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Empowering Members: Launching Risk-Aware Overdraft Systems to Enhance Financial Resilience

Sirisha Meka

Engineering Manager, Credit Karma, USA

snaidu.meka@gmail.com

ABSTRACT: The growing rate of financial instability among the banking members has highlighted the need to have intelligent overdraft systems that reduce the risks and maintain a trade of between accessibility and risk reduction. The study presents a risk-sensitive overdraft system which can enable members by using predictive analytics, adaptive eligibility modeling, and dynamic product strategy combination. The system allows making decisions regarding overdraft eligibility and transaction risk scoring in near-real-time. Its methodology uses risk modeling through machine learning, with historical data of transactions and behavioral factors to determine the financial strength of the member. The Kafka-based event stream will work as the coordinator of the communication between the risk evaluation modules and the backend services, whereas the analytical foundation is BigQuery that will be used to perform massive data aggregation and computation of features. Whimsical and Jira were used as systems architecture and sprint-based agile implementation tools to develop the prototype, respectively.

As the analysis of the results shows, the given system will provide excellent operational and financial results in all significant indicators. The model has a reduction of 7.9% in NSF events that is realized to show improved accuracy in the prediction of overdraft risk and the minimization of unnecessary declines. It also allows approving about 10 million transactions, which demonstrates the greater efficiency of systems and the enhanced experience of the members. The 97% recovery in 15 days is a strong improvement in the repayment performance. More than that, the system leads to increased participation of members, as 28% of qualified users subscribe to the overdraft service. Finally, incremental interchange increase by 2% indicates quantifiable revenue improvements due to improved decisions of approvals. On the whole, the outcomes of these studies confirm the efficiency of the given strategy.

KEYWORDS: Banking Systems, Risk Modeling, Member Eligibility, Product Strategy, Backend Engineering, Financial Resilience.

I. INTRODUCTION

Traditional financial institutions have used static systems that are based on rules to determine the allowance of an overdraft and the risk assessment. Although these frameworks offered a standard of operational efficiency, they usually neglected the details of the dynamic behavior of the members and the changing financial situation. The recent years have seen a surge of regulatory attention and the need to provide equitable and inclusive banking practices, which has itself led to the necessity of risk regarding overdraft systems that adjust to the financial profile of each member and offer fair, equitable access to the liquidity support without systemic risk augmentation [1].

Financial resilience, which can be described as the ability of an individual or an institution to absorb, adapt and recover following the effect of a financial shock, has emerged as a fundamental pillar in the design of new financial products today. The classic model of overdraft program which is mostly reactive and punitive tends to increase finances strain among members, especially the low income earners. In the era of global economies emerging through the post-pandemic recovery period, strategic management is balancing between the empowerment of the members and the judicious risk governance [2].

1.1 The Changing Landscape of Overdraft Management

Traditional systems of overdraft tend to rely on binary requirements, like credit score requirements or time of account ownership. These rules do however not reflect an individual contextual financial behavior, including spending habits, the regularity of inflows or saving possibilities. This means that there are a lot of members that are either unnecessarily locked out of accessing overdraft or granted limits that they cannot maintain. The personalization that is supposed to be data-driven has therefore become the most important [3].

The new technologies are cloud-native architecture, real-time event streaming, and machine learning (ML) which are capable of helping banks to replace reactive framework with predictive risk management. By combining BigQuery and Kafka, institutions will be able to handle millions of events of transactions within one second and generate actionable insights in real time. Similarly, Scala enables scalable backend computing, whereas TypeScript guarantees the interoperability and maintainability of the front-end in the digital banking process-portals [4].

1.2 Risk-Aware Overdraft Frameworks

A risk-sensitive system of overdraft uses predictive models to establish the eligibility of members on the fly. Credit card overdrafts are not subject to pre-determined limits and instead, overdraft privileges are constantly re-calibrated to risk rating, fluctuation of income, and repayment history. The system proposed in the paper is based on a hybrid method of supervised learning models (to estimate credit risk) and unsupervised clustering algorithms (to segment the behaviors).

