C.O.R.E. AI–ML Integration in Banking: A Conceptual Framework for Cognitive Transformation

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Abstract. This paper is a conceptual treatise on how banks can integrate artificial intelligence and machine learning into one unified system based on a framework that is pegged on four pillars that are stable: Customer Experience, Operational Intelligence, Risk Management, and Financial Innovation (C.O.R.E.). Instead of listing these tools as a collection of gadgets, they are viewed as an engine of strategic action to power the digital agenda of the bank. The model aims at uniting the use of AI-ML to the entirety of the banking. Each of the pillars is discussed as an independent area of focus and a dynamic node in a networked system as a cognitive structure to facilitate smart and adaptive banking processes. The paper is centered around end-to-end interoperability, explainable AI, ethical compliance, and responsiveness to the changes in the market and regulatory framework in real-time. It determines how AI-ML can move beyond standalone applications to embedded and self-reinforcing systems that enhance customer trust, operational resilience, and risk management by looking forward through the analysis of real-world use cases and the incorporation of multidisciplinary theory. As opposed to earlier models that address AI as a component add-on, the C.O.R.E. model introduces a new federated model where intelligence in one pillar dynamically informs and strengthens the others, making a bank an AI-native institution that can learn and innovate.

Keywords: Artificial intelligence, Banking, AI–ML integration, conceptual framework

1 Introduction

In the banking and finance sector, recent technological advancements and disruptions in the processes due to the impact of fintech and digitalization in various service sectors have emerged [1]. The banking sector is passing a critical phase of digital transformation, where it is being faced with new opportunities and issues brought about by the accelerated pace of financial technology, especially the introduction of mobile banking and internet finance [2]. According to a recent bibliometric review, there has been a shift in the paradigm of banking technology, whereby the growing scholarly interest in FinTech, digitalization, innovation, and e-commerce. Notably, the period of 2017-2023 is a phenomenal growth in the number of research outputs, which suggests an accelerated application of digital technology in the banking industry [3]. The results suggest

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that the long-term supporting effect of digital transformation (DT) is significant on the profitability of banks. Bank-specific factors like net interest margin and capital adequacy ratio and macroeconomic factors like GDP growth also support this effect [4].

Artificial intelligence (AI) and machine learning (ML) are the foundations of this change, which have ceased to be peripheral elements but the backbone of modern banking ecosystems. Nevertheless, recent significant IT inventions made the potential of AI shockingly popular [5]. Banking 1.0 that was founded on conventional banking practices was transformed into Banking 4.0 that applies modern technology, including artificial intelligence, in most of its departments. Banks have been adopting new technology in order to be competitive and relevant [6]. The use of AI in banking has many applications in the modern world such as the back end (intelligent contract architecture analysis), the mid office (fraud prevention initiatives, risk management, and complex legal and compliance processes), and the front office (voice assistants and biometrics) [7]. Although the fundamentals of banking have not changed, AI has shown new dimensions of interacting with clients, decision-making, and automation, making it imperative to ensure complete integration to minimize financial and non-financial risks [8].

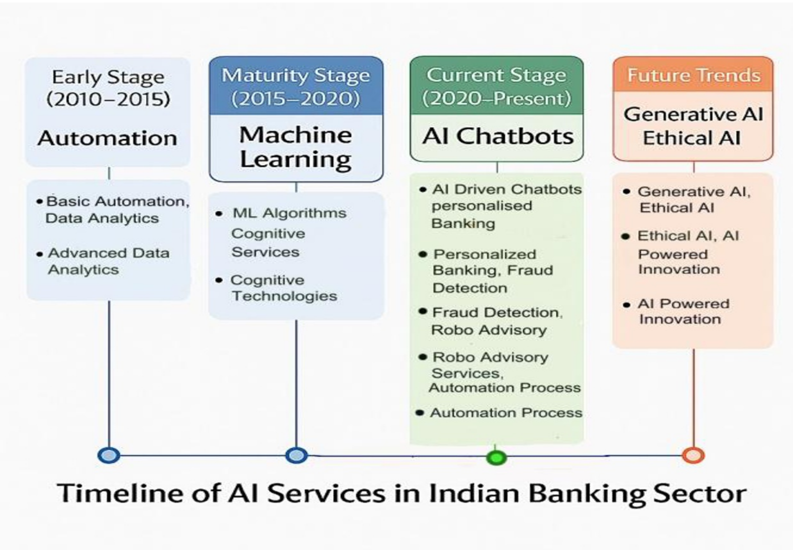

Fig. 1. Evolution of AI and ML in Banking Source: [8]

As shown in Fig.1. the history of AI and ML in the banking field, starting with simple automation, moving on to sophisticated data analytics, and finally, generative and ethical AI. Placing the C.O.R.E. model in this pathway, the paper highlights the reason why banks should not just stop at isolated applications, but transform cognitive system-wide.

