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Cognitive Core Banking: A Data-Engineered, AI-Infused Architecture for Proactive Risk Compliance Management

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Abstract

The long list of AI governance challenges motivates the need for new solution approaches. A portion of these issues are general to deploying AI models. An exploration of the broader concerns attempting to address the high-level risks of AI use in financial services is presented. There is however a perceived gap between those objectives, and the practical applications supporting the mass adoptions of AI systems in the sector. The focus is on the latter. It is acknowledged that a vast amount of work remains to deliver the promised economic potential for society, first and foremost the widespread understandability and trustable AI systems. The financial services industry is undergoing a profound transformation from static compliance to continuous adjustment of short-term risks. Such transformation requires a decision-making system that can well respond to the proactively evolving operational environment in real time.

Such awareness has pointed out a long list of risks induced or amplified by AI systems. It is agreed that improper use can result in severe harm and entanglement. Critics have broadly categorized the hazards falling into bias, security, accountability, and oversight. The financial services are a significant application area of AI systems. This broad "financial services" comprises a vast ecosystem that includes different business activities involving personal, institutional or governmental finance. Several of the breakthroughs in machine learning and artificial intelligence have been leveraged by the finance sector, which has long been a source of fundamental research questions, particularly in the areas of prediction, time series, and optimization. Today most of the leading global financial institutions have adopted or are exploring the adoption of AI systems across their business activities, for B2B or B2C. The variety and complexities of AI systems used in the financial services, however, have also revealed a range of new challenges.

Keywords: Proactive risk, core banking, banking AI, banking risks monitoring, risk event prediction,

1. Introduction

The growing importance of and elevated reliance on the quality and services delivery of financial services are major results of the evolution and pace of the modern world economy. Financial institutions are under pressure to be competitive and profitable, while providing a wide range of financial instruments, from personal banking for individuals to corporate banking for corporations. This augmentation, indicated by the worldwide competitiveness to attract deposits and diversify their financial services, leads to the necessity of never-

ending renewals in the information systems of financial organizations.

Moreover, it can be seen that the public authorities demand quite stringent rules to regulate and control the activities of those organizations. Thus, as well as competition rises between institutions, it is unavoidable that compliance issues come into prominence. Especially for the banking sector, the prudential supervision which is actualized by the public authorities to maintain the stability of the financial system and to safeguard the deposits of the people holding bank accounts at these institutions are needed to take the advantage of high level automation support systems. On the other hand, the institutions are under surveillance of public administrations continuously due to the competition to utilize the latest technology together with the efficient and effective usage of the financial instruments in the market. Also, the recent updates in several regulations taken place in the global arena in the last decade have caused financial institutions to renew their core banking systems. Taking into account all of those findings, the actual requirements, as well as the general regulatory issues, the need for a novel core banking architecture was highlighted and proposed. It is a data-engineered and AI-infused architecture coordinated by a cognitive risk engine to fulfil regulatory functions in the pro-active way in terms of interest of compliance of the institutions. The proposed cognitive core banking architecture is expected to master the necessities of the new era banking business. This will ensure that the institutions are always compliant with the taxation requirements more than ever creating any chance of being ahead of the regulatory activities. Each action related to the deposit, loan, or any other possible probable transactions within the time is concerned and defined with corresponding penalties in advance. This catalyzes the institutional compliance operation, and eliminates the benefit of any disobedience strategy by the institutions. Besides, providing the facility to analyze and simulate the effects of new products, new customer portfolios and regulatory impacts. Any decision taken within the scope, probably affecting other mechanisms, is instantly checked, and either cancelled or enabled, if some criteria are not satisfied replicated with simulation. This will also provide a competitive advantage to implement such ideas in an institution. What is most remarkable is the fact that the whole view is designed in a compact way on any laptop or the equipment distracted with the institution of the members, giving centralized control to the bank top management. The contemporaneous compliance, on the other hand, will give the institution a flawless reputational compliance report ensuring the ongoing business with no disturbance. This is because the institution, in this era of increased scope of scrutiny, is always under examination of prospective partners, boards, or public publicity.

