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The Architecture of AI Governance in Banking: Bridging Compliance and Explainability Gaps

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Abstract

The adoption of AI in the banking sector has made its way into various functions of the banking business such as credit assessment, fraud detection, risk management, compliance, and customer service, thus introducing fresh challenges in the realms of transparency, accountability, and risk management of banking models. This paper reviews the challenges of governance of AI in banking, focusing on the limitations of explainability, regulations and how AI model risks intersect with traditional banking risks. Explainability is not a single technical property but rather a governance capability that helps to document, reconstruct, challenge and monitor decisions throughout the model lifecycle. The regulatory and standards expectations are discussed, such as lifecycle governance, independent validation, data lineage, documentation, monitoring and senior management accountability. Special focus is placed on the constraints of the post hoc explanation, the performance vs. interpretation dilemma, the need for different explanations for different stakeholders and problems in the cases of complex and emerging AI models. Practical application patterns illustrate the application of interpretable models, post hoc methods, counterfactual explanations, audit trails, human oversight, and ongoing testing. Third party models, data quality, cyber security, model drift and integration with existing credit, market, liquidity, operational, compliance and reputational risk models are also taken into account. By leveraging AI, a coordinated governance strategy integrating technical validation, regulatory alignment, traditional risk management, documentation, and necessary human oversight can enhance accountability while addressing the real-world constraints of complex AI systems in regulated banking settings.

Keywords: AI Governance, Explainable AI, Banking Regulation, Model Risk Management, Financial Risk.

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Introduction

Banking AI governance is an area of study and practice focused on the process of designing, deploying and managing AI and machine learning systems in highly regulated financial markets. It combines explainability, model risk management, lifecycle governance, and internal controls to help ensure that AI-driven decisions are transparent, auditable, and meet regulatory expectations [1]. It is relevant in various applications like credit scoring, fraud detection, customer service and risk management, especially in the context of consumer protection, market integrity and institutional accountability. One of the key issues is to obtain meaningful explanations without a significant loss of model effectiveness. The governance led explainability addresses traceability, evidence of decisions, data lineage, and audience appropriate explanations that are embedded into the data and into the data to decision process, which is increasingly being followed by banks [2]. Increasingly, explainability is seen as an architecture and governance requirement rather than just a technical feature added to the end of a model's development process. This approach involves the involvement of compliance officers, risk managers, technical teams and business users throughout the model's lifecycle [3]. In banking, the concept of explainability is not limited to the

explanation of model predictions. Governance explainability demands to give reasons for the approval of a model, how it was tested, what data and assumptions were drawn on, and how its performance was monitored. Decision level explainability involves understanding what factors led to a certain customer or operational result, or whether these factors can be expressed in understandable language [4]. However, continual review must also occur to detect modification in the models' performance, data quality, risk exposure, and regulatory compliance. All these elements create a governance model where interpretability, monitoring, accountability and documentation are all interconnected as controls. The regulatory requirements are more and more focused on traceability, repeatability, effective internal controls, data integrity, independent validation and continuous testing [5]. Model risk management practices are demanding proper development, validation, monitoring and governance of the models in the USA. The European Union (EU) has already introduced some high-risk requirements for specific AI applications, like credit scoring, and this is an example of shifting from documenting checks to operational obligations. In the United Kingdom, explainability is dealt with, primarily, in the context of existing accountability and consumer protection mechanisms such as senior management responsibilities and obligations relating to customer outcomes [6]. As AI becomes more widespread, traditional banking risk management plays a crucial role as well. There should be linkages between model risk and existing credit risk, liquidity risk, market risk, operational risk and reputation risk controls. This integration provides a way to avoid situations where an AI system works well at a technical level, but it also exposes an institution without them knowing it [7]. Evidence trails should be auditable, linking model decisions with data sources, version of the policies, test results, risk reports and outcomes to enable review and reconciliation of decisions with wider risk management and capital planning. While significant advances have been made, there are conflicting demands between model complexity, interpretability, regulatory expectations, and model performance in adapting to evolving bank environments [8]. For effective AI governance, it is not only about choosing an explainability tool or complying with a documentation mandate. It demands ongoing monitoring throughout the entire data, model, decision, and reporting journey, with accountability and the typical risk management processes.