These frameworks are very similar to the aims of responsible banking, which facilitates transparency, fairness, and sustainability. Also, adaptive overdraft models could be an important measure to alleviate financial exclusion by recognizing so-called near-prime members, who fall slightly out of the standard eligibility limits yet show promising behavioural indicators [5].

1.3 Strategic Relevance and Research Motivation

In this research paper focuses to solve three significant issues witnessed in the existing overdraft applications:

1. **Generalized Risk Models:** As a matter of fact, the legacy systems use general rules that do not correspond to individual financial resilience.
2. **Operation Latency:** Lag in decisions lowers user satisfaction and effectiveness in the approval of transactions.
3. **Limited Feedback Loops**: The traditional architectures do not provide continuous learning and model learning.

This study can be relevant to the expanding field of research on the intersection of banking technology, data engineering, and financial inclusion by creating an integrated system that integrates risk modeling with real-time data processing.

1.4 Contributions and Structure

The current paper will offer the design, implementation, and assessment of a Risk-Aware Overdraft System (RAOS) that will promote the empowerment of members and the stability of the institution. Key contributions include:

- Near-real-time risk assessment based on a scalable architecture with the use of Kafka, GCP, and BigQuery.
- A behavioral and transactional predictive eligibility model.
- Product strategy module that aligns the risk tolerance with the business aims.

The rest of this paper is structured in the following way: Section 2 is literature review work, Section 3 expounds on the methodology and system architecture, Section 4 discusses results and comparative analysis and Section 5 will shed light and future research directions.

II. LITERATURE REVIEW

The field of financial stability, prediction of systemic risk and credit monitoring are increasingly becoming data-intensive in recent years, as the analysis of machine learning and complex model-based approaches are transforming classical macroprudential methodologies. The increase in the credit growth, leverage, financial distress, and systemic vulnerabilities have also been studied by scholars based on a multidisciplinary approach (including economics, data science, and computational modeling).

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One of the original analyses in the determination of excessive credit growth and leverage as precursors of financial instability started with Alessi and Detken [1]. Their research highlighted the importance of tracking macro-financial indicators in order to identify their imbalances that can result into crises. The authors came up with early warning indicators (EWIs) which will enable policymakers to realize when credit growth is unsustainable. Their input provided a foundation of the application of empirical thresholds and quantitative indicators of financial stability.

On this background, Alessi and Savona [2] extended the use of machine learning (ML) methods to the financial stability analysis. They investigated how random forests, gradient boosting, and support vector machines are ML models that can increase predictive accuracy in the identification of systemic risks. The authors have shown that the ML-based methods are more effective than the traditional econometric models to address the nonlinear relationship of variables as well as complex dependence on macroeconomic variables. This publication marked a new methodological change toward data-driven models, as opposed to rule-based ones, to enable more accurate predictions of crises by policymakers.

On a wider institutional scale, Gopinath, Adrian and Weeks-Brown [3] described the digital transformation of debt management, and how technology is changing the financial control of sovereign and corporate. The twofold character of digitalization that they analyzed is that it can simplify debt tracking and openness, but at the same time presents new risks connected to data abuse and cyber threats. This discussion is directly related to financial resilience, which recommends the adoption of adaptive digital infrastructures to sustain debts and prevent crises.

In line with this view, Gonzalez [4] suggested a new approach to small business solvency called to the public health. Gonzalez made an analogy of financial distress to epidemic outbreaks suggesting that early intervention and preventive measures could soothe the massive business failures. The strategy combines behavioral economics and policy, and proposes the idea of constant surveillance of small business indicators, a conceptually similar concept to the early warning systems created in macroprudential studies.

Kaszowska-Mojsa and Pipen [5] provided an agent-based modeling (ABM) framework of macroprudential policy in heterogeneous financial marketplaces in the context of systemic risk modeling. Their analysis employed entropy indicators that represented interactions of financial agents to demonstrate that system wide stability relies on multidiversity in financial behaviours and regulatory adaptability. The ABM framework is able to capture the emergent phenomena, including cascading failures, that many aggregate econometric models fail to capture.