Integrated AI in banking implies a comprehensive implementation of AI in all functional sectors risk, compliance, operations, and customer service, which improves collaboration, regulatory compliance, and operational efficiency and overcomes the existing shortage of holistic implementation [9]. [10] stated that there is a need to holistically incorporate the emerging technologies in the entire ecosystem. The main sphere of artificial intelligence application in big organizations is on the backend services. Nonetheless, it is still not widely used in customer-facing operations, which are of paramount importance to commercial banks, as well as lending and payments, although the pressure of near-banking competitors is increasing [11]. As the use of artificial intelligence in the banking industry continues to grow, it is estimated that the introduction of products and services based on this technology will simplify the process of product enhancement and service provision, which will eventually result in a rise in the overall value [12].

Although there has been an ever-increasing literature on AI and ML implementation in banking, the available literature mostly discusses these technologies in terms of disjointed functional applications or technology-oriented views, which provide minimal information on the adoption of AI in the systemic implementation of the banking value chain. Conversely, this research paper goes a step further to develop an integrative thinking approach by introducing the C.O.R.E. AI Integration Model, which frames AI-ML integration in four interdependent banking operations, namely Customer Experience, Operational Intelligence, Risk Management, and Financial Innovation. The framework specifically highlights cross-functional interoperability, ethical governance, and adaptive learning, which separates it from the previous digital transformation and AI integration frameworks, which mainly target siloed or platform-specific implementations.

The present study offers a Customer Experience (C), Operational Intelligence (O), Risk Management (R), and Financial Innovation (E) based proposal of the so-called C.O.R.E. AI Integration Model. The C.O.R.E. framework model provided by us is centered around the leaving of the disjointed, individualistic, and deploy AI tools for a cohesive, interoperable, and ethically consistent platform. In this regard, just as customer sentiment promotes real-time operational analytics and insights in risk management to promote proactive and progressive security environments. The explainable and auditable platforms enhance operational intelligence by ensuring compliance with strategic planning, which in turn enables scalable innovation.

The C.O.R.E. approach sets itself apart based on three guiding principles:

a. The approach ensures interoperability across functional domains through the use of shared data and architecture.

b. The approach ensures ethical compliance through the use of explainable AI, inclusive design, and accountability mechanisms.

c. Adaptability by means of continued learning systems that react to regulatory, market, and technological shifts.

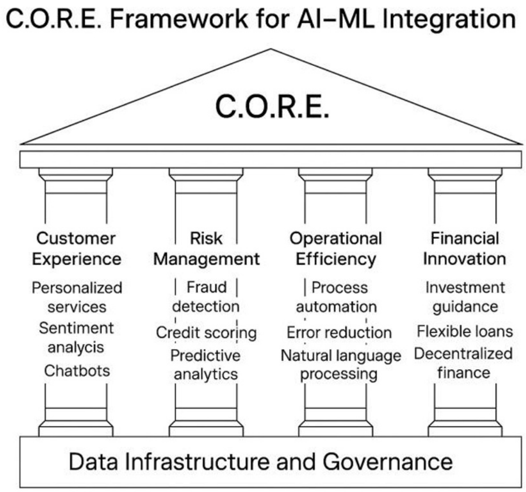

Fig. 2. Pillars of the C.O.R.E. Model, Source—Author's work

On these four pillars as represented in Figure 2, we shall be offering a framework that will outline how artificial intelligence (AI) and machine learning (ML) can be holistically integrated into four fundamental banking functions Customer Experience, Operational Intelligence, Risk Management, and Financial Innovation to form a unified, adaptive, and cognitive banking institution. This paper will attempt to develop a conceptual framework that supersedes the disorderly AI adoption process in favor of a federated, system-wide model of cognitive transformation.