Regulatory, Standards, and Explainability Landscape in Banking AI

Model risk management, regulatory accountability and compliance with international prudential standards are increasingly central to banking AI regulatory and standards. Basel frameworks set minimum standards with respect to risk based capital, liquidity, leverage, large exposures and prudential standards. Assessments for the jurisdictions and topics assess the extent of the consistency of implementation of these standards throughout the banking systems, and monitoring assists in the timely adoption of these standards in the domestic legislation and regulatory framework [9]. It fosters uniformity, stability and strength in the supervision of financial institutions. SR 11 7 is a significant reference within model governance on lifecycle based model risk management. It shows the need for processes to be structured and followed when building models, validating models, deploying them, monitoring them, and reviewing them periodically. Validation includes conceptual soundness, implementation accuracy and reasonableness of model outputs [10]. In parallel, governance expectations have been established in the regulatory environment in the United Kingdom, Canada, the European Union and elsewhere, resulting in broadly similar expectations on governance, model oversight and model validation. Typical elements that are evaluated during regulatory examinations include model inventories, validation reports, monitoring data, issue logs, remediation data, and independent review evidence. Validation functions are expected to be independent from model developers and business units and boards/senior management will be held responsible for governance, escalation and risk decisions [11]. Common pitfalls are lack of model validation, lack of post deployment monitoring, weak documentation, and lack of model drift / anomaly detection. The integrity, relevance, and applicability of third party models, vendor data and external information sources should also be considered.

Compliance Realities and Interaction with Traditional Risk Limits

In banking AI, the concept of explainability is becoming well understood as being context-dependent, and no single method will meet all regulatory, technical, and consumer protection goals. Boards and senior executives therefore are encouraged to engage with practical governance questions such as the decisions that an AI system can impact, the data it can access, and how the performance of the AI system is tested [12]. This view focuses more on operational control, accountability and evidence than on having a universal explainability metric. It is also acknowledged that

explainability practices can differ by the nature and level of risk of a model. Non compliance does not automatically follow if a certain explainability approach is not followed, but the lack of adequate model risk management or the practice going against laws may lead to supervisory action if there is an unsafe or unsound practice. Banks are therefore responsible for making sure they use their model in a prudent way and adjust their explainability practices depending on the specific decision context [13]. Ensuring compliance becomes a result of the structure of AI systems is the practical governance principle. The practical governance principle is to ensure compliance as a result of the structure of AI systems. When a model isn't fully interpretable, end to end data lineage, documentation, repeatable processes, and defined controls are crucial. Banks should hold inventories of AI systems, prioritizing based on risk, and exercise appropriate oversight [14]. Similar governance efforts to those applied to internally developed systems should also be applied to vendor and third party systems, encompassing documentation, performance reporting metrics by relevant customer groups, the mechanisms used to update the system, contractual accountability etc. Also, third party models and external information sources should be regularly evaluated for integrity and applicability. Their risks should be part of current reporting and oversight processes and should continue to be visible, alongside conventional risk measures, alongside model exposures [15]. Overall, compliance with limited models that explain their actions relies on constant monitoring, documentation, suitable explanations for stakeholders, and AI systems associated to banking risk limits.

Governance Frameworks, Operating Models, and Mitigation Strategies

In the banking sector, governance structures are formally established to govern and define the roles of model risk management, policy development and assurance activities to ensure that models are suitable for decision making. Model governance is a framework of policies, procedures, accountability and oversight, and the operating model comprises people, processes and technology to enable independent review and effective checks and balances [16]. Typically, governance becomes more formal as it evolves from ad hoc to optimized and even more automated as it gains tangible benefits like audit readiness, data quality, and incident response, which can be measured. RACI modelling can provide clarity on who is responsible to whom, business unit to business unit, risk to risk, compliance to compliance, and senior management to senior management. Hybrid operating models can also help achieve a balance between centralized governance and local regulations, such as the use of sovereign cloud strategies when applicable [17]. The following should be included in the design of effective model governance: Independent review, model ownership, internal controls, information inputs, processing methods, and reporting output. People, Processes, Technology and Ethics can be incorporated into a wider governance framework. This allows for the consideration of elements such as accountability, procedures, data lineage, cataloguing, automation, fairness, and responsible AI practices all at once. Cloud based and AI enabled governance platforms are being increasingly developed to integrate governance, data quality, security and compliance functions (Table 1) [18]. With observability capabilities for continuous monitoring and governance, there can be a reduction in the duplication process and enhancement of auditability, as well as support for alignment in overlapping regulatory requirements. Governance, technical controls, and operational practices can be used throughout the AI lifecycle to address explainability gaps (Figure 1). If possible, models that make sense and are accessible to explanation can be used, and post hoc explanation methods applied selectively, with domain review to evaluate their relevance and fidelity. When there are uncertainties in explanations, confidence scores and top N rationales can help in operational oversight and exception handling [19]. Lastly, continuous monitoring and testing should detect performance degradation, bias, model drift and unexpected behaviour. Technical information should be translated into information for the risk that can be used for management and there should be linkages to escalation processes. Explainability efforts should be consistent with regulatory guidance and industry guidance, taking into account factors such as, but not limited to, the nature of the decision, audience and level of risk.

