Transforming Credit Risk Assessment and Basel Compliance using AI-Driven Techniques

# Introduction and Background

Banking forms the cornerstone of the modern economy, enabling financial intermediation and promoting sustainable economic development (Aracil et al., 2021). Its central role in maintaining monetary stability underscores its indispensable contribution to national progress. However, banks remain inherently susceptible to systemic risks, including financial crises, which threaten their operational resilience and erode public trust. The 2008 global financial crisis vividly demonstrated how interconnected banking networks can transmit and amplify economic shocks.

Banks must manage a broad spectrum of risk categories that challenge institutional stability. These include credit risk from borrower defaults, market risk due to asset value fluctuations, and operational risk arising from internal process failures or external disruptions. Non-performing assets (NPAs), a direct manifestation of credit risk, represent loans that borrowers fail to repay and pose a serious threat to profitability and financial soundness. Addressing such multifaceted risks necessitates robust risk management frameworks to safeguard both institutional viability and economic continuity (Bashir et al., 2025).

In response, global regulatory regimes have evolved to establish uniform standards for risk oversight and capital adequacy. The Basel Accords, formulated by the Basel Committee on Banking Supervision, serve as a global benchmark for banking regulation. By prescribing minimum capital requirements, stress testing protocols, and liquidity buffers, these accords aim to strengthen financial institutions against systemic vulnerabilities and enhance resilience during economic shocks (Anguren et al., 2024; Bank für Internationalen Zahlungsausgleich & Basel Committee on Banking Supervision, 2022).

However, financial regulation has grown increasingly complex. Regulatory texts such as the Basel Accords span thousands of pages, weaving dense legal language, technical detail, mathematical formulations, and extensive annotations (Cao & Feinstein, 2024). While Basel I comprised approximately 30 pages, Basel II expanded to over 300 pages, and the fully realized Basel III framework alone spans more than 600 pages (Jones & Zeitz, 2017). This dramatic rise in complexity imposes substantial compliance burdens on banks.

Estimated costs of implementing Basel III capital norms have been significant. A World Bank–linked analysis of Swiss systemically important banks noted how elevated CET1 requirements and implementation demands translate into upward of hundreds of millions in effective compliance costs—often interpreted in the order of a few hundred million CHF through capital forgone and resource deployment (Junge & Kugler, 2018).

Regulatory intensity has also intensified globally. Quantitative studies tracking the U.S. regulatory corpus identified steep increases in both the volume (“temperature”) and scope (“diversity”) of regulations over time, reflecting heightened supervisory scrutiny (II & Katz, 2017)**.** This surge in regulatory demands underscores the strategic importance and resource intensity of compliance efforts.

Non‑compliance with Basel norms can trigger severe penalties: monetary fines, operational restrictions, and limitations on capital distributions such as dividends or share buybacks. In cases of repeated or material breaches, regulators may impose higher capital buffers, restrict new product offerings, or enforce governance reforms. Beyond financial sanctions, non‑compliance may damage reputation, erode investor and customer confidence, result in credit rating downgrades, raise cost of capital, and constrain market access. Collectively, these enforcement mechanisms reinforce regulatory discipline, deter systemic risk exposure, and ensure banks maintain robust internal controls and adequate buffers to absorb financial shocks.

As the financial sector accelerates its digital transformation, emerging technologies are reshaping traditional banking models by driving innovation in risk management, compliance, and decision-making. Among these, Artificial Intelligence (AI) is playing an increasingly pivotal role, offering advanced capabilities that go beyond automation to include intelligent analysis and strategic foresight. In particular, two branches of AI—Predictive AI and Generative AI (GenAI)—are transforming banking by enabling more accurate forecasting, intelligent automation, and efficient regulatory compliance. While Predictive AI focuses on using historical and real-time data to anticipate future outcomes and risks, Generative AI emphasizes the creation of new outputs—such as textual interpretations, executable logic, or automated responses—from complex input patterns. Together, they offer complementary capabilities to strengthen financial institutions’ operational resilience and strategic agility.