2 Theoretical Background

The evolution of AI and ML in the banking sector has increased significantly in recent years and has progressed from basic automation to the realm of intelligent transformation. A bibliometric analysis suggests that the academic journals about finance and AI have shot up since 2015 and address various fields—bankruptcy prediction, anti-money laundering (AML), behavioral finance, and portfolio management [13]. This trend represents the increasing effects of AI on the financial value chain. The banks are constantly testing the application of AI in the operation activities and customer service, but the integration of AI across the business operation remains a far-fetched dream [14] The rise in defaults on loans, credit card fraud, identity theft, and money laundering has augmented the need of institutions to apply AI and ML solutions [15, 16].

2.1 Dynamic Capabilities Theory (Teece)

In order to achieve a competitive advantage that is sustainable, the dynamic capability theory emphasizes the importance of businesses being capable of responding to changes occurring in their dynamic environment through sensing and seizing opportunities and rearranging resources. One such example of specific application of artificial intelligence (AI) to the underlying process of dynamic capacities is the network mediating model of enterprise artificial intelligence use, digital adaptability, market perception, and enterprise innovation capability [17] This model provides help to the businesses to improve their competencies in raising awareness, collaboration, and reorganization of the resources in a rapidly evolving environment through the improvement of the digital versatility [18]. The perceived adaptability is manifested by the manner in which the businesses enhance their capacity to adapt and respond to changes in their environment through the application of artificial intelligence technologies [19]. The ability to be flexible to the society assists in maximizing the efficiency of intra- and inter-organizational collaboration, which consequently facilitates the integration of resources and value creation [20]. Within the C.O.R.E. framework, Dynamic Capabilities Theory is not confined to a single functional pillar but operates across multiple domains. While it strongly informs the Customer Experience pillar by enabling banks to sense evolving customer needs, seize personalization opportunities, and reconfigure service processes through AI-enabled learning, it simultaneously underpins the Risk Management pillar. In this context, sensing involves early identification of emerging financial, behavioral, and regulatory risks; seizing refers to deploying adaptive AI-driven controls and mitigation strategies; and reconfiguring reflects the continuous realignment of risk models, governance mechanisms, and compliance processes. Thus, dynamic capabilities serve as a cross-cutting theoretical foundation that supports both customer-centric adaptation and proactive risk governance in AI-driven banking systems.

2.2 Resource-Orchestration Theory

The Resource Orchestration (RO) theory came in to correct the gaps that were identified under the Resource-Based View (RBV) of the company [21, 22]. The resource-based view (RBV) of value development is the growth-based perspective, which is an argument that the most significant part of value development is the resources of a business. The rationale is that an effective orchestration involves planning a portfolio of resources in a film, combining the resources to create abilities, and utilizing the abilities to design and create value. Managers play central roles in resource-based theory, as they are responsible for the efficient management of resources [23]. Moreover, the understanding and responsiveness of the managers towards the coordination and mobilization of the resources directly affect the use of the resources [24]. In addition, resource orchestration maps the diverse ways of organizing resources (e.g., acquiring, growing, divesting), bundling capabilities (e.g., stabilizing, improving, pioneering), and leveraging them (e.g., mobilizing, organizing, deploying) into new capabilities and exploiting potential markets [21]. As a result, the competitive forces and industry dynamics that companies have to work with differ [25]. Besides, environmental uncertainty includes technology and market factors that present potential risks to the existence of an organization [26].

2.3 Sociotechnical Systems Theory

The concept of 'sociotechnical system' has been examined across diverse literature, encompassing studies on workplace technology, systems engineering, science and technology studies (STS), the philosophy of technology, engineering ethics, and more recently, research on AI and autonomous systems [27]. Although there are notable discrepancies in the interpretation of 'sociotechnical system' across different literatures, a shared principle is the recognition that both technology and diverse social variables are significant. The fundamental idea is that technologies are fundamental elements that are included inside larger systems, regardless of whether they are of a technical or sociotechnical character [28]. A system may be defined as a collection of connected elements (e.g., technology, people, regulations) that collaboratively operate to achieve a common aim or objective [29]. AI systems are sociotechnical systems; nevertheless, [30] deposits that they include extra essential components owing to their autonomy, interactivity, and adaptability, distinguishing them from conventional technologies. This argument suggests that artificial intelligence can learn from its environment and adjust accordingly. Conventional sociotechnical systems are, in fact, capable of self-learning and adaptability, although via the participation of human players. AI systems possess technological components that facilitate environmental learning. [31] therefore recommend two further components for AI systems as sociotechnical systems: artificial agents and what they designate as technical norms. The Financial Innovation pillar of the C.O.R.E. framework is based on the Sociotechnical Systems Theory, which emphasizes interactions between technology, organizational processes, and human actors to facilitate AI-driven financial innovation.

