging technological proposition. For this layer, it is proposed to use a conventional programming language for developing sophisticated mathematical algorithms. All data layers must be communicated but must be independent enough to observe their organic development without mutual interference.

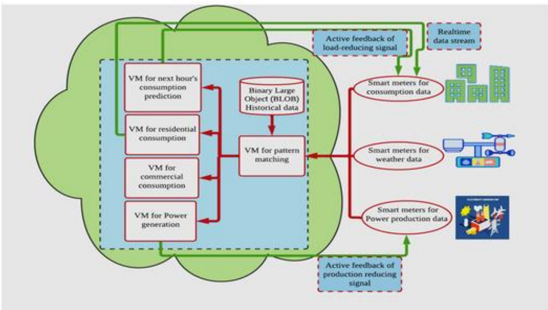

Fig : 3 Big Data Analytics

6.2. AI Integration Strategies

Various initiatives can leverage AI as a technology for system integration, process automation, strategic operational support, customer engagement, and innovative service development, as discussed below.

AI Enterprise Architecture: New spending plans involve the rethinking of enterprise needs for an agile OS based on open technology, often referred to as an API ecosystem. API-based enterprise architecture extends architectures beyond organization boundaries. It includes data lakes in cloud-based ecosystems and process orchestrators combining microservices and hyperautomated processes surrounding these data lakes [9]. Such architectures can be designed to allow for flexible data processing and application strategy integration, by linking data lakes and cognitive services in a data mesh approach. The economic ecosystems built on such hybrid architectures can offer extensive opportunities for increasing the retentiveness of customer relationships, lowering operational costs, maintaining regulatory compliance, and driving innovation.

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AI Exploratory Data Analysis: Exploratory data analysis—referring to the construction of a comprehensive knowledge graph of the data lakes—will be one of the most important efforts in the coming years. Data provenance needs to be analyzed in detail along with data taxonomies. Sophisticated data anonymization, filtering, and selection processes need to be established that even reflect the prescriptions of various data protection regulations. Data-rich scenarios where versatile AI systems can create new customer insights and create new customer intimate models and behavior descriptions need to be identified.

AI Strategy Integration: The economic strategy of the organizations needs to be integrated into the orchestrators on top of the data lakes. As strategy decisions at the corporate and business level typically do not involve strict requirements as commonly applied in process automation, the integration of new, often unstructured activities like strategy simulations based on AI-driven innovations imitating competitors, substantiating strategic options along with the creation of AI-based services needs to be embedded in cognitive components. Beyond monitoring surprises in competitive behavior, key economic figures on solidity or profitability may involve extensive heuristic-based procedures to be negotiated on all levels without formally modeled requirements. Data lakes will contain customer experience data and benchmarking insights to be exploited directly by intelligent systems [10].

VII. REGULATORY CONSIDERATIONS

While Big Data and its complementary technologies hold a great deal of promise for improving banking and insurance operations, the regulatory scrutiny of such development can be expected to intensify in the years to come. Traditional financial regulators focus primarily on the safety and soundness of financial institutions. Given the rising prevalence of data aggregation and AI-aided decision-making in the consumer finance landscape, however, regulatory authorities are starting to increase their focus on consumer protection. For instance, the Dodd-Frank Act has established the Consumer Financial Protection Bureau (CFPB) to regulate the unfair, deceptive, or abusive acts or practices in financial consumer protection issues. The CFPB not only has the power to sunset existing products and services in financial markets; more importantly, it also has broad authority to revise existing regulatory standards, screening for the potential unfairness of certain financial contracts and pricing mechanisms based on consumer characteristics. In particular, regulators are beginning to pay closer attention to the potential discrimination or fair lending risk that might arise from the use of Big Data. This can be expected to include the regulatory assessment of the various stages of the AI modeling pipeline for indirect discrimination effects, which could pose major hurdles to the interpretability and explainability of complex AI algorithms.

Regulators are also likely to increase their scrutiny of the data collection process itself. Online advertisement companies are already facing regulatory challenges on misconceptions with implicit consumer consent for data collection processes. Regulators in the insurance domain can be expected to scale up their regulatory scrutiny with respect of consumer data protection, particularly regarding the use of publicly available data. Recent cases in the United States have revealed how the non-consensual use of alternative data in auto insurance pricing results in the unfair pricing of car insurance coverage based on consumers' associations with higher reported accident areas. These regulatory considerations suggest that insurance and banking companies must pay close attention to their data usage paradigms, balancing the trade-off between innovation and regulatory compliance.