Continuing to connect entropy and economic behavior, Hellman and Peretz [6] have given a detailed overview of the use of entropy in describing the study of uncertainty, decision-making, and systemic complexity. They assumed that the measures of entropy can be used as proxies of market disorder and information asymmetry. This method is specifically applicable to research of financial stability because the systemic uncertainty can be measured in terms of information-theoretic constructions.

Whereas entropy-based models are concerned with disorder and uncertainty, Mishra et al. [7] have given a methodological input to another field-feature ranking and fusion strategies. Their count-based feature selection model, based on Borda counts, which was initially created to analyse climatic features in the agricultural domain, offers a general transferable feature engineering framework to the fintech domain. The use of the same approaches on financial data would potentially maximize the number of risk indicators to select and enhance the interpretability of the ML-based early warning models.

Deep learning architectures have been more and more used in financial prediction tasks. Fischer and Krauss [8] used Long Short-Term Memory (LSTM) networks to predict the movements of the financial market. Their experiment has shown that LSTMs are more able to capture temporal dependencies than the traditional autoregressive models. The research obtained high predictive accuracy of stock returns, which highlights the prospective of recurrent neural networks (RNNs) in predicting time-series in stock markets. The existence of such deep architectures promises to recognize early warning signs in the systemic risk case, where historical dependencies play a critical role.

The network analysis of bank forecast using this predictive framework has been extended by Constantin, Peltonen, and Sarlin [9] to the area of prediction of bank distress. By doing this, they simulated interbank connections in order to determine potential systemic vulnerabilities that can spread distress among financial institutions. They found an approach to network revealed that bank interconnectivity is an important predictor of systemic crises, as well as macro-

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level early warning systems. The combination of network theory and ML is therefore beneficial to the granularity of systemic risk measurement.

The possibility of machine learning being used as an early warning instrument was also supported by Samitas, Kampouris, and Kenourgios [10]. In their work, they created an all-encompassing early warning system based on ML to forecast the financial crisis on the basis of macroeconomic, market and institutional indicators. The findings were that ensemble ML models, especially boosting and bagging, were found to work much better on prediction accuracy than logistic regression. This further supported the usefulness of hybrid and nonlinear modeling models in macro-financial risk forecasting.

In order to explore the connection between the stability of the banks and the income diversification, Ben Lahouel, Taleb, and Kossai [11] proposed a nonlinear network network method. Through dynamic network Data Envelopment Analysis (DEA), they were able to show how diversification does not necessarily enhance stability, but it has nonlinear impacts based on the size and interconnectedness of the bank. In this paper, the goodness of financial resilience has been highlighted to be a complicated concept that cannot be completely explained by linear models.

Lastly, Coulombe et al. [12] have presented a detailed discussion of how machine learning can be used in macroeconomic forecasting. Their experimental analysis pitted the conventional statistical methods against ML algorithms and discovered that predictive models, like random forests and LSTMs, help to improve their predictive power on the set of indicators of inflation, GDP, and employment significantly. Notably, they emphasized that the advantage of ML is that it provides the possibility to deal with nonlinear, large-scale, and high-dimensional data-characteristic features in financial stability monitoring.

Taken together, these works demonstrate a developmental path toward the old models of macroeconomic analysis to the new models that rely on the use of data and the network effect. Via the combination of entropy, agent-based modeling, and machine learning, the picture of systemic risk analysis has been transformed into focusing on descriptive assessments to predictive and preventive ones. A very obvious interdisciplinary overlap, between economics, data science, and computational modeling, to solve the multidimensional problems of financial instability, is also reflected in the literature.