Predictive AI plays a pivotal role in advancing forward-looking credit risk management. By analyzing borrower-level transactional data, repayment behavior, and credit histories—supplemented by relevant macroeconomic indicators—it enables early identification of potential defaults and credit deterioration. These insights allow banks to move beyond static, retrospective credit assessments toward proactive and dynamic risk evaluation. Key applications include real-time credit scoring, early-warning systems, and stress testing of loan portfolios under adverse scenarios. This predictive capability enhances the precision of credit underwriting, supports risk-based pricing, and strengthens alignment between credit decisions and evolving risk exposures.

Generative AI, by contrast, addresses the complexity of regulatory compliance and risk reporting. It can translate intricate financial regulations into machine-readable logic, reducing reliance on manual interpretation and mitigating the risk of non-compliance. GenAI can also automate the calculation of Risk Weights (RW) and Risk-Weighted Assets (RWA) during client onboarding, enabling faster and more accurate exposure evaluation. Furthermore, its ability to simulate the effects of regulatory changes allows banks to proactively adapt their strategies—transforming compliance from a reactive obligation into a source of strategic advantage.

However, despite the transformative potential of these technologies, a critical research gap remains in their integrated application for proactive credit risk management. Current industry practices largely treat predictive and Generative AI in isolation. Traditional credit assessment frameworks depend on historical data and fixed models, which struggle to adapt to rapidly evolving borrower behavior and macroeconomic volatility. A unified, AI-driven approach—combining predictive analytics for forward-looking credit evaluation with Generative AI for dynamic regulatory interpretation—could fundamentally reshape how banks assess creditworthiness, manage exposures, and respond to regulatory change in near real-time.

# Literature Review

Recent studies have increasingly applied machine learning techniques to improve credit risk assessment. (Khandani et al., 2010) demonstrated that decision tree models outperform traditional credit scoring approaches when applied to consumer lending data. Building on this, (De Lange et al., 2022) integrated SHAP values with LightGBM models to enhance model interpretability, aligning predictive analytics with regulatory requirements for explainability. (Sigrist & Leuenberger, 2023) introduced a time-varying default risk model that incorporates latent risk factors, offering a more nuanced approach to corporate credit evaluation. In a domain-specific context, (Kumar et al., 2023) evaluated various AI models on Indian mortgage datasets to assess both predictive accuracy and operational feasibility. Collectively, these contributions illustrate the evolution of credit risk modeling from basic prediction to frameworks that are dynamic, explainable, and aligned with real-world regulatory expectations.

Parallel to advances in predictive modeling, recent research has explored the application of generative AI in the domain of financial regulation, encompassing tasks such as regulatory retrieval, reasoning, and automation. (Haeri et al., 2025) introduced RiskEmbed, a domain-specific embedding model and benchmark dataset designed to enhance retrieval performance in regulatory question-answering tasks. (Fazlija et al., 2025) evaluated prompting strategies for Basel III interpretation and found that chain-of-thought prompting improves the accuracy of risk weight assignments. In a complementary study, they demonstrated the feasibility of converting regulatory texts into executable Python code, facilitating automation of compliance logic. (Cao & Feinstein, 2024) contributed prompt engineering strategies for interpreting market risk regulations, advancing the development of regulatory question-answering frameworks. (Joshi, n.d.) proposed an end-to-end system architecture for integrating GenAI into financial risk workflows, thereby bridging research and operational deployment. Together, these studies trace a stepwise progression from document retrieval and interpretation to full-scale automation of regulatory compliance using generative AI.

