**Synopsis**

**on**

**Integrating Predictive and Generative AI for Credit Risk Assessment under Basel 3.1**



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DECLARATION

This is to certify that I, a student of the Ph.D. Programme (2023) at the Indian Institute of Foreign Trade, have submitted the synopsis entitled "Integrating Predictive and Generative AI for Credit Risk Assessment under Basel 3.1" as a part of the Course-Work of the Ph.D. Programme. This is an original work. It is neither copied (partially/fully) from any scholastic work, nor is it submitted for any other degree or diploma. I remain fully responsible for any error and plagiarism.

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Ravi Kumar Jain

(Name / Signature of the student)

CERTIFICATE

This is to inform that Ravi Kumar Jain, student of the Ph.D. Programme (2023), has completed the synopsis on the topic "Integrating Predictive and Generative AI for Credit Risk Assessment under Basel 3.1" under my guidance.

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Prof. (Dr.) Anju Goswami

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# Introduction

Banking is a cornerstone of the modern economy, enabling financial intermediation and supporting sustainable economic development Aracil et al. (2021). Its central role in maintaining monetary stability underscores its critical contribution to national progress. However, banks remain inherently exposed to systemic risks, including financial crises, which can undermine operational resilience and erode public trust. The 2008 global financial crisis illustrated how interconnected banking networks can transmit and amplify economic shocks (Beutel et al., 2019; Coffinet and Kien, 2019; Shrivastav, 2019; Ari, Chen and Ratnovski, 2021).

Financial institutions face multiple categories of risk that challenge their stability, including credit risk from borrower defaults, market risk from asset value fluctuations, and operational risk arising from internal process failures or external disruptions. Non-performing assets (NPAs), a direct manifestation of credit risk, threaten both profitability and solvency. Addressing these risks requires robust, adaptive risk management frameworks that protect institutional viability while safeguarding economic continuity Goswami and Gulati, 2019. Prior research highlights how advanced methods—support vector machines, neural networks, adaptive neuro-fuzzy inference systems, and ensemble models—improve credit risk modelling and stress testing (Khandani, Kim and Lo, 2010; Butaru et al., 2016; Sigrist and Leuenberger, 2023; Ahmed, Mehdi and Mohamed, 2023; Kumar et al., 2023; Tavana et al., 2018; Kellner, Nagl and Rösch, 2022).

In response, international regulatory frameworks such as the Basel Accords have sought to strengthen financial stability through harmonised standards for capital adequacy, stress testing, and liquidity management Anguren et al. (2024). Yet, the regulatory corpus has grown substantially in both length and complexity, moving from approximately 30 pages in Basel I to over 600 pages in Basel III Jones and Zeitz (2017) and Basel 3.1 expanded to 1847 pages (The Basel Framework, n.d.). This expansion imposes significant compliance costs Junge and Kugler (2018) and intensifies the operational challenge of maintaining continuous alignment with supervisory expectations II and Katz (2017). Non-compliance carries material consequences, including financial penalties, operational restrictions, reputational damage, and reduced market access (Park et al., 2021; Wong and Wong, 2021; Moffo, 2024). For India, the global financial crisis was also shown to have weakened intermediation efficiency, especially in the presence of rising NPAs (Goswami, 2022c).

Parallel to these regulatory developments, the financial sector’s digital transformation has created new opportunities to improve risk management and compliance processes. Artificial intelligence (AI), in particular, offers capabilities that extend beyond process automation to include advanced analytics, predictive modelling, and knowledge extraction. Two subfields—predictive AI and Generative AI—hold particular relevance. Predictive AI uses historical and real-time data to anticipate future outcomes, supporting applications such as dynamic credit scoring, early-warning systems, and stress testing (Hu et al., 2021; Kyeong, Kim and Shin, 2022; Fraisse and Laporte, 2022; Kellner et al., 2022; Krivorotov, 2023). Generative AI can interpret complex regulatory provisions, translate them into structured logic, and potentially assist in the automation of risk-weighted asset (RWA) calculations under Basel 3.1 (Fazlija et al., 2025; Haeri, Vitrano and Ghelichi, 2025; Cao and Feinstein, 2024; Joshi, n.d.).

Despite these advances, existing literature and practice largely treat predictive and Generative AI as separate tools. Traditional credit assessment frameworks remain constrained by their retrospective orientation and limited adaptability to rapidly changing borrower and market conditions (Altman et al., 1994; Singh et al., 2024; Dawood et al., 2019; Al-Sultan and Al-Baltah, 2024; Kozodoi et al., 2022). Similarly, regulatory interpretation processes often rely on manual analysis, which can be slow and resource-intensive (de Lange et al., 2022; Sigrist and Leuenberger, 2023; Joshi, n.d.; Lokanan, 2024). This separation creates a conceptual and methodological gap: there is little empirical evidence on the benefits, challenges, and feasibility of combining predictive analytics for forward-looking credit evaluation with Generative AI for dynamic, machine-readable regulatory interpretation.

This gap motivates the present study, which aims to investigate whether an integrated, explainable AI framework can improve the timeliness, transparency, and regulatory alignment of credit risk assessment under Basel 3.1. The research focuses on methodological evaluation rather than system deployment, contributing to the scholarly discourse on AI-enabled risk management and regulatory technology (Haeri et al., 2025; Fazlija et al., 2025; Cao and Feinstein, 2024; Joshi, n.d.).

More specifically, the study will provide an empirically grounded assessment of whether combining predictive modelling with regulatory capital computation can enhance credit decision-making, extend explainable AI frameworks in finance by uniting predictive validity with supervisory interpretability, and demonstrate the methodological potential of Generative AI for automating compliance logic. It will also examine the role of unstructured data in strengthening early-warning signals of credit deterioration and deliver curated synthetic datasets and benchmarks to enable replicability and comparative research (Nazemi and Fabozzi, 2024; Dawood et al., 2019; Al-Sultan and Al-Baltah, 2024; Khandani et al., 2010; de Lange et al., 2022).

