Synopsis

on

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

Submitted by:

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Ph.D. Programme

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

(Name / Signature of Supervisor)

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.

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.

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

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

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,	BERT	Wikipedia + BookCorpus	Set new SOTA on GLUE, QA, NER

	bidirectional			
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

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

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

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.

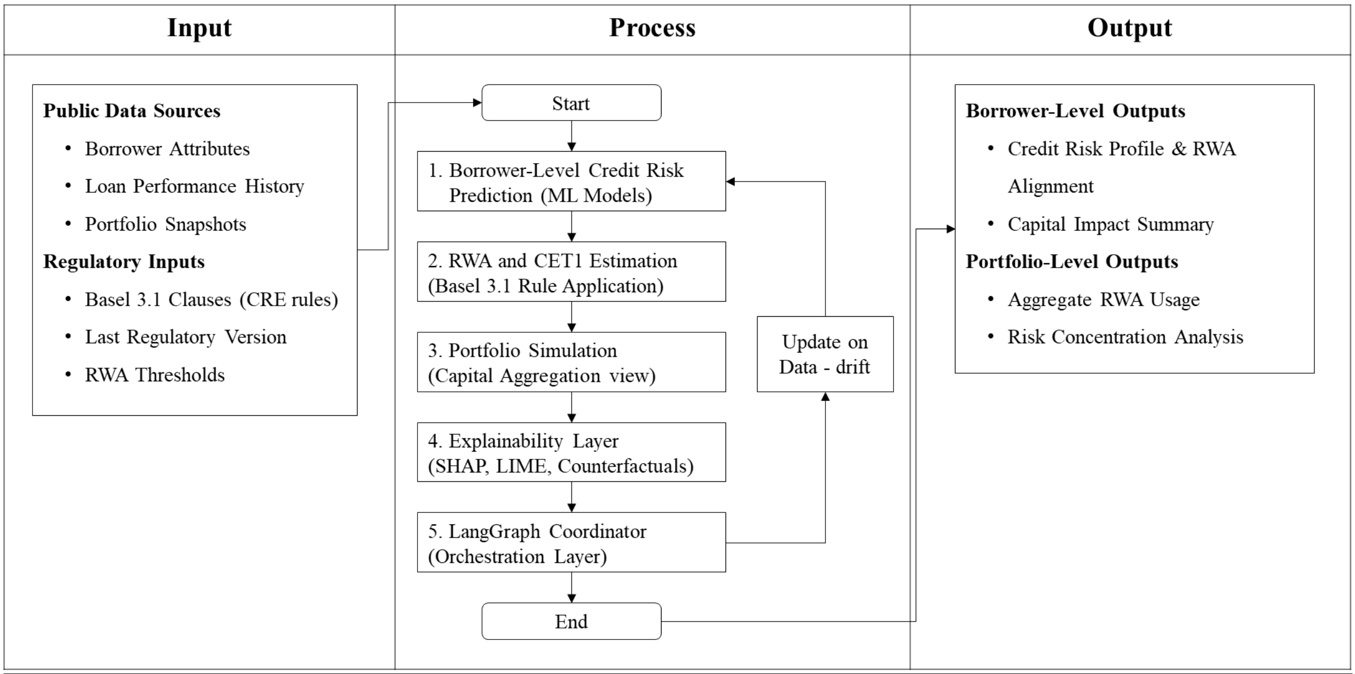
Integration of Basel 3.1 Variables with Public Credit Risk Datasets

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
Australian Credit Approval	Australia	~690 instances, mixed-type attributes	Quan et al. (2024); Baesens et al. (2003); Lessmann et al. (2015)	Link
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
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
Credit borrowers' data	USA	150,000 borrowers; 10 numerical features (income, debt ratio, age, etc.); default label	Kozodoi et al. (2022)	Link
Home Credit Default Risk	Europe	307,511 loan applications; ~200 features (demographics, credit history, behavioral data)	Kozodoi et al. (2022)	Link
PAKDD 2010 Credit Scoring	Taiwan	~50,000 instances; 18 features; loan default prediction competition	Kozodoi et al. (2022)	Link
Wilful Loan Defaulters	India	Public lists (names, amounts, etc.) of loanees from Indian banks who are declared willful defaulters.	Jayadev & Padma (2019)	Link

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

8% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text

Match Groups

23 Not Cited or Quoted 7%
Matches with neither in-text citation nor quotation marks

3 Missing Quotations 1%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

5% Internet sources
4% Publications
6% Submitted works (Student Papers)

