Optimization of credit processes in retail banking

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Abstract. Machine learning credit scoring technology is becoming an essential part of retail banking's process for predicting risks associated with customer loans. However, technology that improves prediction accuracy is not always an indicator of improved operational efficiency or stability of the lending portfolio. Using Sherstiuk Retail Credit Process Optimization Framework (SRCPOF) as an example, the author of the study demonstrates the incorporation of ML-based credit risk evaluation into retail banking operational workflows. The SRCPOF framework is based exclusively on contemporary peer-reviewed articles regarding credit risk assessment, use of alternative data, explainable artificial intelligence (XAI), and process analytics. The framework used balances the precision of credit risk prediction with the calibrated risk assessment (decision) thresholds and the orderly integration (slicing?) of the operational workflows. The author proposes that decision thresholds should be considered as one of the managerial optimization variables involved in balancing anticipated losses and operational load. SRCPOF uses the combination of ensemble learning, feature optimization, alternative/exogenous data, explainability, process routing, and workflows to convert credit scoring from an evaluative tool into a process optimization system. It is also proven that prediction (risk analytics) embedded in branch-level decision systems improves early risk detection, reduces the overall approval cycle time in credit decision process, enhances risk control and governance transparency, and strengthens (or improves) the portfolio. The study primarily aims at integrating credit risk modeling with business process management. It also strives to provide banking institutions a fully scalable framework that integrates business process optimization and risk management.

Keywords: Retail banking; credit risk management; machine learning; process optimization; threshold calibration; explainable AI; open banking data; portfolio efficiency; business process integration.

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Introduction

The credit operations of retail banking contribute significantly to profitability, stability of portfolios and assurance of compliance to regulations. Banks are being compelled to develop new ways of approaching credit scoring given the complexity in the market, the growing amount of both structured and unstructured data due to digitalization and the traditional ways of scoring credit.

The most recent research indicates that there is rapid growth in using machine learning and hybrid analytic methods in the credit risk field. Mestiri (2024) [12] and Chang et al. (2024) [5] assert that the use of ML and deep learning is better than traditional methods in predicting probability of default using logistic regression. Also, Souadda et al. (2025) indicate that optimized ensemble models are useful in improving the stability of predictions made in peer-to-peer lending [17]. Although there has been predictive accuracy improvement, operational credit workflows have insufficient structure.

Balina and Idasz-Balina (2021) note that retail credit risk drivers are multi-dimensional, but most institutions employ fragmented evaluation approaches that do not utilize the data streams at their disposal [2]. Hjelkrem et al. (2022) demonstrate that using data from open banking transaction systems is useful in enhancing credit scoring of the applicants [8]. This reflects the necessity of using alternative data in the modern process of credit evaluation.

At the same time, explainability has become critical in ML-centric credit evaluation. De Lange et al. (2022) [7], and Hjelkrem and de Lange (2023), show that the SHAP (SHapley Additive exPlanations) based explainable AI (XAI) frameworks strengthen transparency and trust from the regulators towards Credit Decisioning Models (CDMs) [9]. Transparency and trust in CDMs are critical given the fact that there is a heightened demand from the regulators to understand the working of a model. There has been progress, but still three fundamental gaps in the literature remain: 1) predictive ML models have poor assimilation into holistic (or end-to-end) retail credit systems; 2) predictive performance and reduction in operational cost have poor assimilation; 3) there are no frameworks that are designed to streamline the convergence of risk prediction with business processes.

The recent works in business process analytics have started to fill this void. Ni et al. (2025) [14], and Zhang et al. (2025) [20], show that a data driven evaluation of business processes facilitates efficiency in the operation of a commercial bank. Li et al. (2025) shows that techniques from process mining enhance the detection of anomalies in credit processes [10]. However, these studies do not seem to explicitly combine credit risk modeling with process optimization. This paper closes this gap by presenting a new vision on the Credit Process Optimization Framework (CPOF) integrating: advanced ML-based credit risk prediction; dimension reduction and feature optimization techniques [13]; alternative data enrichment [1; 8]; explainable ai mechanisms [7]; business process evaluation and enhancement tools [14; 20]. Thus, the main research question is: How can machine learning-based credit risk models be operationally embedded into retail banking credit processes to reduce default risk while improving process efficiency?