**Literature Review**

Research on AI in banking and financial regulation has developed along two complementary dimensions: (i) theoretical models that advance methods and architectures for credit risk and regulatory automation, and (ii) empirical studies that evaluate these approaches on real data or worked regulatory cases. The combined evidence shows substantial gains from predictive machine learning in credit risk modelling and a growing body of work on Generative AI (Gen-AI) for regulatory interpretation. At the same time, both strands treat prediction and regulation as separate problems, with little integration across the two. (See Tables 1–4.)

*2.1 Theoretical approaches for modelling credit risk and regulatory AI*

*2.1.1 Predictive AI for credit risk*

Foundational statistical models established the template for borrower-level default prediction (Altman, 1968; Altman et al., 1994). Subsequent machine-learning work broadened the repertoire to decision trees, ensembles, and neural networks (Baesens et al., 2003; Bellotti & Crook, 2009; Khandani, Kim & Lo, 2010; Lessmann et al., 2015; Louzada et al., 2016), with dynamic and frailty-aware formulations improving multi-period risk estimation (Sigrist & Leuenberger, 2023). Recent studies explore fairness–accuracy trade-offs in consumer credit (Kozodoi et al., 2022) and report deep-learning/transformer advances on card and retail datasets (DeRisk, 2023; Transformer Credit Default Study, 2024). (Table 1.)

*2.1.2 Generative AI for regulatory interpretation (Basel 3.1)*

The Gen-AI literature relevant to regulation builds on the transformer family (Vaswani et al., 2017; Devlin et al., 2018; Radford et al., 2018; Brown et al., 2020; Raffel et al., 2020; Touvron et al., 2023) and applies prompt-engineering, retrieval, and reasoning strategies to financial rules. Studies show improved question-answering and clause-to-logic translation for Basel topics (Cao & Feinstein, 2024; Nazemi & Fabozzi, 2024; Fazlija et al., 2025; Haeri, Vitrano & Ghelichi, 2025), alongside architectural blueprints for end-to-end regulatory workflows (Joshi, 2025). Collectively, these papers motivate translating Basel 3.1 Credit Risk (CRE) provisions into machine-readable logic but stop short of integrating live borrower-level risk estimates. (Table 2.)

The theoretical corpus therefore offers two mature yet siloed lines: (a) predictive AI for credit risk estimation with explainability and fairness controls (Altman, 1968; Lessmann et al., 2015; Kozodoi et al., 2022; Sigrist & Leuenberger, 2023), and (b) Gen-AI for regulatory comprehension and clause operationalisation (Cao & Feinstein, 2024; Fazlija et al., 2025; Haeri et al., 2025; Joshi, 2025). A unifying framework that connects these strands remains largely absent.

*2.2 Empirical literature on AI-enabled credit risk and Basel compliance*

*2.2.1 Credit-risk AI: results and evaluation evidence*

Empirical studies confirm that ML outperforms traditional scoring across retail and corporate contexts. Portfolio-scale analyses show higher ROC-AUC and better early-warning performance for tree ensembles and deep networks (Butaru et al., 2016; Sirignano, Sadhwani & Giesecke, 2018; Dawood et al., 2019). Country-specific work demonstrates feasibility in India and emerging markets (Kumar et al., 2022; Ahmed et al., 2023), while fairness-oriented evaluations quantify accuracy–equity trade-offs (Kozodoi et al., 2022). Recent results indicate gains from transformer-style models on credit-card sequences and noisy, high-dimensional financial data (DeRisk, 2023; Transformer Credit Default Study, 2024). Adoption evidence in Indian banking highlights organisational and supervisory drivers (Goyal, 2025). (Empirical table.)

*2.2.2 Basel norms, comparability, and AI-assisted automation*

The regulatory literature traces the evolution from Basel I to Basel 3.1 and documents rising complexity and compliance costs (Basel Committee, 1988; 2004; 2010/2011; 2017; Jones & Zeitz, 2017; Junge & Kugler, 2018). Empirical and policy studies assess IRB vs SA comparability (Behn, Haselmann & Wachtel, 2019), buffer usability in stress (Drehmann & Yetman, 2020), and post-Basel-III capital/risk-taking dynamics (Anguren, Jiménez & Peydró, 2024; Bashir et al., 2025). Early Gen-AI evaluations for regulatory QA and clause translation demonstrate promise but remain proof-of-concept in scope (Cao & Feinstein, 2024; Fazlija et al., 2025; Haeri et al., 2025). (Table 4.)

*Research gap*

Across Tables 1–4, no identified study empirically integrates predictive AI with a Gen-AI-translated Basel 3.1 engine to produce a single, explainable pipeline that outputs borrower-level risk and capital impact in one pass. Predictive works prioritise accuracy and governance but stop short of regulatory computation; Gen-AI papers translate rules without coupling to live risk estimates; Basel studies focus on comparability, costs, and policy rather than end-to-end AI pipelines. This gap motivates the present research agenda to test an integrated, reproducible framework in which predictive outputs feed a machine-readable CRE rules engine, evaluated jointly for predictive accuracy, fairness and transparency, rule-match/reconciliation, and computational efficiency.

**Relevant Basel 3.1 Sections for the Study**

While the Basel 3.1 framework spans multiple standards, only a subset directly informs this research. The sections on Scope and definitions (SCO), Definition of capital (CAP), and Risk-based capital requirements (RBC) provide necessary context for the regulatory environment within which banks calculate capital adequacy. These set the boundaries, capital eligibility criteria, and overarching requirements that credit risk capital computations must adhere to.