2.4 Institutional Theory

The Institutional Theory, firstly introduced by [32] and subsequently elaborated by other researchers such as [33], is a phenomenon that focuses on the impact of institutional situations on organizational structures, behaviors and legitimacy. The concept claims that the rational decision-making process that aims at maximizing efficiency is not the only one that influences organizational actions, but the necessity to follow the expectations and norms of the society regarding legitimacy [34]. The idea of institutional isomorphism, which was developed by DiMaggio and Powell, states that the organizations in a common field grow more similar to each other over time due to three types of pressure Coercive pressures: It is the result of political influence and the necessity to be legitimate. Normative pressures: Associated with the professionalization and standardization. Mimetic pressures: It is the result of traditional responses to ambiguity [34]. Many studies have linked the institutional theory to the adoption of digital developments. [35] demonstrated how businesses adopt IT systems in response to the institutional demands, whereas [36] demonstrated the impact of professional standards on the practices in organizations. A recent study by [37] pertains to the use of artificial intelligence and the influence of institutional logics. Institutional Theory forms the foundation of the Risk Management and Financial Innovation cornerstones of the C.O.R.E. model, as it identifies the way in which pressures based on regulation, norms, and cognition influence the usage of AI and ML within the banking system, with a need to integrate AI-enabled systems with regulation and ethics to sustain legitimacy.

2.5 Need for Integration

The theoretical consistency of the application approaches to artificial intelligence and machine learning (ML) in the banking sector has not been able to keep up with the rapid introduction of this technology. Earlier models, including the FinTech stack, banking-as-a-platform (BaaP), and the digital maturity models, have provided official paths to digital integration. Nevertheless, these models tend to see artificial intelligence technologies as features and modules instead of aspects that are highly interconnected and enable cognition. In the vast majority of situations, such models focus on vertical silos that comprise channels, goods and processes, but they do not consider the cross-functional intelligence that AI can improve when it is planned.

The growing complexity of the ecosystems, which underpin the financial transactions, requires integration. Customers are insisting on hyper-personalized experiences, regulators are insisting on explicable regulations and markets are insisting on rapid innovation. The more traditional digital structures cannot offer a cohesive solution to these ever-changing demands. The final effect is that the thoughts and efforts that are put in place are broken and replicated. Moreover, a large proportion of financial institutions have shifted to the adoption of automation to improve their operational efficiency; however, most of the institutions fail to incorporate such systems into larger decision-making systems. Due to this reason, the existence of a cognitive framework that incorporates artificial intelligence in the context of consumer interaction, risk intelligence, operations, and financial design is extremely required. The Dynamic Capabilities Theory directly influences the Risk Management pillar as it focuses on responsiveness to the regulatory and market changes. The Operational Intelligence is based on Resource-Orchestration Theory as it demonstrates that the efficiency of the work is improved with the help of structure and exploitation of resources with the help of AI. Sociotechnical Systems Theory reinforces the Customer Experience pillar by emphasizing the interaction of human agents with AI systems in points of contact with customers. The pillar of Financial Innovation is based on the Institutional Theory, which describes the impact of the legitimacy pressure and normative standards on the uptake of AI-based products and services. The shift towards digital banking and the actual cognitive finance is identified by the adoption of such a framework, which does not only promote agility and compliance but also makes the bank a self-optimizing and adaptive system.

The four theoretical perspectives in totality offer a consistent basis to the C.O.R.E. AI Integration Model. The Dynamic Capability Theory will describe how banks acquire learning and adaptive capabilities that are required to maintain a steady AI-driven change. The Operational Intelligence pillar is informed using the Resource Orchestration Theory, which explains the organization, bundling, and exploitation of AI-enabled assets and capabilities within the banking operations. The Sociotechnical Systems Theory emphasizes the mutual optimization of technical and social factors, which facilitates innovation and the use of AI in a humane way. Regulatory alignment, ethical governance, and legitimacy are the key aspects of the Institutional Theory, which are especially important to risk management and AI-enabled financial innovation.