Literature Review

Determinants of Retail Credit Risk. The ability to ascertain individual credit risk is essential to refining processes within retail banking. Among the borrower-level predictors identified by Balina and Idasz-Balina (2021) are the predictors of retail credit risk [2]. Their research supports the notion that credit risk is multi-faceted, and attempts to encapsulate credit risk using a single variable are destined to fail.

Woo and Sohn (2022) take the discussion a step further by defining the boundaries of behavioral and mental characteristics, and how these can impact the credit risk assessment frameworks of so-called peer-to-peer lending [19]. Their model justifies the idea that borrower description leads to more accurate predictions. This is why advanced retail credit systems need to incorporate more financial and behavioral aspects.

In other contexts, this is what Chen et al. (2023) aim to achieve with the decision-support models for prioritizing credit risk, focusing on the multi-criteria evaluation model [6]. This approach is aligned with the notion that beyond the financial aspects, risk assessment must remain aligned with the decision frameworks that are available to financial entities.

Machine Learning and Deep Learning in Credit Scoring. Recent innovations in machine learning (ML) have increased the accuracy of credit risk prediction. Mestiri (2024) shows that machine learning and deep learning models are superior to classical regression techniques for default prediction in highly nonlinear and dimensional settings [12]. For credit card portfolios, Chang et al. (2024) show that ensemble and neural network models improve predictive accuracy and discrimination [5].

Optimized ML frameworks in P2P lending, identified by Souadda et al. (2025), improve predictive stability and reduce the rate of false positives [17]. Miljkovic and Wang (2025) provide dimension reduction techniques, which improve model performance when addressing the curse of dimensionality present in credit datasets [13]. Empirical work by Machado et al. (2025) shows that Random Forest models outperform logistic regression, SVM, and ANN models in the prediction of financial distress due to extreme class imbalance [11].

The integration of social media and other alternative digital signals is also utilized by Alamsyah et al. (2025) to show that predictive performance and financial inclusion are enhanced through the use of non-traditional data sources in the credit models of Fintech [1]. These studies show that borrowed methodologies in machine learning have become the norm in credit scoring research, yet predictive accuracy is only one element of operational effectiveness.

Alternative Data and Open Banking Integration. The use of open banking APIs has changed how credit assessments can be conducted. Hjelkrem et al. (2022) show that credit scoring models can be enhanced by applying the techniques of credit scoring models to transaction-level data from open banking APIs [8]. The addition of the real time transaction data stream improves the detection of risks.

In Hjelkrem and de Lange (2023) the use of deep learning frameworks on the textual transaction data shows that predictive power and transparency increases by using transformer models with SHAP and model explainers [9]. Alamsyah et al (2025) use the data from the burgeoning fintech credit scoring systems to show the importance of alternative data, particularly in developing economies that lack complete traditional credit histories [1]. The predictive depth of enriched data is supported by the literature. However, how enriched data streams influence workflow and approval time in credit scoring has not been sufficiently addressed.

Explainable AI and Regulatory Transparency. As machine learning (ML) models continue to grow and become more sophisticated, transparency and regulatory compliance become more difficult to manage. In the banking industry, De Lange et al. (2022) suggest that ensuring accountability and trust with customers will require the use of explainable artificial intelligence (AI) techniques, especially those that use SHAP for the model [7]. With regard to credit scoring, Hjelkrem and de Lange (2023) empirically validate the SHAP method and consider it to be effective for this purpose [9]. Their research shows that explainability, or the SHAP method, leads to greater trust from the stakeholders and acceptance from regulators, and has no negative effect on the predictive power of the model. Regarding the stability and normalization of credit risk models, Breeden (2025) states that the models must be sufficiently stable and normalized, especially during periods of economic shocks such as the COVID-19 pandemic [3]. If no normalization is performed, the credit risk model(s) will be distorted for the periods of abnormal risk—this will compromise the models' risk management robustness for the long-term periods. In conclusion, these studies illustrate the need for predictive models to incorporate interpretability, explainability, and stability; this is particularly true for the retail banking industry.

Credit Portfolio Efficiency and Process Optimization. There is little literature that specifically focuses on the optimization of operations. Venugopal (2024) studies the management of loan portfolios and the efficiency of banking institutions, and finds that data-driven strategies for the management of loan portfolios improve the efficiency of both public and private banking institutions [18]. Carrera and Benalcázar (2025) show that the process of collecting debts can be improved using optimized machine learning (ML) techniques, and that these techniques can predict the likelihood of payment at different levels of delinquency [4].