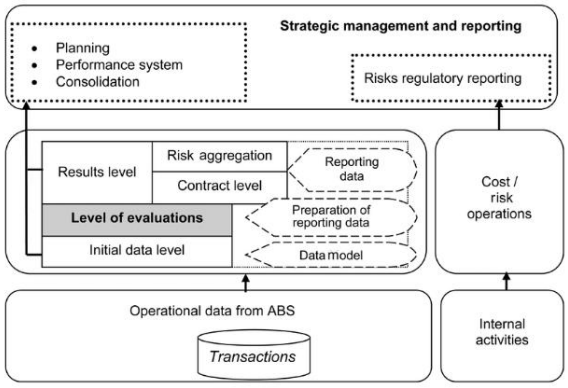

Fig 1: Architecture for risk management Source

1.1. Background and Significance

Background and Significance. Continuous control and requirements of financial institutions by banking supervisors and regulatory authorities lead to the need for transformation of banking software. Along with the development of information technology (IT), these requirements have the tendency to get sophisticated and extensive. Features of requirement as well as requirements themself could be submerged in the vast quantity of normative legal acts of national and international level. Finally, the core of compliance is risk control, making it particularly sensitive. It is likely that information about new requirements will be missed or interpreted by bankers not completely, which increases additional

risks due to, for instance: late and incorrect reporting to a supervisor.

Compliance risk is not only the failure to comply with laws, regulations, and rules, but also the exposure to the bank's reputation and the impact on customer trust. In addition, the regulator on the bank pays much greater attention to the implementation in practice of not only the current requirements, but also the possibility of being able to quickly take new requirements into account in the business processes of the bank. Thereby, the managerial and competitive task for Information Systems Development (ISD) department is the maintenance of knowledge about the requirements in Information Technology (IT).

Since the Basel Committee on Banking Supervision (BCBS) introduced its internationally recognized collection of frequently asked questions on its risk-based data quality regulations, financial institutions around the globe have been better equipped to ensure ongoing compliance. Increasing focus is now being placed on the quality of official statistics, given ongoing financial market volatility and the need to restore confidence. This is important against the backdrop of a changing policy environment, where new or increased statistical reporting requirements are forthcoming or existing ones have been re-prioritized.

Equ 1: Proactive Risk Compliance Management (Optimization)

$$\min_{\mathbf{u}} \left[\sum_{t=1}^{T} C_t(u_t) + \lambda \sum_{t=1}^{T} R_t(u_t) \right]$$

$$R_t(u_t) \leq R_{\max}, \quad \forall t$$

- $C_t(u_t)$ is the cost associated with the actions at time t,
- $R_t(u_t)$ is the risk level at time t for given actions u_t,
- $R_{\max}$ is the maximum allowable risk,
- λ is a trade-off parameter between cost and risk.

2. Understanding Cognitive Core Banking

Money and economic resources are fundamental to all human activities. Banking and financial institutions operate by gathering money in various ways, such as savings, current and term deposits, and creating some credit money, such as debt, through loans. Banks serve these two fundamental functions: to manage and safeguard public money and provide credit to finance the exploitation of the economic sector, trade, agriculture, market, and small-scale industry. The system of banking is a huge network for credit distribution. Banks implement various types of credit systems, such as agricultural loans, industrial loans, tuition loans, and housing loans. The most common demands are cash credit, overdraft, and bill discounting. It is estimated that financial service institutions have an important role in the financial sector. Therefore, the banking sector must be very cautious.

Cognitive Core Banking (CCB) is introduced as an original architecture. It is designed to increase the capacity of a bank to understand its clients and predict banking behaviour by integrating a strong data engineering process with AI services throughout the bank. The banking platform consists of a front office, a middleware layer, and a core banking service with several important components.

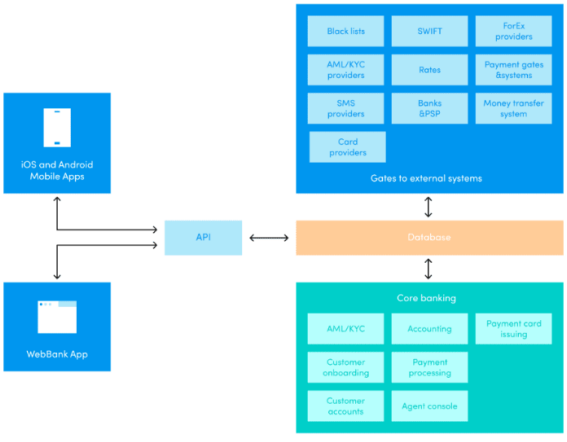

Fig 2: Cognitive Core Banking

2.1. Definition and Scope

A major challenge of conforming to financial solvency requirements and avoiding high fines, market scrutiny and a negative reputation is the

granularity of regulation detail and the complexity of human language used in policy making. Established banks own many-fold more policy documents than financial reporting standards alone. Converting this volume of documents to understandable formal logic fills many volumes of paper. Being offered such a paper can averse a change manager. Data materialisation meta models can provide tangible value and render change actionable. Within the context of the novel directive an infrastructure to harvest meta data is vital. This requires a repository based on a model that expedites access to bank's network share drives. Data access protocols must be general enough to cover all meta models imaginable in many big and complex systems architectures, and in domain policies. Mechanisms must manage a life cycle on homonymous and conflicting metadata. Implementations are necessarily language specific. Unified architecture can only be achieved for a single language. International banks, confronted with a multiplicity of languages, must therefore industrialise in this area – namely must tool support for all policy management data text used in a change project plan. The tool must be agnostic, criteria for such a tool are presented, superior performance being observed for a data dictionary vendor.