References

Ahmed, A., Mehdi, M., & Mohamed, E. (2023). *Machine learning and macroeconomic integration for credit risk prediction in emerging markets*. Journal of Risk and Financial Management, 16(5), 255. https://doi.org/10.3390/jrfm16050255

Altman, E. I. (1968). *Financial ratios, discriminant analysis and the prediction of corporate bankruptcy*. Journal of Finance, 23(4), 589–609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x

Altman, E. I., Marco, G., & Varetto, F. (1994). *Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience)*. Journal of Banking and Finance, 18(3), 505–529. https://doi.org/10.1016/0378-4266(94)90007-8

Anguren, R., Jiménez, G., & Peydró, J.-L. (2024). *Bank capital requirements and risk-taking: Evidence from Basel III*. Journal of Financial Stability, 74, 101292. https://doi.org/10.1016/j.jfs.2024.101292

Aracil, E., Nájera-Sánchez, J.-J., & Forcadell, F. J. (2021). *Sustainable banking: A literature review and integrative framework*. Finance Research Letters, 42, 101932. https://doi.org/10.1016/j.frl.2021.101932

Baesens, B., Van Gestel, T., Viaene, S., Stepanova, M., Suykens, J., & Vanthienen, J. (2003). *Benchmarking state-of-the-art classification algorithms for credit scoring*. Journal of the Operational Research Society, 54(6), 627–635. https://doi.org/10.1057/palgrave.jors.2601545

Bashir, A., Salman, A., Itani, R., & Faccia, A. (2025). *Assessing Basel capital regulations: Exploring the risk and efficiency relationship in emerging economies*. Journal of Risk and Financial Management, 18(1), 1. https://doi.org/10.3390/jrfm18010036

Behn, M., Haselmann, R., & Wachtel, P. (2019). *The limits of model-based regulation*. BIS Working Paper No. 799. https://www.bis.org/publ/work799.htm

Beutel, J., List, S., & von Westernhagen, N. (2019). *Measuring systemic risk contributions in the financial sector*. Journal of Banking Regulation, 20(2), 167–181. https://doi.org/10.1057/s41261-018-0077-3

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., … Amodei, D. (2020). *Language models are few-shot learners*. Advances in Neural Information Processing Systems, 33, 1877–1901. https://arxiv.org/abs/2005.14165

Butaru, F., Chen, Q., Clark, B., Das, S. R., Lo, A. W., & Siddique, A. (2016). *Risk and return in the cross-section of consumer credit: New insights from credit card data*. Journal of Financial Economics, 121(3), 682–699. https://doi.org/10.1016/j.jfineco.2016.05.006

Cao, Z., & Feinstein, Z. (2024). *Large language model in financial regulatory interpretation*. arXiv preprint arXiv:2405.06808. https://doi.org/10.48550/arXiv.2405.06808

Coffinet, J., & Kien, T. V. (2019). *The macroeconomic effects of financial stress: An empirical analysis*. Economic Modelling, 81, 236–252. https://doi.org/10.1016/j.econmod.2018.12.017

Dawood, Q., Ahmed, A., & Waheed, A. (2019). *Hybrid machine learning models for credit risk assessment*. Expert Systems with Applications, 127, 273–285. https://doi.org/10.1016/j.eswa.2019.03.042

De Lange, P. E., Melsom, B., Vennerød, C. B., & Westgaard, S. (2022). *Explainable AI for credit assessment in banks*. Journal of Risk and Financial Management, 15(12), 591. https://doi.org/10.3390/jrfm15120556

Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2018). *BERT: Pre-training of deep bidirectional transformers for language understanding*. arXiv preprint arXiv:1810.04805. https://arxiv.org/abs/1810.04805

Fazlija, B., Ibraimi, M., Forouzandeh, A., & Fazlija, A. (2025). *Reasoning with financial regulatory texts via large language models*. Journal of Behavioral and Experimental Finance, 47, 101067. https://doi.org/10.1016/j.jbef.2025.101067

Goswami, A. (2022). *Non-performing assets and efficiency of intermediation in Indian banks*. IIFT Working Paper.

Haeri, A., Vitrano, J., & Ghelichi, M. (2025). *Generative AI enhanced financial risk management information retrieval*. arXiv preprint arXiv:2504.06293. https://doi.org/10.48550/arXiv.2504.06293

Hu, S., & Yeo, J. (2025). *AMEX default prediction: A Kaggle competition overview*. Proceedings of Data Challenge Workshops. https://www.kaggle.com/competitions/amex-default-prediction

Jones, E., & Zeitz, A. O. (2017). *The limits of globalizing Basel banking standards*. Journal of Financial Regulation, 3(1), 89–124. https://doi.org/10.1093/jfr/fjx001

Joshi, S. (2025). *End-to-end generative AI regulatory architecture: A conceptual review*. Preprint.