Growing scrutiny of anti-money laundering (AML) and fraudulent transaction detection can also pose huge challenges to the operational implementation of staring modeling and its application in credit/risk scoring. Despite the growing excitement around the accuracy discovery of ML-based algorithms, many financial institutions have chosen not to implement such algorithms based on the potential difficulties in satisfying regulatory compliance. With the assurance of transparency and auditability, traditional logistic regression models remain the most widely adopted ones in real-world applications. It can be expected that large-scale models deployed in both the insurance and bank industry are currently only applied in backoffice implementations rather than as part of the customer-facing products. The recently launched European Union Digital Operational Resiliency Act has brought about a huge wave of audits regarding the security and resilience of insurance and banking firms, which poses an enormous challenge to tech-savvy companies that use complex models ([11]).

7.1. Data Privacy Regulations

The emergence and adoption of new technologies introduced by the Big Data ecosystem, machines, human sensorial perception phenomenology, and the advances in Artificial Intelligence (AI) raised risks and concerns about setting and regulating a proper balance between an effective and efficient protection of Personal Information and the availability of such Information for the full establishment of financial services' pricing Invisible Hand. This tension substance calls for investment in a cooperative effort at a global scale and both legally and technically feasible solutions to the fore, whereby

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high standards for the accounting for and safeguarding of Data Assets combined with distributed, decentralized, open standards, and blockchain-like techniques would ideally serve towards a competitive anonymity. The task at hand is monumental, namely to safeguard Privacy in the Big Data ecosystem in the financial industry and society while unleashing its full powerhouse potential. The economic environment of the financial services marketplace has dramatically changed in the wake of the global downturn of 2007-09. Cheap computing and storage power, Social Media, and the sensors of ever-present and ever closer smart devices create a diverse, rich, new, and Big Data set. Data science promises to take the current unclean, raw data into a new realm of Detection, Decision, and Prediction, and Machine Learning and AI close the loop from user interaction, data accumulation, and data-mitigating risk actions [11]. The balance of powers in this new Big Data ecosystem has shifted considerably towards the Data-holders, which gives rise to Privacy and other concerns. The best means to safeguard Privacy Assets in the age of Big Data are still to be discovered and implemented. Simply copying current policies for banks and insurers in order to diffuse concerns about Data-haulage and risk is certainly not the adequate way to go about it. In the context of the venture for mainstream Data Innovation in the financial ecosystem in order to provide cheap and personalized financial services on a mass scale it is important to safeguard the delicate balance between the sufficient protection of Privacy as a foundation of the financial services ecosystem and the availability of such Personal Information, the basis on which treatment policies and risk mitigation can be built. This tension is not trivial. It would, if not handled wisely, potentially result in economic apartheid, whereby the possibility to engage in the subprime market for cheap and personalized Financial Services is gated by disproportionate monetary wealth.

7.2. Compliance in Financial Services

Rising regulatory scrutiny in the financial services industry has brought compliance risk to the board level and increased pressure to the Chief Compliance Officers (CCOs). Stress testing as a practice for evaluating the adequacies and soundness of financial firms in light of executive risks is being applied to compliance risks in the form of compliance stress testing (CST). Even though CST has shown great promise, its implementation is also daunting given the challenge of data scarcity, the need for AI and envisaged risk scenarios. It calls for an automated CST solution that takes well-established compliance controls as inputs to generate a black-box CST model suitable for financial regulators and financial firms.