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| **Author** | **Contribution** | **Model Used** | **Data Input** | **Outcome** |
| Fazlija et al. | Demonstrated improved regulatory reasoning using CoT/ToT in Basel III credit risk | GPT-4o, Claude 3 with Chain-of-Thought (CoT) and Tree-of-Thought (ToT) | 6,501 test cases across Basel III Standardized Approach | Up to +13pp accuracy gain with CoT prompting for GPT-4o |
| Haeri et al. | Introduced RiskData and RiskEmbed for improved retrieval in financial RAG systems | Finetuned Sentence-BERT embeddings (RiskEmbed) | 94 OSFI regulatory guidelines (1991-2024) | Improved domain-specific retrieval performance in QA systems |
| Joshi | Reviewed GenAI in finance and proposed hybrid frameworks | LLMs with traditional finance pipelines; Transformer-based models | Literature synthesis, industry and academic sources | Architecture integrating LLMs with credit scoring, VaR, macro sims |
| Cao and Feinstein | Prompt engineering to translate Basel III regulatory text to math/code logic | GPT-4, Claude, Gemini, with prompt strategies | Basel III capital requirement case studies with simulated assets | GPT-4 most accurate; improved mathematical precision in regulatory interpretation |
| Fazlija et al. | Evaluated LLMs in generating regulatory implementation code (CRE20) | General-purpose and code-generation LLMs (e.g., GPT variants) | 6,000+ Basel III CRE20 test cases with risk weight rules | Up to 91.67% pass@10 in Python code generation for risk weight rules |
| Sigrist & Leuenberger | Developed LaGaBoost: frailty-integrated tree boosting for multi-period defaults | LaGaBoost (Tree Boosting + Latent Frailty) | Corporate default datasets across multiple periods | Higher AUC for long horizons; better portfolio tail risk prediction |
| Kumar et al. | Compared ML models for mortgage loan risk prediction | Logistic Regression, Decision Tree, Gradient Boosting | Mortgage loan dataset (case study) | Gradient Boosting performed best in commercial insight extraction |
| Khandani et al. | Built ML models from credit bureau and transaction data to predict delinquencies | Nonparametric ML (ensemble models) | 2005-2009 customer transactions and bureau data | 85% RÂ²; 6â€“25% savings via early credit line adjustments |
| de Lange et al. | Applied XAI (SHAP) to LightGBM for explainable credit scoring | LightGBM with SHAP vs. Logistic Regression | 13,969 unsecured loan customer records (Norwegian bank) | Better prediction and variable-level explainability vs. traditional models |

# Objectives and Contributions of the Study

Credit risk remains the largest component of capital requirements under Basel 3.1. However, prevailing credit scoring models primarily estimate the probability of default (PD) at the time of onboarding, without dynamically linking these outputs to Basel-compliant Risk-Weighted Asset (RWA) computations. This disconnect prevents banks from capturing the real-time capital impact of credit decisions and leads to batch-based risk reporting that lags behind operational needs.

This research aims to address these limitations by designing a real-time, explainable credit risk engine that integrates predictive AI/ML models, generative AI (GenAI), and a LangGraph-based orchestration framework. The solution will predict PD, LGD, and EAD at the point of decision using structured and unstructured data sources—including bureau records, financial statements, ESG disclosures, and market news. Predictive modeling techniques such as Random Forest, XGBoost, CatBoost, and deep learning architectures will be employed to capture non-linear borrower behavior. Fairness-aware algorithms and SHAP-based interpretability methods will ensure that model decisions are transparent, bias-mitigated, and explainable.

In parallel, the system will leverage Generative AI techniques to operationalize complex Basel 3.1 regulatory text. This includes using Retrieval-Augmented Generation (RAG) to ground responses in precise regulatory clauses, alongside experiments with instruction-tuned LLMs (e.g., GPT-4, Mistral-7B, LLaMA2, Claude) to directly reason over text. The solution will evaluate trade-offs between prompting strategies, domain-specific fine-tuning, and zero-shot inference, balancing explainability, accuracy, and computational efficiency.

To support portfolio-level decision-making, the system will interface with COREP/FINREP regulatory data, enabling relationship managers (RMs) to visualize how new exposures affect CET1 ratios and sectoral or geographic risk limits. A dedicated explainability layer will present model drivers using SHAP or LIME, enhanced by GenAI-based summarization and counterfactual simulations, allowing RMs to understand and act on model outputs with confidence.