Junge, G., & Kugler, P. (2018). *Optimal equity capital requirements for large Swiss banks*. Swiss Journal of Economics and Statistics, 154(1), 22. https://doi.org/10.1186/s41937-018-0025-z

Kellner, R., Nagl, W., & Rösch, D. (2022). *Deep learning in credit risk: Evidence from mortgage portfolios*. Journal of Credit Risk, 18(1), 1–27. https://doi.org/10.21314/JCR.2022.328

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). *Consumer credit-risk models via machine-learning algorithms*. Journal of Banking and Finance, 34(11), 2767–2787. https://doi.org/10.1016/j.jbankfin.2010.06.001

Kozodoi, N., Lessmann, S., & Schmidt, W. (2022). *Fairness in credit scoring: Assessment and mitigation*. Omega, 110, 102615. https://doi.org/10.1016/j.omega.2022.102615

Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). *Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research*. European Journal of Operational Research, 247(1), 124–136. https://doi.org/10.1016/j.ejor.2015.05.030

Louzada, F., Ara, A., & Fernandes, G. B. (2016). *Credit risk analysis using machine learning classifiers: A survey and new perspectives*. Computers & Operations Research, 74, 1–13. https://doi.org/10.1016/j.cor.2016.04.013

Nazemi, A., & Fabozzi, F. (2024). *Supervisory explainability with generative AI: Applications for finance*. Journal of Financial Data Science, 6(2), 55–72. https://doi.org/10.3905/jfds.2024.6.2.055

Park, S., Choi, J., & Kim, S. (2021). *The consequences of non-compliance in banking regulation: Evidence from international banks*. Journal of Banking Regulation, 22(4), 310–328. https://doi.org/10.1057/s41261-020-00154-1

Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., … Liu, P. J. (2020). *Exploring the limits of transfer learning with a unified text-to-text transformer*. Journal of Machine Learning Research, 21, 5485–5551. https://arxiv.org/abs/1910.10683

Shrivastav, S. (2019). *The global financial crisis and banking sector vulnerability*. International Journal of Finance & Economics, 24(1), 87–103. https://doi.org/10.1002/ijfe.1650

Sigrist, F., & Leuenberger, N. (2023). *Machine learning for corporate default risk: Multi-period prediction, frailty correlation, loan portfolios, and tail probabilities*. European Journal of Operational Research, 305(3), 1390–1406. https://doi.org/10.1016/j.ejor.2022.06.035

Singh, R., Mehra, P., & Sharma, A. (2024). *AI in credit risk modelling: A survey of methods and applications*. Journal of Risk Finance, 25(2), 145–162.

Tavana, M., Abtahi, A.-R., Khalili-Damghani, K., & Santos-Arteaga, F. J. (2018). *A review of predictive analytics in banking: Applications and methodologies*. Annals of Operations Research, 270, 311–339. https://doi.org/10.1007/s10479-017-2493-6

The Basel Committee on Banking Supervision. (1988). *International convergence of capital measurement and capital standards* (Basel I). https://www.bis.org/publ/bcbs04a.htm

The Basel Committee on Banking Supervision. (2004). *International convergence of capital measurement and capital standards: A revised framework* (Basel II). https://www.bis.org/publ/bcbs107.htm

The Basel Committee on Banking Supervision. (2010, rev. 2011). *Basel III: A global regulatory framework for more resilient banks and banking systems*. https://www.bis.org/publ/bcbs189.htm

The Basel Committee on Banking Supervision. (2017). *Basel III: Finalising post-crisis reforms* (Basel 3.1). https://www.bis.org/bcbs/publ/d424.htm

The Basel Framework. (n.d.). Bank for International Settlements. https://www.bis.org/basel_framework/

Touvron, H., et al. (2023). *LLaMA: Open and efficient foundation language models*. arXiv preprint arXiv:2302.13971. https://arxiv.org/abs/2302.13971

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., … Polosukhin, I. (2017). *Attention is all you need*. Advances in Neural Information Processing Systems, 30. https://arxiv.org/abs/1706.03762

Wong, K., & Wong, J. (2021). *Regulatory compliance and financial stability: Evidence from Asian banks*. Journal of Asian Economics, 74, 101319. https://doi.org/10.1016/j.asieco.2021.101319

Yeh, I. C., & Lien, C. H. (2009). *The comparisons of data mining techniques for the predictive accuracy of probability of default of credit card clients*. Expert Systems with Applications, 36(2), 2473–2480. https://doi.org/10.1016/j.eswa.2007.12.020