3 Development of the C.O.R.E. Framework

3.1 Customer Experience (C)

Customer experience is regarded as a key element of the attainment of the competitive advantage and corporate success and can bring unique and sustainable benefits to organizations [38]. This includes the pre-buy, purchasing, and post-purchase stages of the journey of the customer. A customer journey is a set of interactions, which includes moments of interaction between service providers and clients [38]. Artificial intelligence (AI) is increasingly playing an increasingly important role in shaping the consumer experience [39].

The extended community has integrated AI to make the company activities, such as customer experiences, are optimized, thus driving online sales and value creation, as well as improving the operations and productivity [40]. The artificial intelligence can allow the marketer to gain deeper insight into the target market. However, the interactions with AI can have some difficulties, which might lead to frustration, confusion, and dissatisfaction with the clients [41, 42].

Previous studies have focused on customer experience based on a limited set of perspectives. [43] determined the relationship between artificial intelligence, service quality, and customer engagement, and also evaluated the role played by emotional intelligence and artificial intelligence in customer satisfaction [44].

3.2 Operational Intelligence (O)

Artificial intelligence (AI) has become a major technology that is revolutionizing the business processes in most industries within a short duration of time. Its uses are the automatization of routine tasks and the simplification of complex decision-making processes, therefore helping businesses to improve their production and encourage innovation [45]. Artificial intelligence systems, such as deep learning algorithms and natural language processing, are structured to analyze large amounts of data, identify patterns, and offer suggestions or predictions that are both fast and accurate at a scale never before seen [46]. AI has become a critical aspect of contributing to the efficiency of operations whereby firms have been able to maximize resources, reduce costs, and improve overall performance. AI reduces the human input in tasks that can be tedious and prone to error, including chatbots in customer service and mechanized supply chain management [47]. AI also helps companies by offering predictive opportunities, which allow them to act proactively besides enhancing productivity [48].

The transition to the predictive varieties of the decision-making process is an important step in the way businesses approach the management of the problems, beginning with inventory management and concluding with marketing policies [49]. Individualized interactions with consumers, such as customized product recommendations and personalized advertising, are the potential of AI to dramatically increase the company performance by increasing customer pleasure and loyalty [50]. However, even though the possible uses of artificial intelligence in business environments are quite numerous, it is also subject to significant ethical issues that should be studied. The application of AI systems, and those that require the use of personal or sensitive information, provokes the concern of privacy, security, and transparency.

3.3 Risk Management (R)

Management of risks has been an intrinsic component of organizational strategy as it is an insurance policy against any financial, strategic, operational and reputation losses [51,52]. Risk management is not only about preventing crises but also the process through them with the least damage and eventually developing resilience after the crisis. Risk administration in the 21st century could be a major paradigm shift with the emergence of computational intelligence (AI) [53]. AI, capable of operating and analyzing large volumes of data in speeds and accuracy that cannot be achieved by humans can be revolutionary. It is able to increase the capacity to locate potential threats and opportunities more specifically and hence maximize decision-making processes. Machine learning theories and, in particular, the ones that rely on deep learning are invaluable instruments as far as predicting market trends, identifying fraudulent behavior, and automating risk assessment procedures are concerned [54]. Image data constitute an informative and multifaceted one, with the minute patterns being easily missed by the conventional type of data [55]. It is supreme in the context of the risk management. The convectional neural network models (CNNs) are deep learning algorithms that have proved to be very promising in extracting information about picture data in numerous applications [56]. The manufacturing, energy, maritime, finance, and medical industries can apply the capabilities of these AI systems to create predictive models that will be capable of identifying any possible issues in an unmatched precision. It is possible to incorporate AI-generated insights into the domain knowledge to enhance the strategies in order to make organizations flexible and confident in their response to risks [57].