2.2. Historical Context

Complying with BCBS 239 is a major challenge for established, legacy banks. Cognitive Core Banking is a novel concept of a data-engineered transaction evolution architecture for reaction proactivity and automation to operate with the help of explainable, trained ML systems. It maps the full service and product data lineage from point-of-sale across all heterogeneously modeled and hierarchically ordered abstractions of data systems. Brave experiments show that the industry model operates technically on the same foundational panorama of transactional traceID-hierarchical data with transformation daisy chains and assembles product services from consumer data. Moreover, CCP induces a frontline dissemination approach in the business organization that empowers the creation of ML-systems directly by the business itself, hence leveraging competitive advantage. Key challenges concerning CCP are the glossary of transaction data, the required organizational adjustment, the technology developed to manufacture CCP living per business areas, and data-incompatible franchise teaching. Compliance with the principles for effective risk data aggregation and risk reporting, as set out in Principle 1 to 11 of BCBS 239, is a major challenge both for banks in general and for Deutsche Bank in particular.

The maintenance of a sustainable CCP environment is at risk for BCBS 239 due to the future transformation of trained ML systems. In reaction to CCP, the business organization defines a new service product model in a firmwide data taxonomy, basically per product architecture. This conflicts in many corners with the underlying service-for-division model structures. As banks give up the trade-off between income and complexity adopted during the crisis, nothing about operation time requests and trade-offs is known. The compliance of CCP-living training by business areas is an enormous challenge. Modeled hierarchical transaction data in the MARS architecture as a barrier to new, innovative ML-systems directly trained from it. Reactively activated explainable ML-systems is the answer.

3. The Role of Data Engineering

Financial institutions are data-centric. The data can provide a deeper understanding regarding how organizations like banks perform their operations and visual autonomy between data and processes. However, providing a global view of data that is regularly changing, together with privacy and security restrictions, is still a challenge. Moreover, due to market regulations, financial institutions are required to manage a vast number of reports, to meet a long range of conditions, using much of the organization's resources that, otherwise, could have been used to offer financial products and services. To meet these requirements teams of experts continuously check the internal data, and correlate it with external ones to evaluate if the institution is

facing risks, like credit risks or if it is respecting the market laws, like the one against laundering money.

To visualize the data-analytic pipeline, besides the traditional data-driven one, dedicated processing elements have been tested. Banking data sets, under the format of business-Artifacts of a certain temporal range, are already provided. Job1 retrieves the business-Artifacts schema and distributes the text files across the cluster and other jobs as well. At the high-level, Jobs 0 to 3 run a map-reduce-based data-engineered pipeline to process the provided data sets to produce the Knowledge-Base. The idea of a Knowledge-Base is at the core of the data-engineered pipeline and it is articulated around financial knowledge items (FKIs). This asset is added to the report data sets to better favor the risk-compliance estimation. Several approaches to interact with the Kb have been developed and tested. Transformed into RDF, knowledge content is handled by dedicated tasks to inspect it. Moreover, a web-interface has been set-up to query the Kb.

3.1. Data Collection and Integration

The endeavor of the current care research under study is to assist banks in managing their risk exposure effectively, enhance the fairness of the risk modeling of banks in developing and emerging markets, and finally to promote financial addition under the guard. This is achievable by creating a behavior analytics structure that merges several models from opinion to deep learning for advance marketing based on customers' bank details. The architecture's iterative visual aspect allows the conduct of highly interpretative risk behavior analytics by banks for customers with the intention to affect their bank account's regular behavior. The data collected from the instances is then kept at remote servers for forensic data analysis. If the banks do not want a remote advance to be used on data, they can destroy the evidence of the attack. This is reasonable in several circumstances; since the data is big or the analysis is difficult, the distant edge of the data is more publicly available. Privacy concerns may arise. The dataset followed is not shown in the table because they cannot be shared. The data is classified because it would cause the police to be discovered. To protect the data, it is shown in a group of files; techniques can also be realized in the same pattern. Each technique could be utilized to request queries and store the data in a particular section of servers. One of the most recent methods is the usage of data management in cloud services. Third party companies are offering services to scale and distribute the dataset. In a similar pattern, the service providers can extract the dataset using APIs at the same location, in three different databases. This method has been broadly employed by a few commercial financial institutions. Alternative setups can be made by enterprises by obtaining the Report and Score API. Alternatively, enterprises can benefit from Data Datasets to request queries and gather the receipt in the DATASET.