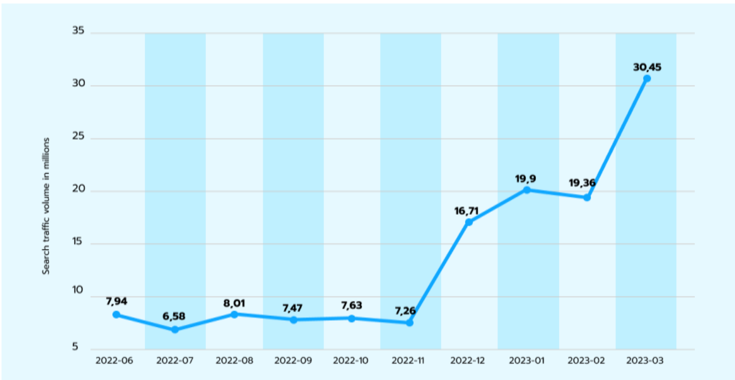

Fig : Enterprise AI In Banking And Finance

AI systems experience flourishing adoption in the financial services industry, aiding organizations in making automated and optimal decisions. However, their utilization raises interpretability and explainability concerns. Failure to elucidate mechanisms by which AI systems produce predictions, make decisions, or classify instances can lead to catastrophic consequences. For instance, firms like HSBC and American Express are fined billions of dollars by regulators due to careless AI model developments that obscure regulatory obligations. Meanwhile, legacy governance processes established for conventional models are facing uphill battles to keep pace with AI models that exhibit inherent performance, cost, complexity, agility, and scaling issues. The adequacy of current governance practices for the next generation of AI models is increasingly questionable, particularly in the financial services industry. Consequently, this paper focuses on some of the common challenges in AI model governance and offers analysis as well as solution opportunities. A system-level framework with modular building blocks for the development of such an approach is presented. It is expected to incorporate increased automation, integration and configurability into the AI system towards self-regulation. Moreover, it provides key capabilities to contain the existing challenges and enable more effective and compliant AI solutions.

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VIII. RISK MANAGEMENT IN CLOUD-BASED ENVIRONMENTS

Cloud-based computing has gained significant popularity over the last two decades. The fact that the total revenues in the cloud space have reached approximately 500 billion dollars solidifies this argument. It is assumed that this exponential increase in popularity will continue uninterrupted into the next decade. Most of the internet-based technologies that exist today can be attributed to the innovations that have emerged in cloud computing. [8]

The ISO standards have highlighted that a cloud is an abstraction of integrated physical and/or virtual resources. Resource pooling capabilities provide consumers with a perception that a broader resource pool is available for consumption. Additionally, cloud computing makes the scale of resources consumer-independent by enabling on-demand self-service. The pooling, elasticity, and high throughput capabilities are fundamental and distinguish cloud computing architectures from the previous client-server architectures.

From a consumer perspective, the latest PaaS cloud architectures, which utilize microservices, server-less frameworks, and streaming technologies, provide several benefits that have not been available in the client-server era. The most important of these benefits are reduced capital and operation expenses for hosting proprietary software vendors, as no physical servers need to be purchased, installed, or operated on-site. On the other hand, service availability on the cloud becomes critical, as it subjects large technology conglomerates and country-level data breaches to large regulatory penalties. In the insurance and banking domains, concerns about analytical models and originating datasets being stored externally are very critical. Thus, additional auditing mechanisms to assure that analytical models' outputs were not tampered with by cloud service providers have emerged as important topics for further research and application.

8.1. Identifying Risks

The increased availability of new knowledge data sources improves the capacity for risk assessment and risk modeling in loan default and insurance claim risk events. In general, these data sources result in new and improved risk assessments of both the individual entity distributions and the correlation structure. However, the magnitude of the data complexity at the entity-level can make it unmanageable or impracticable to utilize risk modeling approaches. Among the potentially large number of new knowledge data sources, this work identifies the most important ones that result in a significant improvement in risk assessment/forecast accuracy compared to traditional data sources or models. A hybrid approach that captures both non-structural empirical relationships and structural statistical relationships is proposed to identify the most informative new data sources and input data variables.

New data sources and data variables are identified or "discovered" based on the potential for improved risk assessment or forecast accuracy, as quantitatively determined based on out-of-sample accuracy measures. The knowledge discovery process is tested and validated with the identification of new data variables that result in a significant risk assessment or forecast improvement in a default risk model for publicly listed firms in the US. An overarching hybrid credit risk modeling framework that integrates ratio-based models with the identified new data sources and data variables is then proposed [8]. This approach is tested and validated with an empirical application that significantly improves the out-of-sample default risk assessment performance of several structural risk modeling frameworks based on new knowledge data variables in loan origination and utilization.