3.4 Financial Innovation (E)

The integration of artificial intelligence (AI) technologies into the banking and finance sector has transformed the usual manner of operations and has transformed the dynamics of the business [58]. As the financial institutions worldwide enter the digital transformation process, the importance of AI innovation in improving the financial well-being of financial institutions has become one of the most prominent research and discussion topics [59]. The development of AI-solutions, including predictive analytics, risk management, customer service, and fraud detection, has created a new set of opportunity and competition among banks worldwide [60]. As banks failed to address the changing consumer needs, regulatory needs, and the competitive landscape, strategic implementation of AI technology has become one of the main sources of innovation and performance increases [61]. As the market continues to get more competitive, the banks are advised to utilize AI technology to make their work more efficient, improve the customer experience, and identify new income sources that can be utilized [62]. The regulatory authorities are struggling with the issues that the AI-enabled innovation has introduced such as data privacy, algorithm bias, and system risk. The financial outcomes of AI are of great importance to comprehend the regulation of AI and strike the balance between the technology and the risk management. The financial industry is heavily investing in artificial intelligence technologies to have a competitive advantage and to adjust to the dynamic situation in the market [63].

3.5 AI Infrastructure Layer

AI Infrastructure and Governance Layer is one of the primary elements of building scalable, reliable, and accountable AI systems within the banking sector. Data lakes, interoperability, ethics, accountability, MLOps (Machine Learning Operations), and federated learning are the main aspects of this layer that enhance safe and efficient AI-driven environment. Data lakes are also centralized data warehouses where structured and unstructured data are stored so that banks can consolidate, store, and retrieve various datasets that are required to train AI models [55]. Interoperability shall help make the integration between the old and new systems more seamless so that AI applications can be applied to digital transformations [17] This tier of governance targets the goal of prioritizing ethical AI, transparency, fairness, and accountability. Some of the issues that are covered by ethical governance guidelines include the existence of algorithmic bias, explainability, and consent management [64]. The legal framework, such as GDPR and PSD2, needs to be adhered to in order to ensure the safety of the data and the reasonable use of AI [65]. MLOps solutions enable simpler installation, monitoring and management of artificial intelligence model lifetime and, as a result, improve efficiency and lower the risks of such operations. Federated learning makes it simpler to utilize the artificial intelligence models to be trained on decentralized sources of data. This will improve privacy and security because it allows sensitive information to be stored locally and at the same time allows collaborative intelligence [66].

3.6 Interrelationship between the variables

The four pillars of the concept of Cognitive AI-Driven Bank include Customer Experience, Risk Management, Operational Intelligence, and Financial Innovation. These four pillars do not exist as isolated spheres; instead, they are connected to each other and support each other through shared AI infrastructure and feedback loops. The self-directed learning and sensitivity that they create are a result of a reciprocal reinforcement that is vital in bringing about cognitive change.
Risk Management With a Focus on Customer Experience:

Chatbots, as well as AI customization, enhance the quality of the service and customer trust. These touchpoints are used to enhance credit scoring models and fraud monitoring systems as they gather both behavioral and transactional data at the same time. Therefore, higher risk accuracy assists financial institutions to offer more personalized and secure financial services that also improve the overall customer experience

The customer experience is a product of operational intelligence. Automation of processes and the use of natural language processing (NLP)-based analytics makes possible the increase in operational efficiency and, at the same time, the ability to communicate in real-time and offer a personalized experience across channels. By applying such synergy, customer-facing services will remain consistent, timely, and cognizant of the situation. The front-end experience is increasingly becoming fluid and easier to use, in line with the evolution of back-end technology.

Operational Intelligence incorporated into Risk Management: With the help of advanced analytics, predictive monitoring can be provided, and, consequently, it will be possible to identify fraudulent behavior in time and implement adaptive compliance processes. It is with these new insights that internal processes are enhanced and governance models enhanced. Conversely, the smarter and more responsive the operational tools are, the larger datasets they provide to risk assessment.

Innovative Financial Practices Across All Pillars: The new technologies like alternative financing and decentralized finance rely on risk algorithms, which are reliable, operations that are on time, and customer- centric interfaces. The creation of a reliable and flexible infrastructure, as well as standardization of regulatory standards, are one of the necessary elements, which should be the foundation of new products. It is through the combined efforts of all the three components that one will attain this specific objective.

Infrastructure for Artificial Intelligence as a Unifying Layer: A number of factors bring the pillars together, including the study of federation, data lakes, MLOps pipelines, and ethics standards. These are the uniting forces between the two. They make it feasible to collectively learn, to standardize and to conduct ethical oversight, which ensures that no region will grow in isolation but rather as a component of a shared cognitive fiscal system. The synergy between the four pillars is ensured by governance structures, MLOPs practices, and ethical AI principles since it ensures that customer insights are transparent, operating processes are available to audit, risk models transparent, and financial innovations are compliant. With this, the AI Infrastructure Layer serves more as a connective tissue, whereby the intelligence in one pillar can dynamically enlighten and empower the others. The literature review has made the framework highlight that infrastructure is not a background factor, but an enabling holistic integration of strategies.