Zhang et al. (2025) [20] and Ni et al. (2025) [14] work on business analytics in banking. Zhang et al. (2025) show that business process management can be improved by data-driven predictions of defaults. Ni et al. (2025) use hybrid analysis to construct multi-dimensional frameworks for the evaluation of business processes in commercial banking [14]. Li et al. (2025) applies process mining techniques, augmented by domain knowledge, to detect anomalies in the workflows of commercial banking, and show that the integration of machine learning with processes improves operational efficiency [10].

Furthermore, the study on the predictive modeling of the bank loan approval process published in the Procedia Computer Science (2025) journal stresses the need to connect the results of machine learning with structured decision-making systems. Most of these studies show that predictive models and operational processes can improve efficiency. However, there is very little literature that describes a single architecture for combining: ML risk prediction; threshold optimization; evaluation of process performance; regulatory compliance

Identified Research Gap. The literature establishes four critical pillars (See Table 1): 1. ML and deep learning improve credit risk prediction [5; 11; 12]. 2. Alternative data enhances model performance [1; 8]. 3. Explainable AI is essential for regulatory acceptance [7]. 4. Data-driven business process evaluation improves operational performance [14; 20].

Table 1. Comparative Overview of Credit-Risk and Process-Optimization Approaches

Study	Main focus	Data / method emphasis	What it contributes to your paper	Key limitation your ICPOF resolves
Balina & Idasz-Balina (2021)	Retail credit-risk drivers	Retail borrower risk determinants	Justifies multidimensional predictors	Limited linkage to workflow integration
Roy & Shaw (2021)	Credit decision support	Multi-criteria model (BWM–TOPSIS)	Shows structured decision logic	Not embedded into end-to-end credit processes
de Lange et al. (2022)	Explainable AI	XAI for bank credit assessment	Supports transparency requirement	XAI often not connected to process redesign
Hjelkrem et al. (2022)	Open banking scoring	Transaction data in application scoring	Supports alternative data enrichment	Doesn't formalize operational routing impacts
Woo & Sohn (2022)	Behavioral drivers	Psychometric features in scoring	Supports non-financial predictors	Limited process-level operationalization
Hjelkrem & de Lange (2023)	XAI in deep learning	SHAP explanations for DL scoring	Supports explainability + actionability	Not linked to workload economics
Chen et al. (2023)	Decision support	Novel evaluation/prioritization model	Supports multi-criteria prioritization	Not integrated with workflow performance KPIs

Mestiri (2024)	Model comparison	ML/DL in credit scoring	Supports ML superiority narrative	Technical focus; limited operational embedding
Chang et al. (2024)	ML/DL prediction	Default prediction in credit cards	Supports generalizability to retail portfolios	Doesn't connect prediction to process cost
Venugopal (2024)	Portfolio efficiency	Efficiency and management of portfolios	Supports efficiency framing	Not specific to process-level credit routing
Alamsyah et al. (2025)	Alternative data	Social media for inclusive scoring	Supports enriched signals	Operational governance not the focus
Miljkovic & Wang (2025)	Feature efficiency	Dimension reduction for categorical big data	Supports simplifying models without losing power	Doesn't tie simplification to workflow gains
Carrera & Benalcázar (2025)	Collections optimization	ML prediction by arrears stage	Supports stage-sensitive interventions	Typically downstream; not end-to-end credit process
Breeden (2025)	Model stability	Pandemic normalization	Supports robustness across shocks	Not connected to workflow redesign
Machado et al. (2025)	ML model performance	Comparative ML analytics	Supports evidence for ensemble performance	Mostly model-centric
Procedia Computer Science (2025)	Approval decisioning	Predictive modeling pipeline	Supports decision-pipeline integration	Often lacks explicit workload threshold economics
Ni et al. (2025)	Process evaluation	Multi-dimensional process framework	Supports process-analytics linkage	Not credit-model specific
Li et al. (2025)	Process mining	Anomaly detection with domain knowledge	Supports control/monitoring logic	Not directly tied to credit scoring thresholds
Zhang et al. (2025)	BPM enhancement	Default prediction + process mgmt	Supports predictive-to-process link	Needs explicit governance/threshold calibration
Souadda et al. (2025)	ML optimization	ML for P2P risk prediction	Supports model selection + validation logic	Not integrated with branch-level protocols

However, no existing study integrates these components into a unified retail credit process optimization framework. Specifically, the literature lacks: a structured architecture linking ML predictions to operational credit workflow redesign; a calibration mechanism balancing predictive precision and operational workload; a feedback loop connecting portfolio risk reduction to process efficiency metrics.