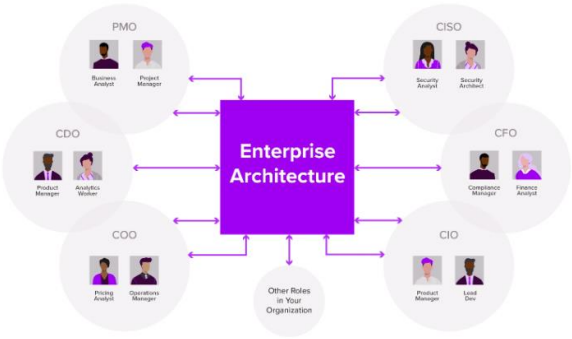

Fig 3: Data Collection

3.2. Data Quality and Governance

Banks have long treated data as an important asset in the context of compliance and governance. With the digitalization of the financial services industry, compliance and governance have elevated; Open Banking API compliance has also become key. These regulatory challenges have been traditionally addressed through fines and MDR tools. The former can break trusts between banks and fintech, while the latter falls short of abating the API openness risk barred by the PSD2 regulatory framework. Trustworthiness of Open Banking data in the long run relies on the degree of banks' proactiveness in managing the API compliance risks. To this end, this proposes the cognitive core banking architecture to

help banks better handle the proactive compliance management tasks as supervisory needs evolve and gain a comprehensive, near real-time understanding of API risk enforcement. With the support of the cognitive architecture, banks are enabled to achieve the ultimate target of prompt initiation of API compliance enforcement requests. In the context of banking compliance, this strategic shift entails a radical transformation of the underlying risk management and governance processes.

Banks are encouraged to implement explainable data governance and compliance. One noticeable challenge in the explainability of the cognitive architecture is the ontology drift, which may appear in either the customer objections ontology or the key launch & monitor (KLM) risk category taxonomy. Efforts are proceeding towards the setting of minimum standard taxonomies as reference to the explainability toolchains. Industry-level progress is required to establish an agreed standard for each embarking taxonomy, which is also shared among competition authorities. Banks of different sizes or with different sets of supporting technologies could have different degrees of ontological sophistications. There's a need for further information aggregation mechanisms so as to allow a more comprehensive sensitivity analysis to serve as input in fine-tuning.

Equ 2: Risk Detection and Alert Generation (Real-time Monitoring)

$$R(t) = \sum_{i=1}^{n} f_i(x_i(t))$$

Where:

- $R(t)$ is the overall risk at time t,
- $f_i(x_i(t))$ is the risk function for the i^{th} monitoring volume, customer behavior, etc.),
- n is the number of variables being monitored.

4. Artificial Intelligence in Banking

Financial stability is a key priority of the Bank of England. Financial stability (or systemic stability) is a property of a financial system that prevents events in a financial market from immediately becoming economic crises that threaten wider economic conditions. As of 2018, many banks have begun to integrate FinTech into their services because customers want more choices, flexibility, and control over banking. AI is the next evolutionary step in that direction. AI forms a branch of FinTech specialising in machine intelligence—an area where banks, as CSOs of financial systems, always require stronger resilience and systems that adhere to a wider range of safety margins. As such, the financial sector (in particular, retail banking) is a particular area where AI and FinTech can significantly offer banks an opportunity to improve the efficiency and substantially reduce the operating costs of these systems. Unfortunately, however, there has been very limited research into how to design such FinTech systems with AI arbitrators within the domain of the retail banking sector. Specifically, an in-depth understanding of the benefits of such systems, together with an appreciation of the wider challenges they pose, remains relatively underexplored.

Against such a backdrop, the following research critically investigates the interplay between AI and retail banking as a new form of FinTech systems by closely collaborating with a group of AI experts in five leading UK business schools and nine UK banks. To address its research questions, a set of 133 in-depth, semi-structured interviews are specifically conducted at the midpoint of the larger project. By interviewing with banks, the empirical data collected offer some detailed topical context on a set of investigations on how banks have been involved creatively in developing AI-FinTech solutions in retail banking. At the same time, the in-depth demos of the experimental prototypes present a set of tech samples of how such collaborations from a wide perspective could affect the design of future retail FinTech services with AI arbitrators.