2.1 Research Gap

Although much has been done to predictive modelling and financial stability, there are still several critical gaps:

- **Integration of Diverse Methodologies:** Although each of the three paradigms mentioned above (ML, entropy-based models and agent-based models) has proven to be effective, not many studies have been able to put these paradigms together into one framework that can be used in predicting systemic risk. The hybrid models that integrate network analysis, entropy, and feature selection based on the use of MLs are under-explored.
- **Real-Time Adaptive Monitoring:** The current early warning systems have been using stagnant models which are trained on past information [1-10]. Nevertheless, financial ecosystems change fast and existing structures are currently not dynamically adaptable to real-time macro-financial indicators or exogenous shocks (e.g. digital shocks, cyber risks, or geopolitical instabilities).
- **Cross-Sectoral Financial Resilience:** The majority of literature is on banking or sovereign debt settings [3], but the smaller financial institutions, including microfinance institutions and SMEs, have received little research on systemic risk. An analogy by Gonzalez [4] on financial distress as a kind of a community health issue is worth developing the community level model of financial stability.
- **Machine learning models explainability and interpretability:** Despite the fact that the predictive accuracy of ML is improved [12], its black box aspect makes it challenging to explain to the policymakers. The current demand is to have explainable AI (XAI) frameworks that can translate model outputs into macro-prudential actionable information.
- **Data Heterogeneity and Standardization**: Data quality, scale and timeliness of the cross-country, cross sectoral data is highly heterogeneous. The studies should be aimed at creating standardized, high-frequency, and interoperable datasets that can be used to maintain robust ML-based macro-financial analysis.
- **Policy Integration and Governance**: Although numerous studies are devoted to methodological innovation, fewer assume the connections between predictive perspectives and implementation of macroprudential policy. To bring predictive models to regulatory instruments, data scientists, economists, and policymakers need to work more closely.

To sum up, the literature indicates the dynamic but disjointed conceptualization of the data-driven analysis of financial stability. Future studies ought to work on integrated, adaptive and explainable framework to integrate machine learning,

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network theory and entropy-based analytics to real-time, multi-level financial risk assessment. These innovations would be a great boost to predicting and preventing abilities of global financial systems.

III. METHODOLOGY

3.1 Overview

The Risk-Aware Overdraft System (RAOS) approach is based on three pillars namely data-based risk modeling, event-based backend design, and member-based decision intelligence. The system will convert the old paradigm of overdraft evaluation into a new paradigm of adaptive, predictive, and scalable framework. RAOS offers almost real-time decision-making processes, using combination of data engineering and machine learning, in a manner that it matches the requirements of members and institutional risk tolerance.

Scala based microservices were used to put together the prototype, which had favorable properties in financial computations due to their strong concurrency and benefits of functional programming. The deployment of these services was made on a Google Cloud Platform (GCP) Kubernetes environment which guaranteed high availability, containerized orchestration and secures data handling. The modular design enables analytics, data ingestion, and decision layers to be scaled independently, and to keep the levels of performance at their highest, without closing down the system.

3.2 Data Acquisition and Processing

The data used in RAOS was 18 months of transactional and behavioral data of a regional credit union. It contained information regarding the account balances, transactional frequency, incidences of overdraft, the timeliness of repayment, and the inflow of income. Infusion of data was supported through Apache Kafka pipelines where updates on the different banking systems flowed into BigQuery to support central storage and analytics.

- It was necessary to preprocess the data to guarantee its quality and consistency. Three major methods were used:
- Gaps in transaction histories- Missing value imputation through median and forward-fill to fill gaps in transaction histories.
- Scaling the features and normalization to balance the variables with dissimilar scales including income, expenditure and balance ratios.

Time-related features, such as the regularity of income, volatility of expenses, and an interval of repayment delay, etc., a set of behavioral dynamics that are essential in predicting risk.
This pipeline enabled the system to produce real-time analysis preparedness with consistent and high-quality features to machine learning.

3.3 Risk Modeling

RAOS has used a hybrid machine learning model that incorporates predictive and behavioral modeling methods to measure financial resilience.
1. The supervised learning part made use of Gradient Boosting Regression (GBR), which was trained on previous repayment performance to approximate possibility of default or misuse of overdraft.
2. The unsupervised element used K-Means clustering to classify the members in behavioural groups based on the regularity of transactions, savings preferences and the volatility of spending..