Methodology

The purpose of the analytical and integrative methodological approach of the study, focuses on the optimization of the retail credit process through the flow of operational decisions and the structured integration of machine learning-based predictive risk technology. The aim is not to invent a new algorithm, but to develop a framework for the integration of existing credit risk predictive modeling innovations to be used in retail banking processes in a way that credit loss and operational efficiency is maximally improved. The method is based on three analytical constructs that are interlinked: predictive robustness, calibrated decision control, and operational integration.

Enhancing Predictive Robustness. The first methodological aspect focuses on the enhancement of credit risk prediction accuracy. Contemporary research shows that machine learning methods, particularly ensemble methods, surpass the traditional regression methods of credit scoring in retail. Mestiri (2024) [12] and Chang et al. (2024) [5] study the effectiveness of tree-based ensembles and deep learning models in boosting the discrimination power of the default prediction. Random Forest models are reported to perform exceptionally well in retail credit portfolios under conditions of extreme class imbalance [11]. Predictive improvement is, however, not only dependent on the chosen algorithm. Effective feature engineering and control of dimensionality are equally crucial.

Miljkovic and Wang (2025) state that feature dimensionality reduction is important for improvement in computational performance retention of strong predictive signal in high-dimensional datasets [13]. Research by Balina and Idasz-Balina (2021) shows the individual retail credit risk dimensions and highlights the importance of careful features selection for the stability of the model [2]. Transaction level open banking data, as illustrated by Hjelkrem et al. (2022) supports improvement of credit scoring at application level [8], while Alamsyah et al. (2025) argues alternative digital signals increase predictive coverage [1].

Consequently, the methodology takes for granted a predictive engine based on ensemble learning models with improved, and where feasible, transaction-level or other data, optimized and enriched feature sets. In accordance with the methodology established by [11] and Souadda et al. (2025) [17], the evaluation of models considers applicable metrics for imbalanced datasets (F1-score, precision, sensitivity, and AUC) case scenario). Furthermore, to maintain stability throughout different phases of the business cycle, the use of normalization proposed by Breeden (2025) is used conceptually to soften the effects of irregular macroeconomic cycles [3].

At this stage, the goal is to optimize probability estimates instead of just maximizing them, as is the case with most models.

Calibrating Decision Thresholds. Predictive probabilities have to be converted into actionable operational choices. Such conversions take place via threshold selection, which is a defining segment of the optimization continuum. Decreased decision thresholds heighten sensitivity, thereby curtailing the likelihood of missed defaults. However, they increase the number of cases to be manually reviewed. Increased thresholds create a burden to operational workload, but possibly create an inability to see the onset of serious declines.

Carrera and Benalcázar (2025) show that collection efficiency is improved when using stage-sensitive predictive calibration [4], and so does Venugopal (2024) [18], but to a lesser extent, as the efficiency of a portfolio is improved when a more aggressive risk allocation is employed. For the purposes of this study, threshold calibration is viewed as a managerial optimization problem rather than just a statistical one. The optimal threshold is set where the trade-off of further reduction of expected losses equates to the expected operational burden that would be caused by the additional case. This calibration of threshold brings predictive modeling into measuring the efficiency of a process. (See Figure 1).

Integrating Risk Prediction into Retail Credit Workflows. The final method involves embedding calibrated risk scores in retail credit processes. Previous studies on banking process analytics show how data-driven approaches improve workflow efficiency. Ni et al. (2025) [14] and Zhang et al. (2025) [20] prove that when combined with structured evaluation frameworks, predictive models improve business process management. Li et al. (2025) shows that process mining with added domain knowledge helps find anomalies in banking workflows [10].

In other words, the methodological innovation lies in recognizing threshold selection as a strategic control variable connecting model output with operational performance.