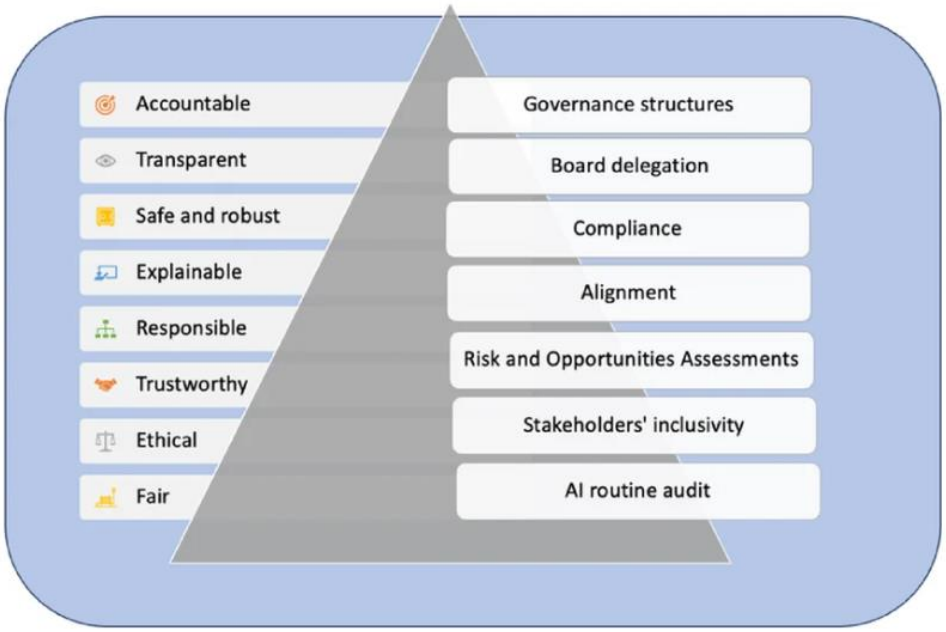


Figure 1: AI Governance Framework Principles [37]

Table 1: Overview of AI Governance Elements and Operational Requirements in Banking

Governance Domain	Key Focus & Operational Requirement	Regulatory & Practical Objective	Reference
Model Risk Management	Lifecycle processes encompassing structured building, independent validation, deployment, and periodic review.	Ensures conceptual soundness, implementation accuracy, and reasonableness of model outputs.	[3]
Explainability Architecture	Embedding traceability, evidence of decisions, data lineage, and audience-appropriate explanations directly into processes.	Moves explainability from an end-stage technical add-on to an integrated architecture requirement.	[5]
Regulatory Compliance	Adherence to prudential standards, senior management accountability, and consumer protection mechanisms.	Aligns AI operations with domestic legislation, transparency demands, and institutional responsibility.	[9]
Third-Party & Vendor Oversight	Evaluating the integrity, relevance, security, update practices, and documentation of external models and data.	Prevents blind spots and preserves institutional accountability when using vendor-supplied AI systems.	[11]

Case Studies and Application Patterns in Banking AI Explainability

Practical application patterns and case studies illustrate the application of financial institutions in implementing explainability and governance in AI-based decisions systems. An AI native methodology created by Bugni Labs provides an example of how explainability is integrated from the very beginning of the software lifecycle. During architecture, explanation requirements are defined, during model integration, models are integrated with the explanation methods, such as SHAP and LIME, in order to assess the accuracy of explanations, a quality assurance process is conducted and in order to monitor the performance of explanations, an operational team is established (Table 2) [20]. This way, you can avoid having to implement fixes after the deployment, and it helps when you need to be transparent at runtime in regulated environments. Another example of explainability operationalization is a UK neobank credit decisioning platform. The system can provide explainable decisions in all affordability and eligibility, credit scoring, and credit limits aspects for any number of products. An event driven architecture with the ability to store decisions and explanations of decisions and then pass edge cases to human underwriters with the context of the decision [21].