However, the primary focus of this study lies in the Credit Risk (CRE) section, which describes the calculation of risk-weighted assets (RWA) for credit exposures. The CRE standards directly engage with borrower-level parameter probability of default (PD), loss given default (LGD), and exposure at default (EAD)—that are central to predictive modelling, and represent the provisions that can be translated into machine-readable logic using Generative AI.

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| **Section** | **Title** | **Scope** | **Relevance to Study** |
| **SCO** | Scope and definitions | Defines the scope of application of the Basel Framework | Provides boundary conditions for which institutions and exposures Basel rules apply |
| **CAP** | Definition of capital | Criteria for capital instruments, regulatory adjustments, and transitional arrangements | Ensures capital used against RWAs meets regulatory eligibility |
| **RBC** | Risk-based capital requirements | Overall framework for risk-based capital calculations | Provides context for integrating CRE risk-weighted assets into total capital adequacy |
| **CRE** | Calculation of RWA for credit risk | Detailed rules for exposure classes, PD, LGD, EAD, and risk weights | Core section for this study; connects predictive modelling with regulatory RWA computation |

# Detailed Focus on Credit Risk (CRE) Section

Banks differ in how they implement Basel 3.1 credit risk rules, depending on supervisory approval, portfolio complexity, and resource availability. Broadly, banks can be categorised by the approach they follow: the Standardised Approach (SA), the Foundation Internal Ratings-Based (F-IRB) Approach, and the Advanced Internal Ratings-Based (A-IRB) Approach.

* Standardised Approach banks (often mid-size or those in emerging markets) rely on regulatory-prescribed risk weights by exposure class and external credit ratings. For these banks, the proposed research provides a mechanism to translate CRE rules into structured variables, improving transparency and reducing compliance costs through automation.
* IRB banks (typically large international banks) estimate parameters such as Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD). For these banks, the research offers predictive modelling tools that can enhance parameter estimation and provide explainability in line with supervisory review expectations.
* Hybrid contexts (e.g., banks under transition, or using IRB for some exposures and SA for others) can benefit from a combined framework where predictive AI refines borrower-level estimates and Generative AI automates Basel logic application.

The CRE section provides the methodological foundation for this study, as it defines how credit exposures are classified, measured, and weighted for capital purposes. Within CRE, specific subsections cover exposure class segmentation, treatment of retail and real estate exposures, use of credit risk mitigation techniques, and the estimation of PD, LGD, and EAD under the Internal Ratings-Based (IRB) approach. These provisions create the regulatory logic that can be mapped into explainable AI frameworks.

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| **CRE Subsection** | **Scope** | **Relevance to Present Study** |
| **Standardised Approach (CRE20–CRE22)** | Risk weights by exposure class (sovereigns, banks, corporates, retail, real estate, equity) | Provides baseline rules for RWA calculation; reference for Generative AI logic translation |
| **IRB Approach (CRE30–CRE36)** | PD, LGD, EAD estimation and output floor requirements | Links predictive AI outputs (PD/LGD/EAD) to regulatory minimums |
| **Credit Risk Mitigation (CRM20–CRM30)** | Collateral, guarantees, credit derivatives recognition | Relevant for modelling risk adjustments and AI-based automation of rule application |
| **Specialised Lending (CRE40)** | Treatment of project finance, commodities finance, etc. | Illustrates how domain-specific rules can be automated using Generative AI |
| **Real Estate Exposures (CRE20.70–CRE20.99)** | LTV-based risk weights; residential vs commercial | Central to borrower-level scoring integration with Basel rules |
| **Retail Exposures (CRE20.55–CRE20.65)** | Segmentation of retail portfolios; SME adjustment | Aligns predictive scoring with regulatory portfolio treatment |
| **Equity Exposures (CRE60)** | Risk weights for equity positions | Example of high-risk class treatment; tested for AI interpretability |
| **CVA (CRE70)** | Counterparty credit risk adjustments for derivatives | Secondary focus; potential for future extensions |
| **Standardised Approach (CRE20–CRE22)** | Risk weights by exposure class (sovereigns, banks, corporates, retail, real estate, equity) | Provides baseline rules for RWA calculation; reference for Generative AI logic translation |
| **IRB Approach (CRE30–CRE36)** | PD, LGD, EAD estimation and output floor requirements | Links predictive AI outputs (PD/LGD/EAD) to regulatory minimums |

**Theoretical Approaches for Modelling Credit Risk and Regulatory AI**

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| **Table 1: Machine Learning–Based Approaches to Credit Risk Assessment** | | | | | | |
| **Author (Year)** | **Country** | **Data** | **Methodology** | **Inputs** | **Outputs** | **Contribution** |
| Altman (1968) | U.S. | Corporate firms (proprietary, not open) | Discriminant analysis | Financial ratios | Default / non-default classification | Established statistical foundations for PD estimation in credit risk |
| Altman et al. (1994) | U.S. / Italy | Corporate firms (proprietary, not open) | Discriminant & logistic regression vs neural networks | Financial ratios, accounts | Default classification | First comparison of statistical vs NN methods; identified trade-offs between accuracy & interpretability |
| Baesens et al. (2003) | Europe | Multiple credit datasets (partly proprietary) | SVM, Random Forest, Neural Nets | Borrower credit features | Credit approval / default | Early benchmarking of ML vs traditional scoring |
| Bellotti & Crook (2009) | U.K. | Credit card portfolio (proprietary) | Survival analysis + ML | Borrower + macroeconomic variables | Time-to-default / default risk | Incorporated time dimension & macroeconomic sensitivity |
| Khandani, Kim & Lo (2010) | U.S. | Consumer lending + transactions (proprietary) | Decision trees, ensembles | Loan-level & transaction features | Default probability | Showed ML with rich borrower data outperforms traditional scoring |
| Lessmann et al. (2015) | Multi-country | German Credit (UCI), Australian Credit (UCI), Taiwan Default (UCI), Give Me Some Credit (Kaggle), + proprietary | Benchmarking across 41 classifiers | Mixed borrower + loan features | Default / non-default | Comprehensive benchmark; established current methodological baselines |
| Louzada et al. (2016) | Brazil | Consumer credit (proprietary) | Hybrid ML (logit + trees) | Borrower features | Default / repayment | Demonstrated hybrid models improve credit scoring |
| Kozodoi et al. (2022) | Europe | Consumer lending (proprietary) | Gradient boosting + fairness metrics | Borrower attributes | Default prediction + fairness outcomes | Assessed fairness–accuracy trade-offs in credit scoring |
| DeRisk (2023) | China | real-world Chinese credit bureau data | Deep learning framework + ablation | Borrower & financial attributes | Default / risk classification | Demonstrated deep learning outperforms production-grade models; identified key drivers of performance |
| Transformer Credit Default Study (2024) | Taiwan / global | Credit card client datasets | Transformer-based neural network | Borrower history, repayment sequences | Default / non-default | Applied transformer architecture; captured temporal borrower behaviour, outperforming tree-based models |