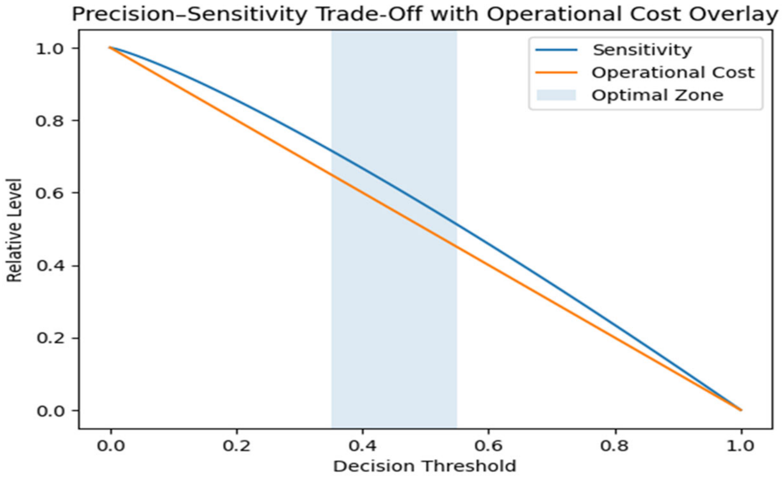

Figure 1. Precision–Sensitivity Trade-Off with Operational Cost Overlay

Still, very few studies focus on how predictive risk outputs should change retail lending workflows. This framework places risk scores in the most critical phases of retail credit processes, which include pre-screening, escalation routing, credit limit reviews, and the activation of early collections. This means that high-risk accounts are given attention in the right timelines and low-risk applications are handled in a more process-efficient way.

Explainable Artificial Intelligence (AI) methods, like SHAP [7; 9] are also added, to address transparency, compliance, and managerial discretion. The methodology integrates predictive analytics and operational routing to go beyond model development to process improvement.

The Sherstiuk Retail Credit Process Optimization Framework (SRCPOF). Synthesizing the above elements, the author proposes the Sherstiuk Retail Credit Process Optimization Framework (SRCPOF). The framework connects three core components:

1. Robust predictive modeling supported by optimized and enriched data inputs;
2. Strategically calibrated decision thresholds balancing risk reduction and workload economics;
3. Structured embedding of risk signals into retail credit workflows with continuous feedback on portfolio performance.

The originality of SRCPOF is not in algorithmic novelty, but in the formal integration of predictive analytics, managerial calibration, and process redesign into a unified retail credit optimization architecture (See Figure 2).

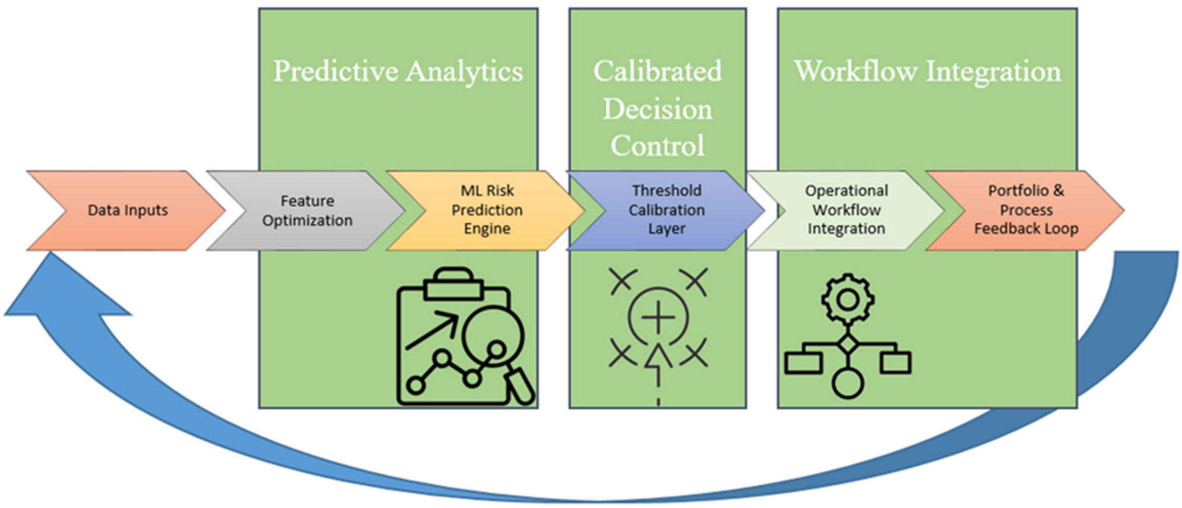

Figure 2. Sherstiuk Retail Credit Process Optimization Framework (SRCPOF)

Research Results

Analytically grounded improvements can be seen in risk control and operational efficiency with respect to workflow operationalization of ML based credit scoring in retail banking. Utilizing existing literature with the framework made in the course of this study outlines four findings.