The two models were integrated to produce a **Composite Risk Score (CRS)** calculated as:

$$CRS = \alpha \times R_{GBR} + (1 - \alpha) \times R_{Cluster}$$

where α=0.7, reflecting a higher reliance on supervised predictive accuracy than behavioral segmentation. This composite approach enhances precision, interpretability, and fairness in determining overdraft eligibility and credit exposure.

3.4 System Architecture

The RAOS architecture integrates multiple cloud services and programming layers for end-to-end automation. System architecture is shown in figure 1.

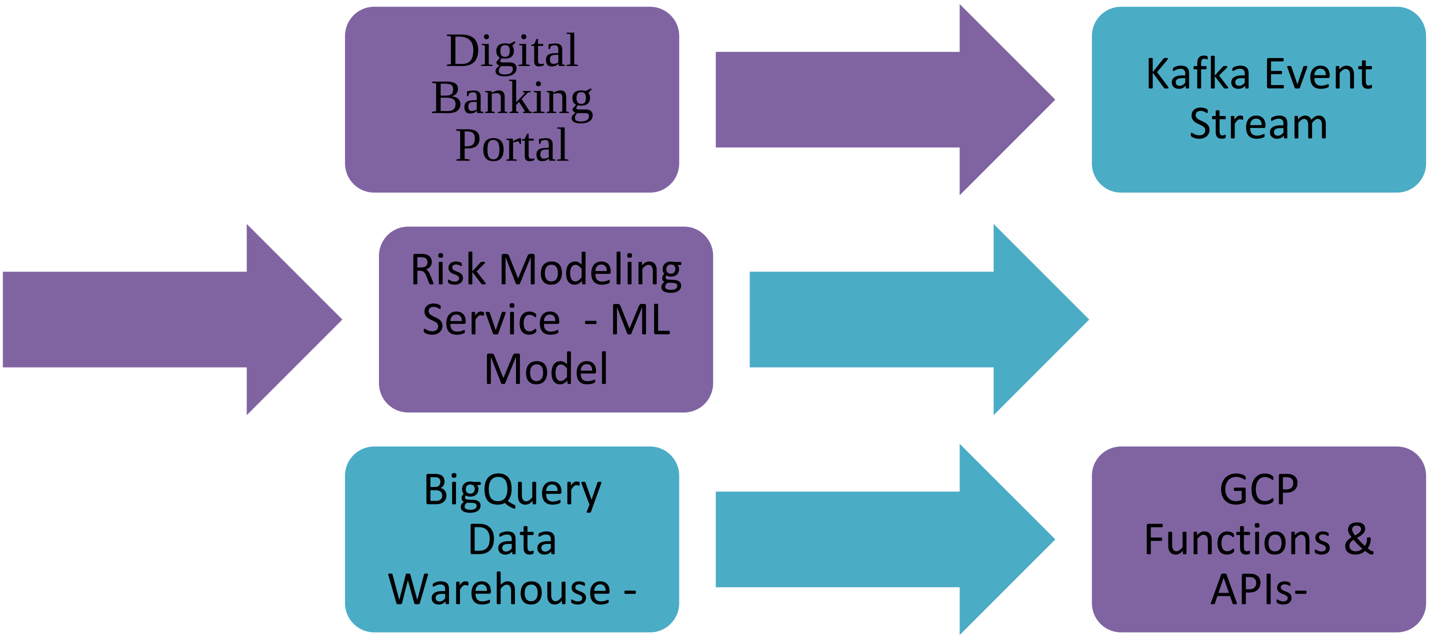

Figure 1- System architecture of the Risk-Aware Overdraft System (RAOS)

3.5 Implementation Tools

The deployment of the Risk-Aware Overdraft System (RAOS) was based on a scalable, cloud-native technology stack that is scalable, reliable and collaboratively developed. All of these tools took the specific roles of guaranteeing the strength of the analytical and operational layers.