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| **Table 2: Generative AI Applications in Financial Regulation** | | | | |
| **Author / Institution (Year)** | **Contribution** | **Model / Method** | **Data / Input** | **Outcome** |
| Vaswani et al. (2017) | Introduced Transformer architecture | Transformer | WMT’14 English–German, English–French translation | Outperformed RNNs/CNNs; parallel training; foundation for modern LLMs |
| Devlin et al. (2018) | Contextual embeddings, bidirectional | BERT | Wikipedia + BookCorpus | Set new SOTA on GLUE, QA, NER |
| Radford et al. (2018) | Generative pretraining for NLP | GPT | Web text corpus | Demonstrated transfer learning in NLP |
| Brown et al. (2020) | Few-shot learning with large models | GPT-3 | 570GB curated web + books | Strong zero/few-shot reasoning; breakthrough in scaling |
| Raffel et al. (2020) | Unified NLP as text-to-text | T5 | C4 dataset | Simplified task framing; strong multi-task performance |
| OpenAI (2022) | Alignment with human intent | InstructGPT / ChatGPT (GPT-3.5) | RLHF on web + human feedback | Improved usability, safe deployment at scale |
| Touvron et al. (2023) | Efficient open-source LLMs | LLaMA | Curated multilingual datasets | Enabled broader research, efficient fine-tuning |
| OpenAI (2023) | Multimodal, aligned reasoning | GPT-4 | Proprietary | Stronger reasoning, multimodal capability |
| Cao & Feinstein (2024) | Prompt engineering for Basel market risk | GPT-3.5/4 with engineered prompts | Basel market risk clauses | Better regulatory Q&A interpretation |
| Nazemi & Fabozzi (2024) | Supervisory explainability with GenAI | GPT-based models | Regulatory texts + finance datasets | Enhanced transparency for regulators |
| Fazlija et al. (2025) | Reasoning with Basel provisions (CoT/ToT) | GPT-4o, Claude 3 | 6,501 Basel III test cases | +13pp accuracy in risk weight assignment |
| Haeri et al. (2025) | Domain-specific embeddings (RiskEmbed) | Finetuned SBERT | 94 OSFI regulatory guidelines (1991–2024) | Improved regulatory QA retrieval accuracy |
| Joshi (2025) | End-to-end GenAI regulatory architecture | Transformers + workflow integration | Literature + industry pipelines | Blueprint for integrating LLMs in risk management |

**Empirical Literature on AI-Enabled Credit Risk Management and Basel Compliance**

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| **Author (Year)** | **Country** | **Data** | **Methodology** | **Results / Evaluation** | **Contribution (Empirical Evidence)** |
| Altman et al. (1994) | Italy | Corporate firms (proprietary) | Discriminant, logit, neural networks | Accuracy and misclassification rates compared; NNs slightly better but unstable | First empirical comparison of statistical vs NN models in bankruptcy prediction |
| Gupton, Gates & Carty (2000) | U.S. | Moody’s LGD Recovery Database | Statistical models for LGD | RMSE, explanatory power of collateral variables | Provided one of the first large-sample LGD modelling studies under Basel II context |
| Malhotra & Malhotra (2003) | International (German Credit) | German credit dataset (UCI) | Neural networks vs logit | Accuracy, ROC curves | Demonstrated NN modestly outperformed logit; introduced UCI data into benchmarking |
| Bastos (2008) | Portugal | Retail bank consumer loans | Logistic regression, decision trees, boosted trees | ROC-AUC, KS statistic | Boosted trees outperformed traditional models in retail credit scoring |
| Bellotti & Crook (2009) | U.K. | Credit card portfolio | Survival analysis + ML | Time-to-default models evaluated with log-likelihood & ROC | Showed dynamic default modelling improves over static PD |
| Butaru et al. (2016) | U.S. | Loan-level portfolio (proprietary) | RF, Gradient Boosted Trees | ROC-AUC ~0.85, accuracy gains vs logit | Demonstrated portfolio-level improvements from ML on large datasets |
| Dawood et al. (2019) | U.S./EU | Bank portfolios | Hybrid ML | ROC, precision-recall | Hybrid models enhanced early-warning signals of credit deterioration |
| Sirignano, Sadhwani & Giesecke (2018) | U.S. | LendingClub loans (millions) | Deep learning (feedforward NN) | ROC-AUC, log-loss | Large-scale DL applied to P2P lending; significant improvement over logistic regression |
| wRamappa (2019) | India | Indian banking datasets | Comparative review of scoring models | Accuracy comparisons (reported in studies) | Documented empirical evolution of Indian credit scoring practices |
| Kumar et al. (2022) | India | Mortgage dataset | RF, SVM, XGBoost | Accuracy >90%, ROC-AUC higher than logit baseline | Demonstrated ML feasibility for Indian mortgage risk |
| Goswami (2022b) | India | RBI bank-level data | Econometric analysis | NPA persistence tested with regression metrics | Showed convergence and persistence of NPAs empirically |
| Kozodoi et al. (2022) | Europe | Consumer lending dataset | Gradient boosting + fairness adjustments | ROC-AUC, profit, fairness indices (EO, DP) | Demonstrated trade-offs between predictive accuracy and fairness |
| Ahmed et al. (2023) | Emerging markets | Bank + macroeconomic data | ML + macro integration | ROC, RMSE | Linked PD/LGD to macro drivers in EM context |
| Charumathi & Thiagarajan (2021) | India | Debt securities (proprietary) | ANN, SVM, RF | Accuracy, ROC-AUC | Applied ML to Indian debt securities; demonstrated predictive gains |
| DeRisk (2023) | Global | Financial datasets (sparse/noisy) | Deep learning + ablation | ROC-AUC >0.90; outperformed ensembles | Validated DL in real-world settings, identified key model ingredients |
| Transformer Credit Default (2024) | Taiwan / global | Credit card datasets | Transformer NN vs LightGBM | Transformer AUC +2–3% vs tree baselines | Showed attention-based models capture temporal repayment sequences |
| Goyal (2025) | India | Indian banks (survey/adoption study) | Empirical adoption analysis | Adoption metrics, qualitative + quantitative | Identified organisational and regulatory drivers of AI use in Indian credit risk |