Data-Driven Scoring Enhances Default Risk Mitigation. The literature shows that ML models have proven to be beneficial in assessing and evaluating credit related risk [5; 11; 12]. In imbalanced conditions and evaluation, risk of default is detected and proven with more confidence with Balina and Idasz-Balina (2021) [2]. Miljkovic and Wang (2025) show that the reduction of dimensions helps in the improvement of the extraction of better signals from complex, and in most cases, undiscovered variables [13].

When combined with alternative data sources like open banking transaction flows [8] or digital behavioral indicators [1], predictive robustness further improves. These improvements, in the SRCPOF framework, increase early detection of high-risk borrowers. This allows for preemptive actions such as credit limit changes or structured repayment plans, reducing the risk for borrowers to be transferred to serious default levels. Stage-sensitive predictive systems have proven to be effective in the management of overdue debts, as confirmed by Carrera and Benalcázar (2025) [4] (See Table 2).

Table 2. SRCPOF Operational Impact Matrix

SRCPOF component	What the component does	Operational impact	Risk-management impact	Primary supporting sources
Predictive risk scoring engine	Produces probability-based risk ranking using ML/DL	Speeds pre-screening; improves consistency	Earlier identification of high-risk borrowers	Mestiri (2024); Chang et al. (2024); Machado et al. (2025); Souadda et al. (2025)
Feature optimization & dimensionality control	Reduces redundant variables; stabilizes model inputs	Faster processing; easier maintenance	Reduces noise-driven misclassification	Miljkovic & Wang (2025); Balina & Idasz-Balina (2021)
Alternative-data enrichment	Adds transaction/digital signals to core features	Improves segmentation and personalization	Improves detection where traditional history is weak	Hjelkrem et al. (2022); Alamsyah et al. (2025); Woo & Sohn (2022)
Threshold calibration (workload economics)	Sets cutoffs that balance risk capture vs. manual load	Controls review volume; prevents bottlenecks	Improves intervention timing without flooding staff	Carrera & Benalcázar (2025); Venugopal (2024)
Workflow integration & routing rules	Embeds score outputs into approval/escalation paths	Shorter approval cycle; better queue management	Faster response to early deterioration	Ni et al. (2025); Zhang et al. (2025); Procedia Computer Science (2025)
Process monitoring & anomaly detection	Flags irregularities in process execution	Reduces errors/leakage; strengthens controls	Prevents operational-risk driven credit losses	Li et al. (2025); Ni et al. (2025)
Explainability layer (XAI/SHAP)	Explains model decisions for staff/regulators	Improves adoption and decision confidence	Enhances governance and auditability	de Lange et al. (2022); Hjelkrem & de Lange (2023)
Stability safeguards (shock normalization)	Protects models from abnormal macro periods	Reduces rework and revalidation churn	Improves reliability across cycles	Breeden (2025)

Automation Shortens Credit Approval Cycles. Retail credit processes commonly face bottlenecks due to the number of reviews that require manual processing and loss of continuity in how decisions are made. Business process analysts have shown that the inclusion of predictive analytics in processes streamlines the flow [14; 20]. For example, removing manual reviews from the processing of low-risk applications by integrating risk scores into automated pre-screening structures is effective. On the other hand, strategic escalation is still performed for high-risk applications. The study in Procedia Computer Science (2025) shows that decision-making predictability and processing time in loan approval systems are considerably improved through predictive analytics [15].

Within SRCPOF, threshold calibration is particularly important. Effectively set thresholds achieve a balance between sensibly limiting unnecessary case escalation while still providing the system the ability to detect emerging risk, thus reducing the manual review of low-risk account cases. As a result, this decreases processing time and improves the customer experience. Therefore, the second finding supports those predictive analytics integrated with calibrated automation increases the efficiency of credit approvals while maintaining an acceptable level of risk control.

Workflow Redesign Reduces Operational Costs. Reductions in operational costs come not just from automation, but from smart redesigning of workflows. Venugopal (2024) connects the efficiency of a portfolio with both tactical assignment of credits and control of management [18]. In the same way, Li et al. (2025) shows that process mining, enhanced by the respective domain, identifying the inefficiencies and the other aberrations in the workflows of banking [10].

SRCPOF incorporates predictive risk scores into the level of branch decision-making with structured escalation rules. This in turn eliminates duplicate assessments, unnecessary cycles of documentation, and proactive management of accounts that deteriorate. Furthermore, the balance between both precision and sensitivity, which is controlled by a certain calibrated threshold, will determine the way in which the balance is allocated for the tasks.