Fig 4: AI in Banking

4.1. Machine Learning Applications

The opportunities that novel AI algorithms and AI models can give from the rise of low example deep learning, information distance, a new series of genomics, very large language models; and their potential impact on banking and financial services is presented. Core banking functional and data architecture (CBA) is introduced, and then a cognitive core banking (CCB) architecture is proposed, which merges CBA with RPA and cognitive services. Cognitive core banking is primarily designed to operate in multi-cloud environments. This "Global First" architecture is meant to guarantee: proactive risk compliance efficiently from a minimum dataset risk control with machine learning; and insightful customer interaction, leading to increased selling efficiency. Global first is an international trend where countries are going to enforce their own governing laws to protect domestic data from flowing out. This global first approach aims to control inherently overseas operations by extracting domestic necessary data in advance, and then proceed to a risk-free transfer and analysis. Data protection and privacy preservation are confirmed by upfront data and data processing around data engineers of the source. Visa risk control: For enhanced risk control, Visa has provided all participating parties with the data necessary for independent risk assessment on behalf of Bank of China. Predicting and classification of fraudulent transactions, Visa risk control will be based on modeling and data provided in an effort to identify highest risk transactions. A resource will provide a response so that BOC can take actions to minimize the unreasonable risk. Most AI providers in the financial industry advertise their AI algorithms that can improve credit scoring, risk assessment, inspection algorithms, and so on, but few can tell how to maintain the ongoing operability of AI operation. With two relevant certifications awarded and in production operation for a year, BOC would like to share the design of an entire data-engineered AI infused RPA enrichment architecture, including how CCB was enabled, further supported with a selection scheme of AI and cognitive services.

4.2. Natural Language Processing

The majority of financial risk/compliance and transaction monitoring systems in existence today are rules-based systems. Historical bank transaction data is manually classified to construct a large number of rules covering all types and classes of financial transactions that a bank customer engages in. These rules are rewritten and maintained as amendments affecting the rule book. A supervised neural network would need to a priori annotate the sentence and even then would likely contain errors with incompatible labels (e.g., "send" vs. "transfer"; "family" vs. "domestic"). Using new developments in weakly supervised learning and natural language processing (NLP) word/token embeddings, it is possible to rapidly and scalably classify bank transactions with lower error rates than the human rule book. A model for categorising bank transactions is presented and validated through experimentation.

There are multiple embedded bank transaction training models readily available. Heuristics and domain knowledge are leveraged to automatically generate, or edit, training data to circumvent reliance on manual annotations. These are then used in the training of a discriminative deep neural network transaction classification model, learned directly on the bank transaction data in the embedding space. An effective and scalable end-to-end bank transaction data pipeline for deploying NLP systems in large Australian banks developed. It consists of data preprocessing, the construction of transaction text embeddings, anchoring, label generation, discriminative neural network training and extra steps and considerations relevant to productionising

a model. With a growing focus on data engineering and the integrity of inputs, a number of ways are considered in which inputs could be altered to avoid errors (such as anchoring). A prototype system used to evaluate this model tested on benchmarked and unlabeled data.

5. Proactive Risk Compliance Management

Abstract Cognitive Banking is a new data-centric banking approach, driven by human-like cognitive capabilities that are delivered by integration of big data and AI technologies into every aspect of financial services. This concept has inspired the birth of Cognitive Core Banking, a data-engineered, AI-infused banking IT stack that transforms banks into "thinking enterprises" and increases customer value. As compliance cost grows faster than revenue, overdue and faults in compliance requirements (especially risk) cost may trip up unexpectedly. An intelligent solution approach for Proactive Risk Compliance Management has been researched. By harvesting discovered relations from big data, banking risks of going into fault in certain periods with high exact rates can be foretold; and by evaluation of bank compliance risks during product request processing, request fault risk and banker liability risk can be calculated, which serves as the compliance risk trade-off base for bank request processing.