Theoretical propositions:

Proposition 1: AI-enabled customer experience enhances risk prediction accuracy via behavioral data feedback loops.

Proposition 2:Operational intelligence capabilities mediate the effect of AI infrastructure quality on financial innovation.

Proposition 3: The governance layer defines the connection between AI implementation and strategic agility.

These propositions are advanced as theoretical anchors consistent with the conceptual nature of this study and are intended to guide future empirical research through methods such as case studies, surveys, and longitudinal analyses.

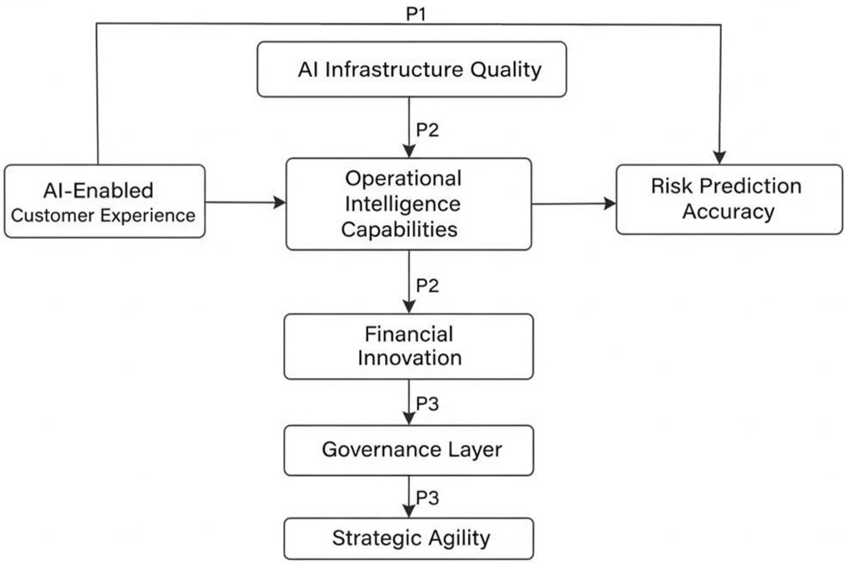

Fig. 3. Proposed framework of C.O.R.E. AI–ML Integration

4 Limitations and Future Research Agenda

Although the paper provides a detailed conceptual framework, that is, the C.O.R.E. model of the holistic AL-ML integration in banking, it is important to note that the strategy has some weaknesses. To begin with, the study is conceptual, and it is reliant on the secondary data sources, theoretical synthesis, and published examples of cases extensively. This study does not involve any kind of empirical testing or primary data gathering. The researchers can investigate the way the various elements of the C.O.R.E. model Customer Experience, Operational Intelligence, Risk Management and Financial Innovation are interacting with each other in case of the implementation of AI. The adoption of AI in these spheres can be either beneficial or detrimental to the intelligence and flexibility of banks and their overall performance, which can be established through surveys or case studies [7]. Second, longitudinal research may focus on the implementation of AI by banks in different departments in the real-life environment and reveal the difficulties, decision-making process, and changes teams undergo in reaction to the ethical or technological problem [67]. Third, future studies could examine how banks develop and operate AI-enabling systems, such as data structure, model testing, and fairness and explainability of AI-based decisions. Comparative analyses of various countries might also show the impact of regulatory conditions, cultural forces and technological infrastructures on the adoption of AI and show where the model of C.O.R.E. is working and where it might require some further refinement [68]. Future empirical research may be guided by the following specific research questions.

RQ1: How does cross-pillar data sharing within the C.O.R.E. framework affect banks' strategic agility and decision-making speed?

RQ2: Does AI governance moderate the relationship between operational intelligence and financial innovation in banks?

RQ3: Which interactions among the C.O.R.E. pillars most strongly influence customer trust and perceived fairness in AI-driven banking?

RQ4: How do regulatory and institutional contexts shape the effectiveness of holistic AI-ML integration across the C.O.R.E. pillars?