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| **Table 4: Literature on Basel Regulatory Frameworks and AI Integration** | | | | |
| **Author / Institution (Year)** | **Contribution** | **Method / Model** | **Data / Input** | **Outcome** |
| Basel Committee (1988) – *International Convergence of Capital Measurement and Capital Standards* | Basel I: first global capital accord | Regulatory text | Credit risk weights (0%, 20%, 50%, 100%) | Established minimum capital ratio 8% |
| Basel Committee (2004) – *Basel II: International Convergence of Capital Measurement and Capital Standards* | Basel II: SA + IRB approaches | Regulatory text | PD, LGD, EAD framework | Linked internal models with capital requirements |
| Basel Committee (2010, rev. 2011) – *Basel III: A global regulatory framework for more resilient banks and banking systems* | Basel III: post-GFC reforms | Regulatory text | Leverage ratio, liquidity ratios, higher capital buffers | Strengthened capital adequacy and liquidity coverage |
| Basel Committee (2017) – *Basel III: Finalising post-crisis reforms* (“Basel 3.1”) | Basel 3.1: final package of Basel III reforms | Regulatory text | Revised SA, IRB input floors, output floor (72.5%) | Harmonised risk-weighted assets; tightened model variability |
| Jones & Zeitz (2017) | Historical analysis of Basel corpus | Document review | Basel I–III | Traced expansion from ~30 pages (Basel I) to 600+ (Basel III) |
| Junge & Kugler (2018) | Basel compliance cost study | Econometric assessment | EU bank panel | Basel rules significantly raised compliance costs |
| Behn, Haselmann & Wachtel (2019, BIS WP 799) | Empirical assessment of IRB vs SA | Econometric modelling | Bank credit data | Showed IRB risk weights systematically lower than SA, raising comparability issues |
| Drehmann & Yetman (2020, BIS WP 859) | Basel III stress test usability | Simulation & policy analysis | Basel capital buffers | Capital buffers may not function as intended in stress |
| Anguren, Jiménez & Peydró (2024) | Basel III capital & risk-taking | Econometric evidence | Spanish/European banks | Basel III increased capital; mixed effects on lending/risk |
| Bashir et al. (2025) | Basel capital rules in EM economies | Panel econometrics | Emerging-market bank data | Basel capital regulations reshape risk-efficiency dynamics |

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| **Table 5: Emerging Efforts to Combine Predictive and Generative AI in Credit Risk** | | | | |
| **Author** | **Contribution** | **Model Used** | **Data/Input** | **Outcome** |
| Currently limited | Literature treats predictive and generative AI separately | Document analysis | Basel I–III frameworks | Basel text expanded from ~30pp to 600+ |
| (Proposed by present study) | Integration of predictive analytics (credit scoring) with GenAI (Basel automation) | Regulatory review | Basel III documents | Summarized capital/stress/liquidity provisions |

# Objectives of the Study

The key objective of this research is to investigate how predictive and generative artificial intelligence can be systematically integrated with Basel 3.1 capital requirements. The specific objectives are as follows:

1. To investigate methods for integrating borrower-level credit risk assessments with Basel 3.1 regulatory capital computations to enable real-time evaluation of capital impact at the point of credit origination.
2. To analyse how the application of predictive and generative AI in credit risk management influences decision quality, risk sensitivity, and compliance with Basel 3.1 regulatory requirements.
3. To evaluate methods for embedding explainability and fairness into AI-based credit risk models, with particular emphasis on ensuring transparency and auditability in line with supervisory expectations.
4. To critically assess model interpretation techniques—such as feature attribution, fairness metrics, and counterfactual reasoning—to determine their effectiveness in clarifying model behaviour without undermining predictive performance.
5. To investigate the potential of generative AI for operationalising Basel 3.1 clauses by converting complex regulatory provisions into structured, machine-readable logic suitable for integration with predictive model outputs.
6. To contribute to the research literature on regulatory alignment by examining both the methodological feasibility and the supervisory implications of combining predictive and generative AI for credit risk assessment under Basel 3.1.