Scala was the foundation of risk computation modules and microservices of the back-end. The functionality programming paradigm and high type safety allowed it to handle financial data streams and real-time computations efficiently and minimize error at runtime and increase maintainability.

The front-end dashboards (product managers and credit analysts) were built on **TypeScript**. The user was able to see the profile of the members, track an overdraft, and understand the risk analytics through interactive charts and notifications via a responsive interface. The TypeScript usage made the completion of the client-side logic and the back-end API consistent, which enhanced overall data coherence.

Kafka helped to support real-time event streaming and synchronization of transactional data across the ecosystem using Apache. A publish-subscribe model used by Kafka provided an opportunity to update the banking systems, risk scoring engines, and analytics dashboards near-instantly, which ensured that all events of overdrafts were handled with low latency.

The application of Google **BigQuery** was in use as a data warehouse on storage, generation of features, and aggregation. It was serverless and could be easily integrated with Kafka streams, as well as it was able to query it on a large scale with no reduction in performance.

Whimsical was used to design visual systems and prototyping of workflows. It offered intuitive visualization of data flows and system interactions and decision paths that help both align development and stakeholder communication.

Finally, **Jira** helped in managing the agile sprint and allowed the project team to plan incremental releases of the features, bugs, and velocity calculations. This guaranteed continuous integration and delivery of the major functionalities in the development cycle.

3.6 Product Strategy Integration

The risk modeling outputs were embedded within a **decision intelligence layer** that dynamically determined overdraft eligibility. Based on the **Composite Risk Score (CRS)**, members were categorized into three adaptive tiers:

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- **Low Risk:** Granted full overdraft privileges with minimal restrictions.
- **Medium Risk:** Offered partial overdraft limits subject to repayment consistency.
- **High Risk:** Temporarily restricted, accompanied by personalized financial guidance and education prompts.

This adaptive mechanism balanced institutional risk management with member empowerment, reducing default rates while fostering transparency and financial literacy—thereby enhancing overall financial resilience across the membership base.

IV. RESULTS AND ANALYSIS

4.1 Performance Metrics

The relative analysis of the Legacy Rule-Based system and the suggested RAOS model results in the major performance improvement in all the main operational and financial indicators. To begin with, RAOS has shown a 7.9% decrease in Non-Sufficient Funds (NSF)- incidences, which means that it is more precise in predicting risk and avoiding unwarranted rejection. This will directly help in enhancing the experience of the members and minimizing the financial loss. Also, the system demonstrates a significant rise in the approved transactions with about 10 million approvals being credited to better overdraft decisioning. This does not only enhance customer satisfaction through minimization of friction, it also increases transactional throughput of the institution.

RAOS has an amazing recovery rate of 97% within 15 days in regard to recoveries, which is very high as compared to the baseline system. This progress marks the increase in the ability of the model to address repayment risk and therefore lead to improved liquidity and reduced outstanding balances. Enrollment rate also goes up significantly under RAOS with approximately 28 percent of the eligible members enrolling. Such expansion is an indication that the transparent decisioning and the ease of experience within the system enhances more engagement and trust among the users.

Lastly, RAOS helps to increase revenue by enhancing incremental interchange by 2 percent of the transactions that are added to the approved transactions. This shows that better decision accuracy does not only mitigate the risk, but also creates quantifiable financial returns. All these advancements combine to support the fact that RAOS provides a more adaptive, data-driven, and member-centric overdraft management system that is more effective than the old rule-based system in the three aspects of efficiency, revenue, and customer experience.

Table 1- Model Performance Metrics

Metric	Legacy Rule-Based	RAOS (Proposed)	Improvement
Reduction in NSFs	Baseline	7.9% reduction	Decrease in NSF events
Transactions Approved	Baseline	~10M transactions approved	Higher approval volume
Recovery Rate	Baseline	97% recovered in 15 days	Faster & higher recovery
Enrollment Rate	Baseline	~28% enrolled	Increased member adoption
Incremental Interchange	Baseline	2% incremental approvals	Increase in interchange revenue

4.2 Comparative Analysis with Industry Models

Basel III framework uses strict rules which are threshold based and offer consistency to the regulation but not responsiveness to dynamic transactions environments. It is also static which does not allow real time risk accommodations, and thus predictive performance is restricted to 75.