1 Introduction The combination of a vast amount of big data, powerful computing systems, and advanced modeling techniques not only has allowed unprecedented achievements in various fields, but also has opened up many opportunities for the transformation of industry and commerce. The concept has inspired the birth of Cognitive Core Banking – a new architecture that transforms the current banking IT stack into a data-engineered, AI-infused "brain", which, by integration of big data and AI technologies into every aspect of financial services, allows banks to see, think, learn, and anticipate complex banking systems with human-like capabilities. The Cognitive Core Banking is marked by itself-cognitive data systems (customer, compliance, market and monetary systems), high-turbo AI brain that employs predictive, prescriptive, cognitive and automatic learning AI models, and action-enabling systems that are capable of transferring real-time insight of banking systems to the foretelling of banking options in actions, designed to help banks to generate smarter financial actions and increase long-term customer activate value. With the development of cognitive technologies and AI systems, extremely accurate risk compliance management and liability prediction for banks is an upcoming requirement. However, the compliance costs for banks are increasing much faster than revenues in the banking sector. Exceptional overdue and defaults in compliance requirements (especially in risk compliance) can trip up banks unexpectedly. Hence, a new solution approach to proactively manage risk compliance in banking by analyzing the internal relationships among big data (customer complaints data, risk control data, cash acceptance data, CRM data, and contracts data) with a focus on risk compliance requirements is highly needed, this from the new perspective of big data knowledge database.

2 State of the art The growing role of new technologies and AI in the era of cognitive banking has been studied, and AI as the next general purpose technology for economic growth has been elaborated with the concept of cognitive banking. In recent years, advances in AI and data technology have widely studied the development and innovation of the banking system which allows the creation of products and services based on big data, advanced analytics, and AI that results in smarter decisions. However, the discussion on new architecture of banking IT stack towards cognitive banking with human-like thinking capability rarely explored compliance management with a big data view on this approach.

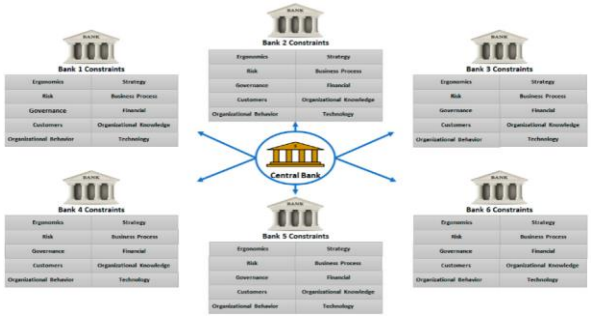

Fig 5: Proactive Management of Regulatory

5.1. Regulatory Frameworks

The banking industry has been subject to increasingly stringent regulatory frameworks since the 2007/08 financial crisis. Ever-evolving supplementary, complementary or updated rules must be closely followed and adhered to by banks to demonstrate operational compliance efficiency. The comprehensive global regulatory framework is the Basel Accord, which sets out international standards for the industry. A bank must not only comply with its respective country's well-nationalized regulatory body, but it must also consider foreign rules when operating on an international level. Accordingly, operations are performed under the approval and monitoring of control bodies such as the Financial Industry Regulatory Authority in the U.S., the Prudential Regulation Authority in the U.K. Legislation regarding data subjects' personal information is also fundamental to banking risk management. Cloud-based private data storage and processing services are becoming common for agility in updating customer-related operations. The ordinary course of business of this industry – making loans to increase capital – is accomplished mainly through an algorithmic mode of data processing, assessing creditworthiness and guaranteeing reimbursement.

The computational model underpinning such a paradigm – named cognitive core banking – receives a substantial amount of structured data related to banking transactions. Developing a branching three-stage model choice architecture to predict the customer's defaulting probabilities at a maturity date, across interchangeable banking institutions, assists in the operational compliance task performed by financial regulators. Regarding data engineering, obstructive sampling processes are designed to annotate Neutral-Examples banks. Such an approach leads to continuous and balanced learning with a minor predicted class. To increase the learning rate and speed up convergence, a rectangular learning rate schedule is introduced for neural networks. After reducing the dimensional feature space, long short-term memory recurrent units process structured data on the second level. On the deepest level, multimodal interaction model structures synthesize scattered data to provide autonomous classification. Compliance increases with the aggregation of synchronous classification results; hence, default prediction scores are maintained over the agreed threshold before encountering the loan season.

5.2. Risk Assessment Models

The heart of each risk-aware banking strategy is a system of risk assessment models, which is enhancing the data-centric information transformation in a set of cognitive banking core functions. Such a modeling system is presented here in a form of computer-aided dialogue between a mindful chief risk and a data engineer. The appended building blocks could be easily integrated into the IT infrastructure of a bank and might be fed by its various data sources. Their ensemble then plays the role of a liver, transforming the incoming data-chemical impulses into a decision-action pathway and vice versa. Each rebuild risk assessment model has an integrated life-cycle and regulation analysis tool, prospective and retro looks engine, risk lessening policy recommendation module. From the regulation point, this modeling approach modernizes the internal risk measurement backbone of a bank, smoothly aligning it with the latest requirements of the Basel pact. From the technology point, this modeling approach stresses the urgency of the AI ethics paradigm to cope with the adverse possibility of a cognitive banking overmind. From the policy-maker and society point, this modeling approach opens a prospect to turn the banking sector into one

of the early AI public reporting areas, which is inevitable for the upcoming sustainable and trustful partnership between finance, state and industry.