***Central Research Hypothesis:*** An integrated, explainable AI framework that combines predictive modelling with Generative AI–based regulatory logic translation can improve the timeliness, transparency, and Basel 3.1 compliance alignment of credit risk assessment more effectively than existing batch-based or siloed approaches.

# Research Questions

1. To what extent can borrower-level credit risk assessments be integrated with Basel 3.1 RWA computations, as demonstrated through simulated frameworks that are auditable and reproducible against supervisory standards?
2. How does the application of predictive and generative AI in credit risk assessment affect decision quality, risk sensitivity, and regulatory compliance, as measured by changes in timeliness, capital impact accuracy, and alignment with Basel 3.1 provisions?
3. In what ways can explainability and fairness be embedded within AI-based credit risk models, and how can their adequacy be assessed using regulatory audit criteria such as transparency, traceability, and absence of bias?
4. How effective are interpretation techniques—such as feature attribution, fairness metrics, and counterfactual reasoning—in clarifying model behaviour, and how can their effectiveness be quantified without compromising predictive performance benchmarks?
5. Can generative AI techniques reliably operationalise Basel 3.1 clauses by converting complex provisions into machine-readable logic, and how can this reliability be evaluated in terms of translation accuracy, consistency across models, and resulting impact on RWA computations?
6. What are the methodological feasibility and supervisory implications of combining predictive and generative AI within credit risk assessment, as evidenced through comparative experiments, error analysis, and alignment with regulatory expectations under Basel 3.1?

# Proposed Methodology and Database

The methodology comprises two interconnected research modules designed to evaluate, in a simulated academic environment, how predictive and generative AI can be jointly applied for credit risk assessment and Basel 3.1 capital impact computation. Only publicly available datasets will be used, ensuring reproducibility and compliance with data protection requirements. Outputs from the first module will feed into the second to enable an integrated evaluation of borrower risk and regulatory capital implications.

**Module 1 – Credit Risk Prediction Layer**

This module will assess the performance of a range of machine learning models in estimating borrower-level default risk and related credit risk indicators. Publicly available datasets that capture borrower demographics, loan characteristics, repayment histories, and delinquency events will be employed. Candidate models will include widely used approaches such as gradient boosting algorithms and deep learning architectures, along with other established techniques where appropriate. Performance will be evaluated using a set of predictive and fairness-oriented metrics, including but not limited to ROC-AUC, F1-score, precision/recall, SHAP-based consistency checks, and fairness indicators. This evaluation will establish baseline predictive performance while testing the incremental value of incorporating Basel-aligned regulatory variables.

**Module 2 – RWA and Capital Impact Engine**

This module will investigate how generative AI can be applied to operationalise selected Basel 3.1 provisions into machine-readable rules. The textual provisions of the Basel framework specify exposure segmentation, risk weight assignments, default recognition criteria, and treatment of different exposure classes. Generative AI will be employed to translate these provisions into structured variables—such as exposure class indicators, loan-to-value regulatory buckets, default status aligned with Basel definitions, and unrated obligor flags—which can then be integrated with the borrower-level datasets. Outputs from Module 1 will be combined with these regulatory variables to compute risk-weighted assets and capital impact. Accuracy will be assessed through multiple criteria, including consistency with Basel worked examples, reconciliation across exposure classes, and computational efficiency.

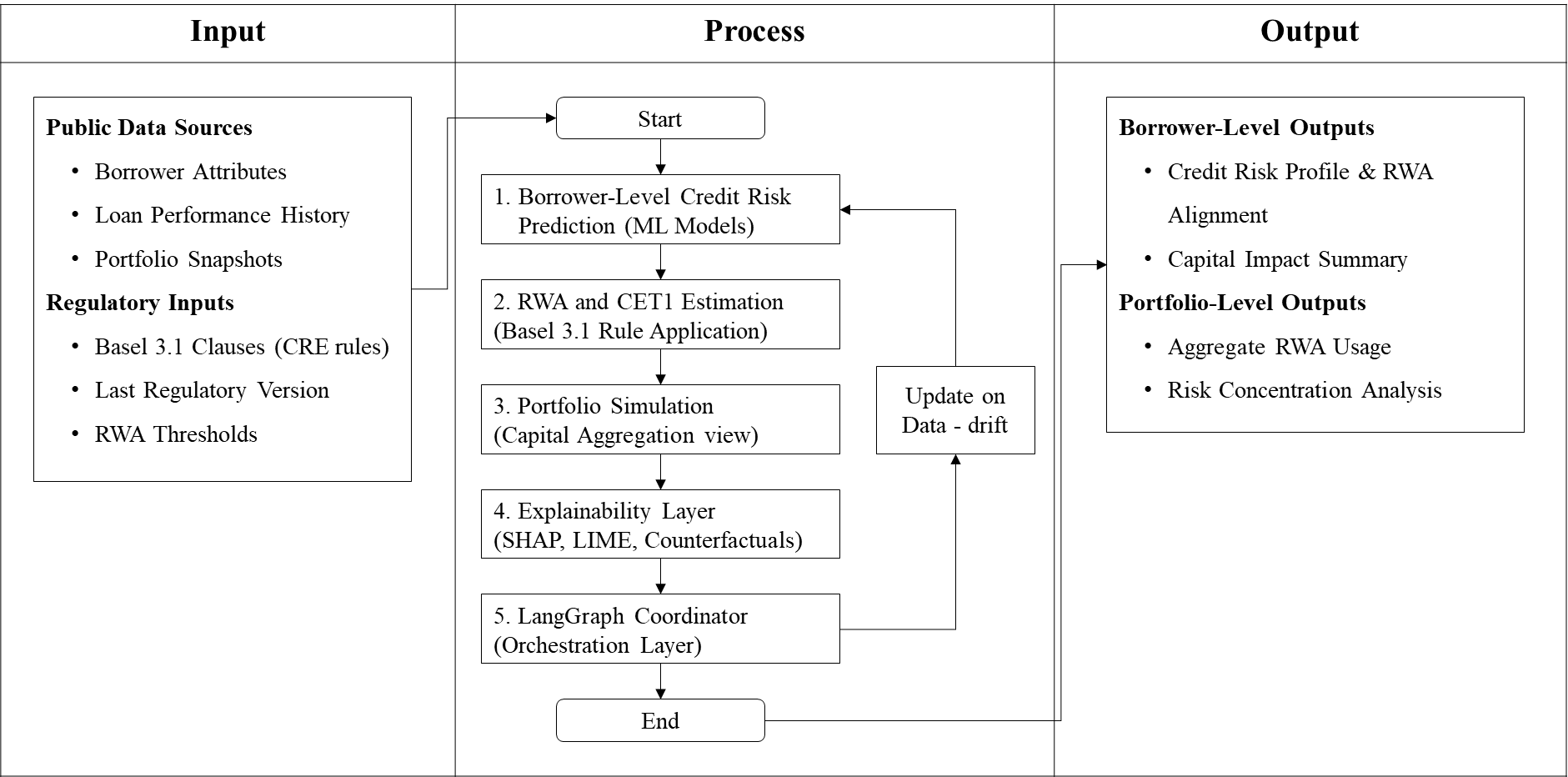
**Integration of Basel 3.1 Variables with Public Credit Risk Datasets**