If a threshold is excessively conservative, staff will experience an overload due to the presence of a high number of false positives; on the other hand, if the threshold is excessively strict, then there will be a delay before an intervention is made. The optimization logic in this study formalizes this phenomenon and elevates the trade-off threshold to be a decision variable for management rather than purely a statistic. Consequently, operational costs are reduced due to:

- Decreased number of manually handled cases
- More precisely targeted intervention approaches
- Reduced costs associated with the collection stage at a later interval

Integrated Analytics Strengthen Early Warning Signals. Advanced data stream processing and predictive modeling have integrated systems that now possess the ability to expedite warnings. Hjelkrem et. al (2022) show the usefulness of transaction data prior to default events to identify declining patterns of financial behavior. Hjelkrem and de Lange (2023) illustrate that risk drivers can be granularly diagnosed through explainable deep learning models [9]. De Lange et al. (2022) explain the need for trust from regulators and the explainable [7].

Within the SRCPOF, real time dashboards are able to combine and display risk scores and principal indicators, which include signals that influence behavior, levels of exposure, and trends of delinquency. This form of immediacy/access to risk scores is able to shift the credit assessment paradigm from being static to being a continuously monitored portfolio.

Normalization and stability, across Breeden (2025) cycles, are of high importance. Embedding these principles of normalization within the structure of the framework will ensure that macroeconomic shocks will not compromise the reliability of early warning signals [3]. The fourth finding substantiates those integrated analytics improves the interpretive and the time in which the early warning systems become operational.

Discussion

The results of this research must be placed within the context of the evolving retail banking sector towards utilizing data and making decisions from a digital perspective. Even though machine learning credit scoring has been accepted as better than other conventional statistical techniques from a predictive perspective [5; 11; 12] predictive modeling literature has primarily considered this as a stand-alone technical improvement.

Limitations of Traditional Credit Models in Dynamic Environments. With primary retail credit systems, process modeling is more of an afterthought than an embedded component. Credit systems that rely on periodic reassessments, fixed thresholds and simple linear scoring are a major source of frustration. While historical validation and interpretability are valued, they also tend to miss the more complex, nonlinear behavioral patterns of borrowers, particularly in the digital segments of active retail credit. Mestiri (2024) [12] and Chang et al (2024) [5] demonstrate that, under less complex conditions, nonlinear ensemble models are far superior to logistic regression.

Furthermore, in times of economic instability, static credit systems experience difficulty, and Breeden (2025) argues that credit models that are not adaptable during periods of economic abnormalities (such as the COVID-19 pandemic) are unreliable [3]. Lack of adaptive and recalibrated systems is a structural weakness. Often, traditional credit decisions and workflow optimization operate in silos. Predictive scores are generated, but there is no dynamic alignment of escalation and intervention mechanisms with the risk outcomes.

The Strategic Role of Embedded Analytics in Branch Operations. It is increasingly noted in the literature that predictive analytics should be implanted in the organizational processes in order to create value. Ni et al. (2025) [14] and Zhang et al. (2025) [20] demonstrate the effectiveness of data-driven process evaluation frameworks in improving operational performance in the field of commercial banking. Further, Li et al. (2025) demonstrates improved workflow-embedded business processes anomaly detection through the application of process mining techniques [10]. However, these studies do not explicitly address the retail credit decision chains on the level of the branches.

In retail banking, branch managers and credit officers have to operate under the constraints of workloads, regulations, and customer service. The integration of calibrated risk signals in the protocols of decision-making at branches should make credit scoring a real-time tool of management rather than a report. The integration of certain explainable AI tools (e. g. SHAP mechanisms [7; 9] ultimately enhances managerial trust. Model outputs that are explainable to branch personnel assist in improving quality of intervention and compliance and help to understand the reasons for the identification of an application as high risk [16]. In this direction, embedded analytics is paving the way for the shift of focus from ‘prediction for reporting’ to ‘prediction for action.’

Operational Calibration as a Managerial Control Variable. An important aspect of this study is how threshold calibration is advanced from a statistical modification to a form of managerial control. Predictive efficiency is shown to be stage-specific in collection within the collection efficiency of predictive stage strategies, and portfolio efficiency is linked to predictive strategy-based risk allocation [4; 18]. These studies seemingly take for granted the need for a balance between the predictive output, operational capacity, and targeted portfolio.