The solution will also embed Agentic AI capabilities to introduce autonomous, self-regulating behavior across the risk pipeline. These agents will continuously monitor for data drift, regulatory changes, and model degradation, and will autonomously trigger retraining, re-parsing of updated rules, or workflow reconfiguration using LangGraph logic graphs. Over time, this layer is expected to enable closed-loop learning, proactive compliance alignment, and reduced operational dependency on manual interventions—turning AI from a static model into a responsive, adaptive decision-support system.

Built on a modular LangGraph-based architecture, each functional component—data ingestion, scoring, RWA computation, explainability, and dashboard APIs—will operate as an independent yet interoperable node. Document parsing will leverage strategies such as sliding windows, semantic chunking, and recursive text splitting (e.g., using SentenceTransformers) to maximize contextual accuracy and minimize hallucination risks. The design ensures system scalability, production-readiness, and secure integration within banking IT infrastructures.

The expected contributions of this dissertation are fivefold:

1. Development of a real-time credit risk engine that integrates Basel-compliant RWA calculations into credit decisioning at the point of onboarding.
2. Design of an explainability framework for AI/ML models that meets regulatory standards for transparency, auditability, and counterfactual reasoning.
3. Demonstration of GenAI use cases in converting Basel 3.1 regulatory text into executable compliance logic using RAG, prompt engineering, and model fine-tuning.
4. Proposal of a LangGraph-based orchestration blueprint for scalable and modular AI deployment in regulated financial environments.
5. Exploration of Agentic AI techniques to enable autonomous monitoring, learning, and optimization across the end-to-end credit risk and capital assessment lifecycle.

# Research Questions

1. How can AI/ML models for Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD) be made explainable and auditable in compliance with Basel 3.1 guidelines?
2. Can Generative AI (Large Language Models) be applied to parse Basel 3.1 regulatory text and automatically translate it into executable logic for RWA computation?
3. How can portfolio-level capital impact be embedded into point-of-decision credit risk assessment frameworks?
4. What role can unstructured data—such as financial disclosures, ESG reports, and market news—play in enhancing early-warning signals for credit deterioration?
5. How can the proposed AI-based credit risk solution be orchestrated using LangGraph and deployed securely within a bank’s infrastructure?
6. How can Agentic AI capabilities be integrated to enable autonomous learning, monitoring, and optimization of credit risk and capital assessment workflows over time?

# Proposed Methodology and Database

The proposed solution will be structured across six interconnected modules. The first module, the AI/ML Credit Risk Prediction Layer, will ingest structured data to assess borrower-level creditworthiness. Publicly available inputs such as sample financial statements from RBI bulletins, anonymized borrower profiles from academic studies, and curated synthetic datasets will serve as the foundation for training and validation. These will be used to build predictive models—including XGBoost, CatBoost, and deep learning architectures—to generate Probability of Default (PD), Loss Given Default (LGD), Exposure at Default (EAD), and composite credit scores.

The second module, the RWA and Capital Impact Engine, will operationalize Basel 3.1 guidelines, aligned with Indian regulatory interpretations. Using large language models (LLMs) and LangGraph orchestration, the module will simulate the computation of Risk-Weighted Assets (RWA) and their impact on Common Equity Tier 1 (CET1) ratios. This allows credit risk assessment models to incorporate capital sensitivity in line with real-world supervisory requirements.

The third module, the Portfolio Context Interface, will simulate portfolio-level views by aggregating synthetic borrower data. This module will illustrate how the addition of new exposures could influence capital allocation, diversification, and concentration—without relying on any confidential or proprietary datasets. Visualization outputs will mimic those used by bank risk teams, purely for academic and experimental demonstration.

The fourth module, Explainability and Counterfactuals, will ensure transparency and interpretability of AI/ML outputs. The system will use SHAP, LIME, and counterfactual simulation techniques, supported by generative AI-based natural language generation, to explain model decisions. Users will be able to assess how changes in borrower inputs (e.g., collateral, loan tenor) could influence credit scores or RWA treatment.

The fifth module, the LangGraph-Orchestrated Pipeline, will integrate all components—data processing, scoring, RWA computation, and explanation—into a modular architecture. Each stage will be implemented as an independent LangGraph node, supporting reproducibility and maintainability within academic infrastructure.