The central innovation of this study lies in the integration of Basel 3.1 credit risk provisions with publicly available borrower-level datasets through generative AI–enabled variable construction. By aligning dataset fields with regulatory classifications and conditions, Basel-derived variables can be tested alongside native dataset features within predictive models. This enables a two-level evaluation:

1. **Predictive gain** – whether the inclusion of Basel-aligned variables improves accuracy in estimating borrower default risk.
2. **Regulatory alignment** – whether the resulting outputs, when reconciled with Basel risk weights, provide more policy-relevant insights into capital adequacy.

By linking the two modules, the framework will ensure that borrower-level risk predictions directly inform capital adequacy calculations, allowing the research to evaluate not only the performance of predictive models but also their implications for Basel 3.1–compliant regulatory outcomes.

**End-to-End System Architecture –**



**Empirical Foundations: Publicly Available Datasets in Credit Risk Modelling**

The development of credit risk assessment models has relied heavily on publicly available benchmark datasets that enable comparative evaluation across modelling approaches. These open-source databases originate from diverse geographical contexts—ranging from the German Credit Data and Australian Credit Approval datasets to the Taiwanese credit card default records, the U.S. Lending Club loan portfolio, and more recent Kaggle-curated datasets simulating borrower behaviour. In addition, regulatory data initiatives such as the European Central Bank’s AnaCredit and the Reserve Bank of India’s Public Credit Registry provide structured, borrower-level information that holds promise for research once wider access becomes feasible. Table X summarises the most widely used datasets, indicating their origin, key features, representative studies, and access sources. Collectively, these resources form the empirical foundation for testing predictive models, developing explainable frameworks, and exploring the potential of generative AI in credit risk management.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 5: Open-Source Databases for Credit Risk Modelling** | | | | |
| **Dataset** | **Country / Origin** | **Size / Features** | **Papers** | **Database links** |
| **German Credit Data** | Germany | 1,000 instances, 20 attributes (credit history, purpose, amount, etc.); binary risk label | Quan et al. (2024); Lessmann et al. (2015) | [Link](https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data)) |
| **Australian Credit Approval** | Australia | ~690 instances, mixed-type attributes | Quan et al. (2024); Baesens et al. (2003); Lessmann et al. (2015) | [Link](https://archive.ics.uci.edu/ml/datasets/statlog+(australian+credit+approval)) |
| **AMEX Credit Default Dataset** | USA | 458,913 training records, 924,621 test records; >200 multi-temporal features across delinquency, spend, balance, etc.; default label over 18-month window | Hu & Yeo (2025) | [Link](https://www.kaggle.com/competitions/amex-default-prediction) |
| **Default of Credit Card Clients** | Taiwan | ~30,000 instances; demographic + credit history + repayment records | Yeh & Lien (2009); Quan et al. (2024); Hu & Yeo (2025) | [Link](https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients) |
| **Credit borrowers’ data** | USA | 150,000 borrowers; 10 numerical features (income, debt ratio, age, etc.); default label | Kozodoi et al. (2022) | [Link](https://www.kaggle.com/c/GiveMeSomeCredit) |
| **Home Credit Default Risk** | Europe | 307,511 loan applications; ~200 features (demographics, credit history, behavioral data) | Kozodoi et al. (2022) | [Link](https://www.kaggle.com/c/home-credit-default-risk) |
| **PAKDD 2010 Credit Scoring** | Taiwan | ~50,000 instances; 18 features; loan default prediction competition | Kozodoi et al. (2022) | [Link](https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset) |
| Wilful Loan Defaulters | India | Public lists (names, amounts, etc.) of loanees from Indian banks who are declared willful defaulters. | Jayadev & Padma (2019) | [Link](https://dataful.in/datasets/20589/) |

**Variable Framework: Integration of Dataset Features and Basel 3.1–Derived Indicators**

The development of the research model requires a careful definition of dependent and independent variables that are both observable in public datasets and, where feasible, derivable from Basel 3.1 provisions. This section outlines the variable framework adopted in the study. It integrates dataset-driven borrower and loan attributes with regulatory indicators translated from Basel 3.1 Credit Risk (CRE) standards using Generative AI. The intention is to remain methodologically rigorous by restricting the analysis to information that is either directly reported or cleanly derivable, while leaving scope to test how regulatory variables influence predictive performance and supervisory alignment.