The SRCPOF framework solidifies this by rationalizing decision thresholds as economic factors. Instead of targeting AUC or F1, the score focus, threshold calibration is concerned with the balance between the expected loss reduction and the processing capacity. This means that credit risk management is pivoted to a focus predominantly on the two sides of the same coin expectation. These include: minimization of expected losses from defaults; minimization of operational burden on the processes; this balance is what leads to a structurally optimized credit process, as opposed to simply a statistically optimized one.

Implications for Retail Banking in Emerging and Digitally Transforming Markets. Retail banking in emerging markets often needs to adjust to rapid changes in technology use by consumers, the availability of new types of data, and shallow credit histories. Hjelkrem et al. (2022) posit that use of transaction-level open banking data improves predictive capability [8]. In such contexts, integrated frameworks such as SRCPOF are especially useful, as they enable institutions to take advantage of alternative data while adhering to regulations and keeping their operational processes under control. In addition, digital-first customer segments demand rapid credit decisions. With the help of predictive analytics used in automated decision-making processes, the time taken to make decisions is greatly reduced while keeping risk in check. This creates a positive outcome on the overall control of risk and satisfaction of the customer.

The Author's Core Contribution: The Sherstiuk Retail Credit Process Optimization Framework (SRCPOF). The development of the Sherstiuk Retail Credit Process Optimization Framework (SRCPOF) is the main scholarly contribution of this study. SRCPOF adds to the scholarly literature in four different ways. First, it is the first framework in literature to integrate predictive analytics with workflow design. Most of the literature, like [5] and [11], consider these two domains separately, and considers predictive analytics separately from workflow design and focuses on model outcomes, while SRCPOF links performance outcomes to operational outcomes. Second, it conceptualizes threshold calibration as a strategic decision variable where the decision relates to trade-offs between risk and the economics of workload. Most of the literature discusses performance measures in relation to the efficiency of the processes, but do not refer to the explicit relationship to the costs associated with processing. Third, it uses the literature on explainable AI [7; 9] to incorporate explainability into decision protocols to ensure transparency in automated decision systems. Fourth, it connects feedback on the performance of the credit portfolio with adjustments to the credit process, thereby, creating a dynamic feedback system as opposed to a static scoring system. In other words, SRCPOF does not expect to make any additional contributions to the literature in credit scoring models from an algorithmic perspective (i. e. SRCPOF does not claim to offer anything novel in terms of the algorithms involved), but rather SRCPOF's contribution is in integrated systems logic. SRCPOF redefines credit scoring based on machine learning from a predictive tool to a fully operational integrated process for operational optimization in retail banking.

Conclusions

The purpose of this paper is to analyze the potential of systematic integration of machine-learning-based credit risk predictions with processes in retail banking to provide value in both risk and operational efficiency. It is generally accepted that ensemble and deep learning models are superior in predictive performance for credit scoring [5; 11; 12]. However, this research departs from these models to further the theory of process optimization. Integrating the latest research in alternative data [1; 8], explainable AI [7; 9], and data-driven business process evaluation [14; 20], the author proposes the Sherstiuk Retail Credit Process Optimization Framework (SRCPOF). This framework represents the first attempt to unify predictive analytics, decision threshold calibration, and workflow optimization as a unified retail credit management system. The findings in this case study demonstrate that the optimization of credit processes is not the result of advanced algorithms alone. The true credit process optimization occurs when predictive models are integrated with operational process routing and are balanced with workflow economics. In this regard, threshold calibrations are a strategic management control variable that combines statistical risk processing with actual processing capacity. In addition, the integration of explainable AI ensures the preservation of regulatory and managerial confidence.

Theoretically, this study contributes to the literature by bridging the gap between credit risk modeling and business process management. Whereas existing research has largely treated these domains independently, SRCPOF demonstrates their interdependence in retail banking contexts.

Practically, the framework offers retail banks – especially those undergoing digital transformation – a scalable and adaptable approach to improving portfolio stability, reducing manual processing inefficiencies, and enhancing customer responsiveness. By transforming credit scoring from a static evaluative mechanism into a dynamic process optimization tool, SRCPOF supports more resilient and agile retail banking operations.

Future research may empirically validate the framework using longitudinal portfolio data and quantify efficiency gains under varying macroeconomic conditions. Nevertheless, this study establishes a structured foundation for integrating machine learning–driven analytics into operational retail credit systems in a coherent and strategically aligned manner.

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