These examples prove that explainability could be added to real time decision processes not just by changing the underlying algorithm, but also by architectural and governance controls. There are a number of application patterns that are common to regulated banking environments (Figure 2). High stakes use cases, mainly credit decisioning, are typically prioritised as they have regulatory implications and can have a direct impact on customers. Institutions could start with a single product or decision process and then apply that approach to other products. Incorporation with existing machine learning frameworks like scikit learn, XGBoost, and TensorFlow [22]. Domain focused microservices can be used to separate explanation services from model serving, thus versioning, monitoring and scaling explanation components independently of model serving. Overall, these case studies show that achieving successful explainability requires a combination of technical methods and architecture, lifecycle governance, human review, documentation, and continuous monitoring. The focus is then on operational utility, auditability, and maintainability of explanations in the context of evolving banking AI systems.

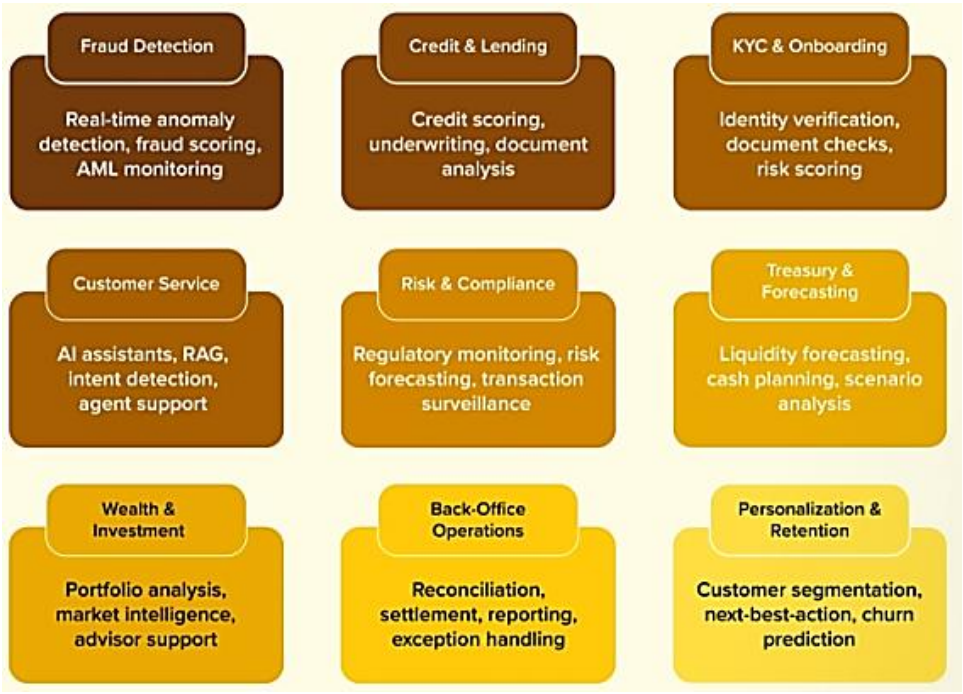


Figure 2: Key Application of AI in Banking [38]

Table 2: AI Application Patterns, Constraints, and Mitigation Strategies in Financial Institutions

Application Pattern	Technical and Operational Constraints	Mitigation Strategy & Governance Control	Reference
Credit Decisioning Platforms	Balancing high-stakes regulatory requirements and direct consumer impact with model performance and complexity.	Event-driven architectures storing decision trails, paired with human-in-the-loop oversight for edge cases.	[12]
Complex & Emerging Models	Performance vs. interpretation dilemma; post-hoc methods can create convincing narratives that hide true computations.	Using benchmark testing, counterfactual analysis, red teaming, drift monitoring, and selective post-hoc validation.	[14],[15]
Cloud & Automated Compliance	Managing siloed controls, overlapping regulatory frameworks, and data quality across regional boundaries.	Deploying cloud-based governance platforms integrating cataloging, data lineage, and continuous observability.	[18]