Equ 3: Risk Assessment and Prediction

$$P(\text{Risk}) = \sigma(Wx + b)$$

Where:

- $P(\text{Risk})$ is the probability of a given risk (e.g., risk of non-com
- $\sigma(\cdot)$ is the logistic sigmoid function,
- W is the vector of weights (parameters learned by the model),
- x is the vector of input features (data),
- b is the bias term.

6. Architecture of Cognitive Core Banking Systems

Compared to conventional core banking, cognitive core banking systems have advanced big data and AI analytics capabilities and include, but not necessarily, all of the following functions: real-time monitoring, analysis, learning, forecasting, and optimization. These applications processed and generated large volumes of transactional and customer behavior data, which can be stored and analyzed to create the means for operational, compliance, and business intelligence. Furthermore, as modern AI can detect patterns and generate complex risk scenarios even far beyond the capability of domain specialists and compliance officers, automation is the only way to handle them. Objectives are to develop a new type of data-engineered, AI-infused architecture for fully proactive and comprehensive risk and compliance management, with particular focus on the risk and compliance functions of the platform.

Cognitive core banking systems require a robust, reliable, and responsive architectural design capable of handling enormous volumes of data transactions and operational tasks. Platform requirements also naturally derive from the AI governance-enforcing platform structure. A generic AI system infrastructure typically includes data processing, modeling, model management, training, validation, deployment, execution, and monitoring. Additional model governance requirements include observability and interpretability, transparency, and auditability as well as blocking, degrading, and enhancement of the models. On the other hand, the fundamental architecture of a comprehensive risk compliance platform consists of monitoring, learning, transfer, forecasting, and optimization functionalities. On top of each function, continuous learning, optimization, and control loops and respective data, model, and action flows need to be implemented.

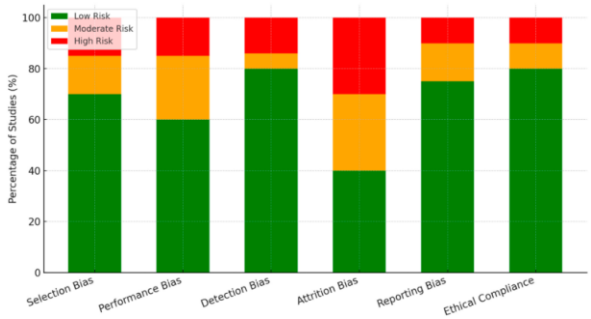

Fig : Cognitive Load Theory

6.1. System Design Principles

The data and bank digitization journey of the past decade has failed to materialize the best in class solutions improving the effectiveness and efficiency of banking risk compliance management. Instead, the most topical, board-level sustenance of banks took up considerable time and resources. This cognitive core banking provides the technical details underpinning the general architecture overview. While the cognitive core banking architecture and solutions are by no means the only possible direction of the digital banking risk transformation in full compliance with the legal banking regulation, the architecture provides a structured framework for a well-grounded and legitimate proactive risk and compliance management.

Several principles govern the architecture design. All customer data processed with the system resides on the banking server premises and is processed by the bank's application. The architecture offers optimization and inference AI services used exclusively by the bank to derive insights from the

bank's own customer data. The bank operates a cloud-based application in compliance with international and national law. The bank's cloud platform is an enterprise subscription service that provides cognitive core banking capabilities to the bank within the secure bank's network domain. The core business of the bank cloud is to provide data-engineered AI services for proactive risk and compliance management of the bank's customer base. The service provides data storage infrastructure, unified and clustered redundantly arranged, distributed and query optimized over a geographically spaced group of devices. The service provides mechanisms to secure data backups through a transaction-based mechanism ensuring financial audit compliant recovery points in time over the span of up to the past year. The service provides a toolbox for quick and easy creation of run-time environments of application containers. By using the service's toolbox, models are run as containers ensuring consistent workload execution and no separate infrastructure dependencies. The AI service provides provenance data storage and secure hash algorithms to track and store the signing date and time of each agreement and data used in the model's deployment. At the deployment, the service captures the model's prescriptive and generative interpretability rational around the variable dependence. The service is provided in compliance with the Model Governance system provisions. The bank's application, consuming the platform's output, is responsible for consent and the right of explanation of the service's output presented to the human. The deployed service call is amenable to the current version of the at the time of AI service agreement signature. The compliance too is malleable to notify the banking service and provide an alternative outcome given the AI governance handling. With the service, run-time monitoring is integrated that revolves around an effective hierarchy of AI operations. BI models transform the data in vectors to establish the links and relations, and form queries of activities of the AI service calling applications. The collected meta-data is then related and interpreted with the modelling operations to confirm the self-regulating AI operation of the service-centric AI governance.