There is a potential synergistic interaction between both research streams, i.e., the integration of these new knowledge data sources with existing risk modeling approaches and techniques commonly applied in risk assessment institutions. This is highly timely given the tremendous rise of new data sources in both the loan origination and utilization stages of personal loans brought on by Fin-Techs, Credit-Scoring-Startups, and the restructuring efforts at the legacy banking industry, as well as by existing firms pursuing similar strategies to better compete with the new entrants.

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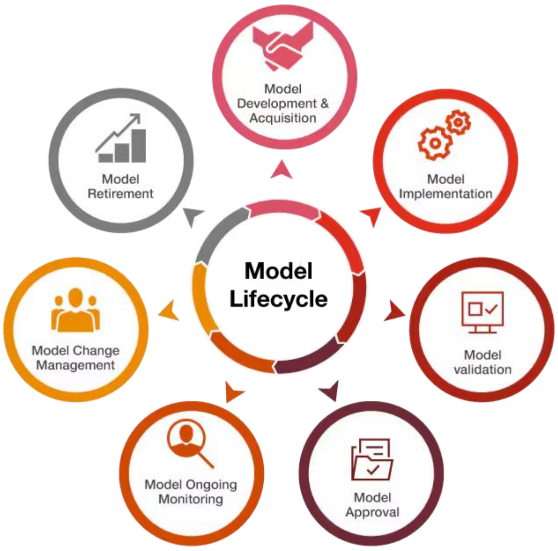

Fig : 4 Financial risk analytics

8.2. Mitigation Strategies

Insurance and banking markets are characterized by information asymmetry. Insurers and banks, as one side of the market, possess extensive data on risks and portfolios, including risk scoring, history, and expected performance. However, they lack historical outcome evidence for the new product business volatility, which could lead to a massive decline in values. A 'silent' disaster or bankruptcy pool with magnitude either small or large relative to data arc may lead to thousands of times loss amplification for insurers and banks. Big data streams, new data processed by varied data sources, and financial firms' ecosystem data in Financial Technology enable deep learning models to predict both the state and uncertainty associated with the state for the new product. Similar to catastrophe modeling, prediction can be both event-oriented modeling under stationary assumption and perpetually-on modeling under non-stationary assumption. The invention of cloud computing allows financial firms to process and manage necessary data without memorizing data for deep learning modeling. Processes with prediction can efficiently handle and prevent future catastrophic events on the misspecified values, enhancing non-Alphas as new Alpha boosts. Multi-core and geographically distributed cloud architectures promoting parallel and distributed deep learning modeling empower financial firms to widen both data input and strategy optimization. Cloud-based financial firms with strong software-level data protection can avoid security breach-based model snatching.

Understanding of recent excess returns is a challenge for insurance and banking markets, due to the time/clustered variant characteristic of shock acceleration and accumulation. The complexity surrounding interpretability is originally defined at a macro perspective on a sample dataset and corresponding test variable. The direct processing method consists of two phases for trained deep learning models in cloud-based insurance and banking ecosystems. The first phase is agent integration, which involves retraining deep learning models in another cloud and accommodating extra agent features for data preprocessing. The interpretation method is built on the collected mini models of the second phase and unwavering network architecture. Each mini model retrieves the state probability of tested inputs at the reward loss function. The final understanding result consists of similarity clusters based on the retrieved state probability dimension and heuristic inference by sketching numerous intriguing insurance policies and the model-based simulated stock market. The comprehensive understanding can take effect to enhance the model predictive ability across jurisdictions. With necessary enhancements on state domain definition and input representation, the understanding method can be extended to computing cloud/edge-based risks and deep learning frameworks of other arts.

IX. CASE STUDIES

This section introduces modeling methods and principles conceptually via a case study using historical and modeled hazard and financial data layers. The technological advances of 'big data' combined with a regime of transparency are creating prerequisites for a sustainable and responsible insurance underwriting process, enhancing credibility and trust among all stakeholders in the (re)insurance marketplace.

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The insurance risk underwriting and transfer market players have an incentive to pursue sustainable and socially responsible practices, demonstrating thorough understanding of risk profiles and skill in fairly managing insured assets. Big data capabilities have the potential to support a new level of utility in awareness analytics, detecting significant gaps between insurance coverage, physical and financial asset values, and human preparedness in vulnerable geo-spatial areas. Continuously servicing the data requires standardization and transparency for efficiency, while data security requires controls on accessibility and usability. This addresses vulnerabilities from exposure to natural perils and climate change risks, including financial liabilities and contingent business interruption risks.