5 Theoretical and Managerial Contributions

This theoretical paper advances the area of artificial intelligence (AI) adoption in the banking sector by proposing the C.O.R.E. framework a theoretical framework that combines four key pillars Customer Experience (C), Operational Intelligence (O), Risk Management (R), and Financial Innovation (E). Following the [69] framework of dynamic capabilities, where sensing, seizing, and transforming the environment in unstable conditions are stressed, the C.O.R.E. model places these capabilities in the context of the AI-ML-era of banking. The model also builds on the work of [70], who argue that collaboration and control restructure with the help of the learning algorithms, making AI performative in its nature. As opposed to traditional approaches which isolate AI applications, this framework encourages integration of banking processes in a multitasking and holistic way. This is similar to [71] who frame the concept of digital transformation as a redefinition of the organizational systems, practice, and institutional logics and assumptions beyond digitalization. Theoretically, the article extends and intersects a number of views:

* Based on the dynamic capabilities theory, it highlights the way banks evolve, combine, and restructure AI capabilities in different functions to become agile and competitive.

* It adds to the growing discourse on the digital transformation going beyond the one-dimensional application of AI tools to provide an ecosystemic model whereby data circulations, learning processes as well as governance interact in an interactive manner.

* It does add to the sociotechnical systems theory in the sense of identifying AI as not a technical artifact but an embedded, co-evolving component in the organizational cognition and design.

* The model is further embedded in institutional theory and platform logic by the introduction of an AI infrastructure layer, which is composed of data governance, MLOps, ethical governance, and interoperability.

5.1 Managerial Contribution

Considering the managerial point of view, the C.O.R.E. framework offers practical advice to the bank executives and policymakers on how to order the investments in AI, align the governance structures, and coordinate the cross-functional implementation of AI. The model provides a framework through which the degree of maturity and interoperability of artificial intelligence among banks can be evaluated when considered in the perspective of management. Such a connectedness is critical, with current studies showing that AI-based transformational activities have a positive impact on a number of areas of firm performance, including customer service, innovation, decision-making, and operational effectiveness [72].These improvements are a sign of the strategic value of introducing AI into front-end and back-end business processes.

The framework helps managers to recognize and prioritize investments in AI in four key areas that have high impact, In Customer Experience, it guides the implementation of AI tools (e.g., chatbots, personalization engines) that can bring about simultaneous enhancement in engagement as well as generation of behavioral data that can support risk modelling. In Operational Intelligence, it requires the incorporation of AI in real-time decision support, process automation and anomaly detection-improving throughput and adaptive capacity. In Risk Management, it defines how AI increases the accuracy of fraud detection, credit risk assessment, and compliance with regulations and states explainability and auditability as a managerial priority. Moreover, in Financial Innovation, it welcomes the application of AI by the leadership to explore new business models such as embedded finance or decentralized lending which keep abreast of the changing customer and regulatory expectations.Also, the AI Infrastructure layer offers advice on how AI can be deployed responsibly and at scale to allow companies to overcome common AI-related challenges, such as bias in algorithms, model drift, and explainability requirements (e.g., XAI, GDPR, RBI guidance).

6 Conclusion

In this theoretical paper, the authors introduced a four-pillar multidimensional framework of AI-ML integration in the banking sector on four crucial pillars, i.e., customer experience, risk management, operational efficiency, and financial innovation. It spread an all-encompassing, ethically consistent, and technically practicable application of AI that is intelligible and interoperable. Each of the pillars demonstrates the opportunities of AI in developing not only technical enhancement but also strategic value in the new era of intelligent, customer-focused, and responsive banking organizations. The most significant results highlight that although AI usage has reached its maturity in such fields as fraud detection and customer service, much more has to be accomplished on the aspects of interoperability to achieve end-to-end performance of operations, particularly in data governance and explainability.

AI-assisted compliance engines, synthetic data, and self-supervised learning will change the way banks model customer behavior and risk in large scale. A smart model of cognitive banking will be forced to balance the needs of institutions and innovation. To survive in the era of hyper-personalization, cyber resilience, and regulatory sophistication, Banks should strategically invest in AI-native infrastructure, model governance, ethical design. The transition of banks to learning adaptive AI infrastructure to continually learn and optimize, based on the inputs of the environments they exist in, should also be considered.

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