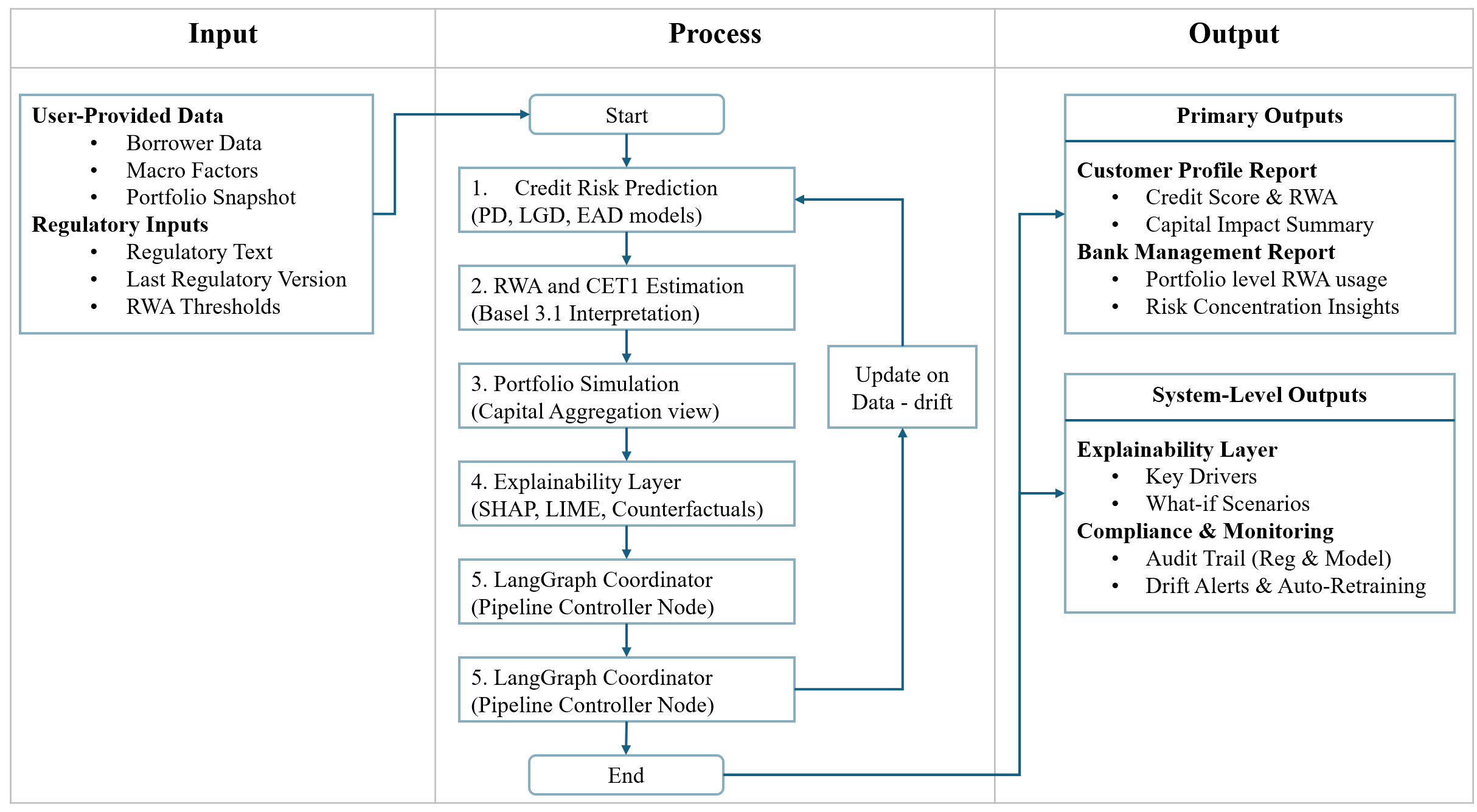
The sixth module, the Agentic AI Execution Layer, will embed autonomous agents to monitor simulated operational signals—such as data drift, model degradation, or changes in regulatory text. These agents will autonomously initiate retraining, regulatory re-parsing, or pipeline updates using LangGraph logic, enabling long-term adaptation and research extensibility.