Eqn.2: Machine Learning for Credit Scoring or Risk Prediction

$$P(\text{default}) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n)}}$$

- x_i are input features (e.g., income, debt ratio, payment history).
- β_i are learned parameters.

The insurance sector is concerned with many business problems of interest to the research community. By analyzing and gaining insights of their claim data and customers' claim patterns, claim costs or resources can be reduced and managed effectively as well as risks or fraudulent claims can be recognized and detected. This paper presents a case study involving an independent insurance group, a small-medium insurance company who insures household appliances and gadgets. The research looks at existing claims, analyses the claim data, and figures out the claim patterns using a variety of techniques within the methods of data mining. In the data analysis, it analysed trends and extracted insights from the claim data; what kind of a claim is driven by a certain set or combined set of factors such as the age of customer, what type of a claim that a customer tends to make. The analysis found that a product claim tends to be a customer who is younger than 35 years old and the claim tends to be made within 1 month of the policy being active.

9.1. Successful Implementations in Banking

Acknowledging the extensive application of big data and AI in various sectors, the Financial Industry Needs section highlights successful implementations in banking, insurance, and securities industries. Nevertheless, most applications are confined to conventional quantitative strategies, and notable integration between financial modeling, big data, and AI remains scarce. In this section, successful implementations in the banking industry are emphasized, but challenges are also acknowledged. The vast amount of market data collected and processed daily by financial institutions is a treasure trove for diversified applications of statistics and machine learning techniques. The initial development of automated stock trading and portfolio construction platforms using traditional statistical and econometric modeling approaches either failed to reflect the non-stationary features of stock markets or encountered numerous dependencies in the modeling process. Conventional financial options pricing and risk management models were either too simplistic, demand-tailored the closed-form solution when in theory, or computationally prohibitive with a high performance requirement when implementing in the stochastic simulation/machine-learning framework.

The banking industry relies on predicting customer churn, assessing credit risk, and loan default prediction. With a comprehensive framework for data processing and modeling, dozens of models for either customer behaviors predicted product deployment or credit scoring can be constructed automatically with a wide range of commonly used statistical and ML algorithms. The performance of each model and ensemble strategies of the top-performing models are elaborated, and the daily model retraining triggered by the label update is focused. The model selection framework is initially introduced but not elaborated due to confidentiality policies. As a pioneer in financial quantization, the extensive application of statistics and ML-based financial models in the banking industry is elaborated, including customer churn prediction, loan default prediction, credit scoring, and automatic customer behaviors analysis.

9.2. Innovations in Insurance

Although the revolution of Big Data, AI, and analytics is a relatively new trend in the insurance business, it has massive and immediate impacts on both the operational and strategic levels of insurance companies. They have started using these innovations in technical areas where they can have the greatest impact and are least disruptive. On the strategic level, there is a large and growing shift toward analytics-based business models to create value. With more businesses harnessing insights from data, there's also a greater concern over families' and individuals' data privacy. Balancing creating value with keeping consumers' data safe is one main challenge to actuaries and other practitioners in this new era of insurance.

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Eqn.3: Financial Modeling: Net Present Value in Cloud-Based Pricing

$$\mathrm{NPV} = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t}$$

- C_t = cash flow at time t,
- r = discount rate (cost of capital or WACC),
- T = total time horizon.

The groundwork for many of these evolving capabilities was laid well before the rapid advancements seen today. Incremental improvements to existing analytic models combined with advances in hardware are allowing insurance companies to revitalize their businesses. But some changes have occurred at an unprecedented pace, bringing new challenges. The introduction of Big Data into insurers' environments has had repercussions across the company, reshaping the ways in which many traditional analytics approaches operate and fit into the overall scheme of who does what and why. It requires companies to rethink not only when and how to take advantage of new data sources, but also how to balance and integrate Big Data approaches with traditional machine learning and statistical methods.