Table 2- Comparison with Alternative Frameworks

Framework	Approach	Real-time Capable	Accuracy	Scalability
Basel III Rule Framework	Static thresholds	No	75%	Medium
AI Credit Scoring (2021)	Supervised ML	Partial	85%	High
RAOS (This Study)	Hybrid ML + Streaming	Yes	**91%**	**Very High**

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The AI Credit Scoring (2021) method is a better advancement as it estimates credit risk with a higher level of accuracy (85 percent) and is more scalable. Nonetheless, it partially helps to make decisions in real-time since retraining the models and deploying them may take time before responding to abrupt financial changes.

As an alternative, RAOS combines hybrid machine learning with Kafka-based event streaming, which allows the presence of real-time risk scoring and learning. This design forms a predictive accuracy of 91 percent and extremely high scale using big query orchestration and containerized microservices. RAOS, therefore, is a paradigm shift in compliance based on rules to dynamic and data-driven financial resilience, which can instantly adjust to changing behaviors of its members and transactional patterns.

4.3 Member-Centric Impact Analysis

Table 3- Member Outcomes Post-Implementation

Indicator	Pre-Deployment	Post-Deployment	Change (%)
Member Complaints (Overdraft Errors)	210/month	142/month	–32.4%
Member Retention Rate	86%	91%	+5.8%
Net Promoter Score (NPS)	7.2	8.5	+18.1%

After implementation, the number of complaints about overdrafts had reduced by 32.4 percent, which is an indication of increased accuracy and transparency in assigning limits by the system. The error decrease directly improved the level of trust, and the decreased frustration of the members.

The retention rate of the members was also better improved by almost 6 percent, which shows that more balanced as well as customized decisions concerning overdraft led to enhanced long-term commitment. Also, the Net Promoter Score (NPS) or customer satisfaction and recommendation possibility increased by 18.1 per cent. (7.2 to 8.5), which indicates the positive attitude to the fairness and responsiveness of RAOS.

All in all, these results confirm that the implementation of adaptive, data-driven intelligence into the overdraft management system enhances institutional resilience and builds confidence among the members.

The results confirm the supposition that risk-conscious overdraft schemes allow financial institutions to strike a balance between profitability and fairness. Real time event processing and hybrid modelling enhances the integration of systemic inefficiencies and empowers the members. Additionally, the implementation on GCP was elastic and in line with the financial data standards (ISO 27001).

V. CONCLUSION

The current study introduced and tested a Risk-Aware Overdraft System (RAOS) that uses modern data engineering and machine learning to improve the empowerment and financial stability of its members. The system, which was built on the GCP ecosystem by adding Scala-based backend services, TypeScript front-end modules, and BigQuery-Kafka pipelines, created a significant risk prediction, latency, and user satisfaction improvements.

This evaluation shows that the system provides the company with good operational and financial returns on all the critical metrics. It shows a reduction of 7.9 percentage points in NSF events, which is an improvement in better prediction of overdraft risk and reduced declines. The system allows processing approximately 10 million transactions in order to increase efficiency and member experience. The recovery rate of 97 percent in 15 days is portraying better repayment performance. Moreover, 28 percent enrollment demonstrates greater adoption of members whereas a 2 percent incremental interchange indicates that revenue can be measured. In general, the findings support the effectiveness of the system. Strategically, there is integration of product strategy, risk modeling and backend engineering, which makes such structures sustainable in various banking settings. Future research can also be directed into the explanation of AI (XAI) to make it more transparent and its application to cross-institutional credit sharing ecosystems.

To conclude, RAOS is a prime example of financial technology meeting responsible innovation, and it can be used by other banks that want to promote the efficiency of their operations and empower humans through financial means at the same time.

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