From a methodological perspective, the study will rely entirely on:

* Publicly available resources such as the Basel 3.1 rulebook, RBI Master Circulars, and published academic case datasets;
* Synthetic datasets generated using generative AI techniques, designed to replicate realistic borrower profiles without exposing any confidential data;
* Public domain financial structures and taxonomy from sample disclosures (e.g., in SEBI/RBI-published reports) to support mapping and testing of credit scoring models.

The AI/ML techniques will include gradient boosting, deep learning, fairness-aware modeling, and generative AI for text-to-logic conversion. Deployment will be simulated using Docker and Kubernetes, with a focus on modularity, reproducibility, and regulatory transparency in a non-production, academic environment.

**End-to-End System Architecture – Inputs, Process Flow, and Outputs**



**Functional Overview of Proposed Modular Architecture**

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| **Module No.** | **Module Name** | **Purpose** | **Key Techniques / Tools** | **Data Sources** |
| **1** | AI/ML Credit Risk Prediction Layer | Assess borrower-level creditworthiness using structured public and synthetic data. | XGBoost, CatBoost, Deep Learning | RBI bulletins, anonymized academic borrower data, synthetic datasets |
| **2** | RWA and Capital Impact Engine | Simulate Basel 3.1-compliant RWA and CET1 impact for Indian banking regulations. | LLMs, LangGraph orchestration, executable regulatory logic | Basel 3.1 rulebook, RBI circulars (as academic reference) |
| **3** | Portfolio Context Interface | Provide a portfolio-level simulation of capital allocation and concentration risk. | Aggregation logic, simulated dashboards | Aggregated synthetic borrower profiles |
| **4** | Explainability and Counterfactuals | Ensure interpretability of model outputs and simulate decision scenarios. | SHAP, LIME, Counterfactual Simulation, GenAI-based Natural Language Summarizer | Derived from previous module outputs |
| **5** | LangGraph-Orchestrated Pipeline | Integrate all functional modules into a cohesive, scalable, academic-ready architecture. | LangGraph, modular node implementation | Interconnections across Modules 1–4 |
| **6** | Agentic AI Execution Layer | Enable autonomous monitoring, retraining, and pipeline adjustment in response to simulated signals. | Autonomous Agents, LangGraph, retraining triggers | Simulated events (e.g., data drift, regulatory text changes, model degradation) |

# Expected Outcomes

This research aims to develop a real-time credit risk engine that directly links client onboarding decisions with Basel-compliant Risk-Weighted Asset (RWA) computations. This integration will allow financial institutions to assess forward-looking capital impacts from the outset of the customer lifecycle, thereby aligning day-to-day credit origination with regulatory expectations related to capital adequacy, risk sensitivity, and supervisory oversight.

A second outcome involves the formulation of an explainability framework for AI and machine learning models applied to credit risk assessment. Designed to meet regulatory standards for transparency and accountability, this framework will enhance model interpretability without compromising analytical depth. It is expected to support regulatory validation processes and foster institutional trust in AI-enabled risk models.

The study will also demonstrate the application of generative AI to automate critical components of regulatory reporting, with a focus on RWA calculations. By embedding audit trails and validation checkpoints into GenAI-enabled workflows, the solution aims to reduce manual compliance burdens while improving accuracy, traceability, and operational efficiency.

In addition, the research will produce a LangGraph-based orchestration blueprint that showcases a modular and scalable architecture for deploying AI systems in financial institutions. This blueprint will emphasize interoperability, operational readiness, and seamless integration across credit, compliance, and risk domains—providing a viable pathway for enterprise-level implementation.

To support benchmarking and promote replicability, the project will release a curated set of open-source synthetic datasets and evaluation metrics specifically designed to measure incremental capital impact. These resources will facilitate further experimentation, enable comparative assessment of AI solutions, and contribute to the broader research ecosystem focused on regulatory technology and explainable AI.

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