X. CHALLENGES IN INTEGRATION

The collection and use of telematics data represents one of the first and most significant developments in the insurance industry regarding collecting data from policyholders' technology. Furthermore, telematics can measure drivers' behaviors such as event-based harsh acceleration, hard brake, and reckless driving in addition to basic driving information such as time and location. These more granular sets of data allow insurers to not only price the insurance policies more accurately, but also provide premiums and loss prevention information on live policyholders. The rapid growth of this information type proxies profound change, hailing not only a development of insurance, but also a transformation of relationship between insurers and policyholders. This innovation can be viewed as part of an even larger trend—the growing willingness of insurers to use new types of information to justify offering consumers different levels of access to insurance products.

XI. FUTURE TRENDS

Emerging financial ecosystems will see robust advancements in business assistance cloud services for insurance tech start-ups and banking fintechs, generated by smart advisors powered by AI and Big Data. Smart advisors will integrate modeling capabilities, enabling financial ecosystems services (e.g., expense insurance, credit limit simulation) for clients to explore product recommendations. Subsequently, a call center for insurance tech start-ups will provide clients with 24/7 service assistance and an integration of process automation to steer end-users through demonstrations and explorations for tailored financial services.

As black-box artificial intelligence (AI) solutions gain traction, the cloud-based financial ecosystem platform will handle a wider range of investor demands and serve diverse financial organizations. Furthermore, next-generation technologies and services will empower financial organizations to mitigate investment risks, adapt delayed financial regulation policies, and pursue business expansion across sectors. Insights generated from streaming Big Data will proactively control risks by preemptively alerting actors about impending crisis exposure. Along with supplying explanatory resources on exterior factors affecting the target institution, cloud-based ecosystems might trace asker's demands across social media or popular news.

Emerging insurance and banking fintech entrepreneurs will be willing to adapt their operating fabric and tools to newly available technological advancement clusters. In the era of smooth multi-channel business automation, streaming Big Data and distributed learning resources will offer even cheaper service options. This will result in assimilation access, enabling even firms with limited capital to provide cheap, highly tailored products and devices. In the aftermath of emerging ecosystems, common sense can be used to visualize modeling requests of insurance tech and fintechs when modeling and running a complex model chains. Because of the complexity of cloud services and the rapid advancement of large AI services, there is an opportunity for knowledge in market engagement and social behavior, especially as it applies to the adoption of technologies in the public sector [10].

11.1. Emerging Technologies

Within the last two decades, the dramatic increase of housing prices and the associated rise of default intensities have made the predictive capabilities of existing models hard to cope with. To address this, it is proposed to develop a computationally efficient nonparametric multi-dimensional model for real-estate collateralized loans. The model

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ingredients are LiDAR data available via cloud computing in combination with different kinds of public datasets on code violations. The proposed hybrid approach combines the inexpensive advantages of a data-smoothing approach based on transepts for predicting default intensities. To assess the quality of predictions, it is validated against recent historical default intensities. A novel data-enhanced Kalman (DEK) filtering approach smoothly updates noisy vehicular traffic data to achieve a robust, accurate estimate of hidden vehicle population density. The DEK approach is tested on simulated vehicular control problems where the connection between actions and results is complicated. Building on existing filters, it is shown that a Kalman filter (KF), properly applied, can be employed to mitigate heavy noisiness in traffic density recordings, obtain robust estimates, and identify hidden dynamics [8].

Nearsightedness, overestimation of own decisiveness, inattention to unexplored alternatives, and blindness toward the future lead to inadequate risk assessment and faulty actions in the novel approach to adapting models to changing environments. Once a new value is established, it is able to efficiently dismiss a large amount of irrelevant information. It thrifts noisy observations with enhanced statistical approaches. Such adaptable models efficiently take into account recent, relevant observations while ignoring past, obsolete information [6].

11.2. The Future of Financial Services

This chapter presents the current theoretical advancements and trends in cloud-based financial services, including blockchain, AI, DeFi, and big data analytics. It integrates analyses from the cloud-based technology, AI and IoT, big data analytics and visualization, and financial technologies domains. The current state of research is investigated, and the future areas where theoretical advancements are needed are identified. This literature review provides future directions for building cloud-based aggregated intelligent analytics financial services and developing sustainable and trustworthy AI in finance [1].