The dependent variables primarily capture default outcomes and repayment performance, while the independent variables span borrower characteristics, loan-level attributes, affordability measures, repayment behaviour, and regulatory features. Generative AI will be employed to convert the textual provisions of Basel 3.1 into structured indicators such as exposure classes, loan-to-value buckets, and risk weights. These indicators will be aligned with available dataset fields, ensuring that any constructed features are empirically grounded.

|  |  |  |  |
| --- | --- | --- | --- |
| **Dataset** | **Country / Origin** | **Input Variables (Columns)** | **Output Variable** |
| **German Credit Data** | Germany | 20 inputs: Checking account status, Duration in months, Credit history, Purpose, Credit amount, Savings account/bonds, Employment since, Installment rate (% income), Personal status/sex, Other debtors/guarantors, Residence duration, Property, Age, Other installment plans, Housing, Existing credits, Job, Dependents, Telephone, Foreign worker | Credit risk classification (good / bad) |
| **Australian Credit Approval** | Australia | 14 anonymised attributes (A1–A14); a mix of categorical and numeric variables. Exact feature semantics were withheld in the Statlog release. | Credit approval decision (approved / rejected) |
| **AMEX Default Prediction** | USA | ~190 anonymised features grouped into categories: D\_\* (delinquency), S\_\* (spend), P\_\* (payment), B\_\* (balance), R\_\* (risk). Features are temporal (monthly profiles), many continuous with missing values. | Binary default indicator (1 = default, 0 = non-default) |
| **Default of Credit Card Clients** | Taiwan | 23 inputs: LIMIT\_BAL, SEX, EDUCATION, MARRIAGE, AGE, PAY\_0–PAY\_6 (repayment status for past 6 months), BILL\_AMT1–BILL\_AMT6 (bill amounts), PAY\_AMT1–PAY\_AMT6 (payment amounts). Plus an ID column. | default.payment.next.month (1 = default, 0 = no default) |
| **Credit borrowers’ data** | USA | 10 inputs: RevolvingUtilizationOfUnsecuredLines, age, NumberOfTime30-59DaysPastDueNotWorse, DebtRatio, MonthlyIncome, NumberOfOpenCreditLinesAndLoans, NumberOfTimes90DaysLate, NumberRealEstateLoansOrLines, NumberOfTime60-89DaysPastDueNotWorse, NumberOfDependents | Serious delinquency within 2 years (SeriousDlqin2yrs) |
| **Home Credit Default Risk** | Europe | ~122 static application features (e.g., demographics, income, loan terms, credit history, external risk scores) plus derived features from related tables (bureau history, previous applications, balances, etc.) | TARGET — whether applicant will default or not (binary) |
| **Default of Credit Card Clients** | **Taiwan** | **23 inputs: LIMIT\_BAL; SEX; EDUCATION; MARRIAGE; AGE; PAY\_0-PAY\_6 (repayment status for past six months); BILL\_AMT1-BILL\_AMT6 (bill statement amounts); PAY\_AMT1-PAY\_AMT6 (prev payment amounts); ID column.** | **default.payment.next.month — binary (1 = will default, 0 = will not default)** |
| **India Wilful Loan Defaulters** | India | Basic exposure info: Defaulter name, Bank name, Amount owed | Wilful default status (all records are defaults) |

# Expected Outcomes

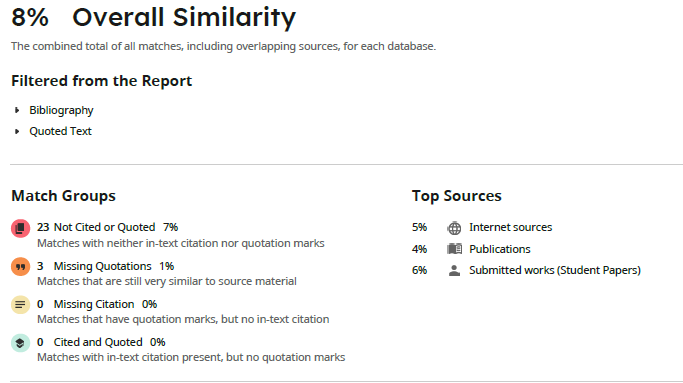
This research is expected to deliver an empirically validated framework that demonstrates how integrating predictive modelling outputs with Basel 3.1–compliant RWA computations can improve the timeliness and regulatory alignment of credit decision-making. By evaluating this integration in a simulated, reproducible environment, the study will provide evidence on its feasibility, benefits, and limitations in enhancing capital adequacy assessments at the point of credit origination.

In parallel, the study will design and empirically assess an explainability framework for AI-based credit risk models. Feature attribution, fairness checks, and counterfactual reasoning will be applied not as ancillary tools but as components to be evaluated directly against regulatory requirements for transparency and auditability, with the aim of determining whether these methods can support supervisory review in a reliable way.

The research will also assess the feasibility of applying Generative AI techniques—specifically Retrieval-Augmented Generation and prompt engineering—to translate selected Basel 3.1 clauses into machine-readable compliance logic for RWA computation. This will contribute to the literature on regulatory alignment by quantifying accuracy, interpretability, and computational efficiency across modelling approaches.

Irrespective of the credit risk approach adopted, the framework developed in this study has the potential to offer useful insights for banks. For institutions applying the Standardised Approach, the use of Basel-aligned variables derived from CRE provisions allows for a structured evaluation of whether regulatory classifications can enhance predictive models built on public data. For banks using IRB approaches, the same framework provides a way to test how predictive modelling of PD, LGD, and EAD might be better aligned with supervisory expectations when Basel rules are explicitly embedded. While the scope of this research is methodological rather than system-deployment, the findings can indicate how different categories of banks may benefit from combining predictive AI with regulatory rule translation in principle.

# Appendix



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