Discussion

AI is being used in more and more areas of the banking industry where conventional risk management, compliance and internal control frameworks existed. Machine learning and other AI techniques are now being used increasingly to assist in credit assessment, fraud

detection and anti money laundering, customer service, portfolio management and operational decision making [23]. This expansion places a governance challenge as well since the predictive power of complex models can outpace the interpretability for users, customers, auditors and supervisors. What is being questioned is whether an AI model can make accurate predictions or whether its decisions can be comprehended, challenged, reconstructed, monitored, and governed during the model's entire life cycle. Explainability is thus an integral part of the banking AI governance [24]. But explainability needs to be seen not just as a single technical characteristic that can be measured regardless of context. The value or usefulness of an explanation is dependent upon the decision to be made, the level of risk, and the nature of the audience, as well as the consequences of an incorrect decision. A model developer might need a lot of technical information on the features and the behavior of a model, while a customer might only be interested in an overview of the main factors that impact a credit decision [25]. Regulators and auditors might instead need to see that the decision can be reconstructed, and that appropriate controls were applied to the decision. This is a reason why it is hard to create a universal standard for explainability. This complexity is further strengthened by the regulatory framework. There are conflicting regimes on how banks manage model risk, prudential issues, consumer protection, data governance, cybersecurity and accountability. In addition to Basel related standards, there are model risk management frameworks, which are more specific on model development, validation, monitoring and governance [26]. The regulatory climate is growing more stringent on banks to prove that models deliver satisfactory results, but also that they are regularly managed and documented. Explainability is then, hence, coupled with governance evidence but not considered as a stand-alone characteristic of the model. The lifecycle aspect is of special significance. The process of governance starts before the deployment of the model and extends to its implementation, monitoring, modification and retirement [27]. As a model is developed, its objectives, data sources, assumptions, intended uses and limitations should be documented. Conceptual soundness and implementation accuracy should be independently validated. Following deployment, performance, stability, fairness, data quality, and potential drift should be continuously monitored. Previous explanations might not be valid when the models change or are significantly altered. Consistency in the explanation of the model across its versions becomes an important operational need. An important governance question is also the difference between the intrinsic and post hoc explainability [28]. Interpretable models may be helpful in highly regulated decision processes by being more structurally interpretable. In some applications like fraud detection where a huge amount of multidimensional data has to be processed, though, more complex models might offer predictive benefits. Although they are not the main techniques of Post Hoc analysis, they can give valuable information on influential features without being used as a substitute to the underlying model [29]. Their use, however, needs to be validated as a plausible explanation does not imply that the explanation is correct and will reflect the actual decision process of the model. Explanations should therefore be understood as evidence that must be tested, and not as a given piece of evidence of transparency of the model. This constraint is especially applicable to new AI systems and big language models. A complex model can create convincing narratives that seem to be understandable but don't really capture the underlying computational process [30]. Under these conditions, the quality of the explanation cannot be evaluated purely by a measure of readability. Other evidence of model behavior can come from benchmark testing, counterfactual analysis, adversarial testing, red teaming, drift monitoring, and controlled scenario testing. Such approaches are especially applicable in situations that could have significant consumer, legal, or financial implications. Third party AI can add another layer of complexity. Banks are now more and more turning to external vendors for models, data, cloud infrastructure, and AI services [31]. The ownership of the underlying technology does not preclude the institution's governance duties. The performance, limitations, data sources, update practices, security, and explainability of vendor models should thus be evaluated. A contract should define reasonable access to documentation, test information, update notifications and accountability mechanisms. Institutions might otherwise be left with problems in reconstructing decisions or evaluating changes if a vendor changes an underlying system [32]. Governance platforms can even integrate model cataloguing, data lineage, documentation, security, compliance monitoring, and even audit, among others. This can help to streamline controls, boost transparency throughout the AI lifecycle, and decrease siloed controls. A federated governance model could enable business or regional units to respond to local needs while offering a shared institutional framework [33-36]. This is especially true in the case of international banking groups with differing regulatory expectations across jurisdictions. Overall, the discussion suggests that explainability must be deeply integrated into a comprehensive framework of model risk management, regulatory compliance, traditional risk management, data management, cybersecurity, and

organizational responsibility in banking to implement effective governance.

Conclusion

AI governance in banking requires explainability to be integrated with model risk management, regulatory compliance, traditional risk controls, and lifecycle oversight. Explainability cannot be reduced to a single technical method because its effectiveness depends on model complexity, decision context, regulatory requirements, and stakeholder needs. Strong documentation, independent validation, data lineage, and vendor accountability are therefore essential. Traditional risk limits should remain connected to AI related model risks to identify emerging exposures and maintain institutional accountability. Overall, a governance-based approach provides a practical foundation for deploying complex AI systems while supporting transparency, auditability, regulatory readiness, and responsible financial decision making.

Author Contributions

M.S.N. Conceptualization, literature search and review, analysis and interpretation of the literature, drafting of the manuscript, critical revision, and final approval of the manuscript.

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