Artificial intelligence financial technologies refer to the collection of software, hardware, algorithms, and interfaces based on machine learning, deep learning, AI, computer vision, natural language processing, and other AI techniques, which can be used to assist, substitute, or fully automate the processes of prediction, classification, visualization, discovery, reasoning, and optimization in the financial domain. The methodology cluster analysis of co-citation profiles reveals that AI finance is a booming and hot research area, especially in the past two years. Besides the general technology focus on ML and deep learning algorithms, traditional theories, such as behavioral finance, market microstructure, asset pricing, and volatility modeling, are integrated with the corresponding AI technologies to improve the general performance and robustness of the research.

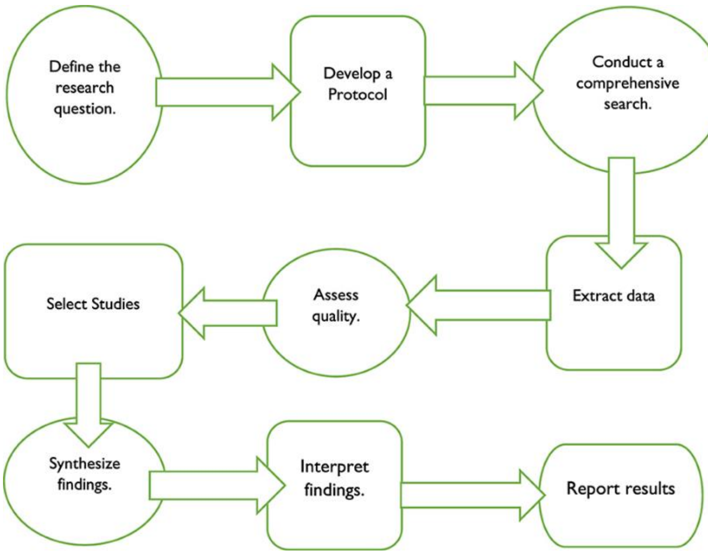

Fig : 5 The role of big data in financial technology

In summary, a review of AI finance literature that covers the breadth and depth of topics, methods, and techniques in this emerging financial technologies research domain is provided. The review reveals the current research status and future research opportunities of AI financial technologies to fill the detected gaps and maintain the ecosystem sustainable and trustworthy. Specifically, future research opportunities and possible research questions are provided for building cloud-based aggregated intelligent analytics financial services from the sustainability and trustworthiness perspective.

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XII. CONCLUSION

Innovative perspectives in performance analytics, privacy protection, and governance standards can significantly augment the capacity of AI to fulfill its potential in the financial services industry. Alternative innovation design and ecosystem governance perspectives allow to assess the value-generation potential of more innovative and dual-use tools such as AI on a transversal level. Consequently, a systematic gaps analysis of current AI innovation and governance regimes is presented to identify factors augmenting the AI health management market failure in the financial services industry. The AI health management ecosystem is proposed as a new innovation-regulatory ecosystem design for the AI conditioning and deployment of investments in AI in the financial services industry, containing an action plan. The AI health management innovation-governance ecosystem can end the current AI health management governance deficit by establishing more complete incentives, regulating dual use, countering monopoly power, and incentivizing orgs to prepare contingencies as well as robust and safety-critical AI. Given the strategic importance of AI in times of increasing geopolitical competition, these solutions provide policymakers a unique opportunity to mutually explore innovative regulations at the global level harnessing economic growth opportunities. A number of revolutionary developments are transforming the financial services landscape. The rapid emergence of AI as a transformative and dual-use technology affects all industries but is of critical importance in the financial services sector.

Innovative tools such as recommendation systems and fraud detectors can augment the capacity of transactions and investment research in capital markets. In addition to the economic upside, emerging market liabilities, however, require economic state capture and a change in market discipline. The design of innovative regulative responses to market failure forms a concurrent research agenda. Global competence in deploying AI entails global competence in regulating AI. The AI health management ecosystem is proposed as a new regulatory ecosystem design for the deployment of innovations to regulate—and thereby verify—the health of AI in the financial services sector globally. AI fatigue in the financial services sector can be addressed by building an AI health management ecosystem to eliminate market failure. The growing whistling of the AI revolution suggests that the initial lift of positions to regulate AI systems seems to have rapidly faded. Given the urgent at risk market trajectories brought about by dual-use applications in the financial services sector, the increased confidence in ruling over the development, deployment and impact of AI activity to assure compliance to a harm-free or just-fair expectation is also in still shorter supply.

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