6.2. Integration of AI and Data Engineering

In Seven, AI and data engineering can be neatly integrated through the cognitive core banking architecture that allows the running of pro-actively acting models to ensure the future compliance of the financial service institution with legislative and other requirements. Cognitive core banking as the future of banking technology design merges artificial intelligence, data engineering and core banking. The current developments in AI, especially in deep learning, have attracted increasing interest in various cognitive solutions, which have mostly been presented in the context of digital banking and future banking branches. However, the core banking services of a financial institution, like account management, saving, and lending have not been impacted by AI nearly as much. The architecture is introduced that allows these services to be supplemented by a particular type of AI models, contrasting those presented in the context of digital or branch banking, for example. These are pro-actively acting fully interpretable models, which run on transaction and customer data, and which by a certain look-forward time provide predictions based on legislative obligations. Additionally, the presented models are designed to strictly respect financial institution's obligations in terms of mathematical representability and exclusivity. The proposed platform architecture combines the data engineering component for the creation and transformation of a feature space with these 3 components. With the worldwide integration and globalization of financial services, the banking sector has also experienced an increase in the number and complexity of regulations. The architecture outlined for Cognitive Core Banking can be seen system wise as five AI components modeling the same domain, which is described in schematized detail.

7. Conclusion

In conclusion, risk management should not be confined to the assessment of the adverse impacts of current operations, but should also take into account potential regulatory implications from the future deployment of new models. The expanded considerations involving both static and dynamic dimensions urge for more proactive risk management solutions. Accordingly, the compliance management requirements on AI systems are greatly increasing with respect to historical demands. There is a growing expectation that AI systems should be able to prevent risky activities before they occur, act fairly and transparently at a predictive and operational level, and learn from their past to enhance their forward-looking risk mitigation strategies. Meanwhile, remarkable gaps in research and development have been identified in the wider discussion, underpinning the data-engineering and AI-infused proactive risk compliance management architecture of Cognitive Core Banking.

AI governance systems are described that help to address risks associated with the deployment of the models by monitoring input, output, or behavior of the AI models. It is an interesting idea to see that a credit risk application could use an early warning deep recurrent neural network as one of the AI models, and the credit risk application could further evolve to predict system-level outputs of the financial institution. Such regulatory outputs of the credit risk ensemble model could be better to coordinate with AI risk-related outputs of the production environment. Potentiality of using models about the AI models provides improved confidence about the compliance and risk profiles. In parallel, the presentation of the risk resilience model could also help financial institutions. This governance model provides an early reference guide on the risks, explains practical configuration requirements for the deployment, and offers the risk relevancy score about the AI deployment-induced potential risks. A library of common problems generated from a holistic modeling view of the AI systems together with their mitigation strategies is a good base for inspection to avoid risky outcomes.

7.1. Future Trends

The AI-driven predictive automation could include applications that use predictive analytics for customer intelligence purposes in the front office, such as chatbots or intelligent virtual assistants based on transactional and behavioral big data analysis, and advanced emotion recognition as multichannel customer interfaces.

Another interesting non-technical issue is security and surveillance technologies from the data protection and privacy viewpoint. Rich customer data exploitation for profiling and targeting purposes from a proactive risk compliance architecture contravenes the respective GDPR principles since it can be performed even without additional information as long as the data is well-known previously. This is especially true when it is combined with advanced emotion recognition detection, which can provide a more intimate overall view on individual customers. Therefore, any data-feature engineering procedure, intentional or not, that exposes such functionality would need to be detected and attempts made at controlling and neutralizing it, not fully cancelling data analytics outcomes, but at least reducing its effectiveness to under the sensitive issue threshold.

Group data on dinosaur context and previous examination facts on a per exhibit basis that all regard revenue administration, are given, and for the nesting period, an additional “target” column as a dependent variable is also included. Given data have been pseudonymized, and therefore no information more than the one outlined before can be provided. Most of the indicators should be self-explanatory, except maybe product_GB, which is indicative of the geological/biological assortment of the group in question, and employee_area, representative of the more wide-ranging area within which the group has been inspecting the exhibits.

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