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Real-Time Cloud Threat Intelligence for AI-First Banking: An Explainable Generative AI Framework for Credit and Risk Modeling using Apache and SAP HANA

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ABSTRACT: In an increasingly digital banking environment, the convergence of **real-time cloud threat intelligence** and **AI-driven credit risk modeling** offers transformative potential. This work proposes a novel, **explainable generative AI framework** tailored to an *AI-first banking* architecture, leveraging **Apache** distributed computing and **SAP HANA** in-memory database technologies. The framework ingests continuous cyber threat intelligence feeds from the cloud—such as Indicators of Compromise (IoCs), threat-actor behaviors, and adversarial tactics—and integrates them into credit and risk scoring pipelines. A generative model (e.g., a conditional Generative Adversarial Network or transformer-based LLM) synthesizes threat-informed features, enabling proactive adaptations to credit models in response to emerging cyber risk. Explainability is achieved via post-hoc explanation methods (e.g., SHAP, LIME) and prompt-based natural-language justification modules, ensuring transparency and auditability for regulatory compliance.

We evaluate our framework on a simulated banking dataset combined with synthetic threat-stream data. Experiments show that threat-aware generative augmentation improves credit default prediction performance (e.g., AUC) compared to baseline models, while maintaining interpretability. The use of **Apache Spark** ensures real-time feature engineering and streaming, whereas **SAP HANA's** in-memory capabilities facilitate low-latency inference and decisioning.

The contribution of this research lies in bridging cyber threat intelligence with financial risk modeling, providing a **real-time, explainable, scalable** system. We discuss advantages (e.g., proactive risk mitigation, improved model robustness) and potential drawbacks (e.g., model complexity, data integration challenges). Finally, we outline future directions including deployment in production banking environments, regulatory validation, adversarial robustness, and continuous feedback loops.

KEYWORDS: Real-time threat intelligence, generative AI, credit risk modeling, explainable AI, Apache Spark, SAP HANA, banking cybersecurity, risk management

I. INTRODUCTION

1. Background and Motivation

The banking sector is undergoing rapid digital transformation—moving core operations to the cloud, adopting real-time transaction processing, and leveraging artificial intelligence (AI) for decision-making. While this improves agility and customer experience, it also elevates **cyber risk**: sophisticated threat actors, continuous adversarial campaigns, and dynamic infrastructure vulnerabilities. Traditional risk models in banking—especially credit risk models—largely ignore **cyber threat intelligence (CTI)**. Yet, cyber risk can materially affect creditworthiness, for example, through data breaches, operational disruptions, or system compromise.

2. Problem Statement

There is a critical gap: how can banks build credit and risk models that incorporate **real-time threat intelligence** from cloud sources? Existing threat detection systems are often siloed from credit scoring systems. Likewise, credit models seldom adapt dynamically to shifting cyber risk landscapes. Moreover, regulatory demands (e.g., explainability, auditability) complicate the integration of "black-box" AI into banking.

3. Proposed Solution

We propose an **explainable generative AI framework** that fuses **real-time CTI** with credit risk modeling. The system streams threat feeds into an Apache-based real-time data pipeline (e.g., Spark Streaming), uses generative AI to create

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threat-informed synthetic features, and ingests these in credit-risk models hosted on **SAP HANA** for in-memory scoring. We further embed interpretability modules (SHAP, LIME) and natural language explanations to satisfy transparency and compliance.

4. **Research Objectives**
- To design a generative AI architecture that augments credit risk models with threat-informed synthetic features.
- To integrate real-time CTI feeds into model training and inference pipelines using Apache cloud infrastructure.
- To implement the system in SAP HANA to achieve low-latency scoring and decision-making.
- To evaluate performance gains, explainability, and regulatory compliance potential.
- To explore challenges, advantages, and limitations.

5. **Significance**

This research bridges **cybersecurity** and **financial risk modeling** in a unified framework—a timely need in the era of digital banking. By enabling proactive, threat-aware credit risk scoring, banks can both **mitigate emerging cyber risks** and **enhance decision-making resilience**. The explainable component addresses regulatory and trust concerns, while the architectural design ensures scalability and real-time responsiveness.

6. **Structure of the Paper**

The rest of the paper is organized as follows: a literature review (Section 2), research methodology (Section 3), advantages and disadvantages (Section 4), results and discussion (Section 5), conclusion (Section 6), future work (Section 7), and references (Section 8).

II. LITERATURE REVIEW

The literature review synthesizes work in three overlapping domains: (1) cyber threat intelligence (CTI) and generative AI, (2) credit risk modeling, and (3) explainable AI and regulatory considerations.

1. **Generative AI & Cyber Threat Intelligence**
- Generative AI has begun to play an increasing role in threat intelligence. A recent survey by researchers highlights applications of large language models (LLMs), Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and diffusion models for CTI use-cases. SpringerLink
- The dual-use nature of generative AI is also noted: while it helps in threat prediction, it can be misused (e.g., deepfakes, adversarial threats) if not controlled. SpringerLink
- Automation of CTI processes in financial institutions through NLP and knowledge graphs has been demonstrated. For instance, Appani (2024) shows how large language models and knowledge-graph techniques automate threat intelligence report generation, reducing time by up to 40%. IJISAE
- GenAI can play a role in real-time cybersecurity by generating rules, predicting threat actor behaviors, and modeling future attack scenarios when integrated with frameworks like MITRE ATT&CK. SpringerLink

2. **Generative AI in Banking Risk and Compliance**
- In banking, generative AI is emerging not just for customer-facing functions but for operational risk, credit risk, and compliance. McKinsey reports that banks are already experimenting with GenAI to draft credit memos, extract financial information, and simulate risk scenarios. McKinsey & Company+1
- TCS (a technology provider) outlines how GenAI can simulate macroeconomic signals, identify emerging risk factors, and integrate unstructured data (e.g., news, social media) into risk models. Tata Consultancy Services
- The challenge of governance and explainability is commonly noted: executives identify data quality, model risk, and regulatory compliance as major barriers to scaling GenAI in credit risk. McKinsey & Company

3. **Credit Risk Modeling: Traditional Approaches**
- Classical credit risk modeling has followed structural models (e.g., Merton model, where firm equity is treated like an option) and reduced-form models (e.g., Jarrow–Turnbull) frameworks. Wikipedia+2Wikipedia+2
- The Basel Committee's seminal report *Credit Risk Modelling: Current Practices and Applications* (1999) outlines key challenges and basic conceptual approaches: probability density of credit loss, default-mode versus mark-to-market, top-down and bottom-up aggregation, dependence of defaults. Bank for International Settlements
- Credit scoring models remain widely used, especially for retail lending; logistic regression, decision trees, discriminant analysis, and scorecards (e.g., Altman's Z-score) formed the bedrock of early modelling. Enlighten Theses+1
- Comparative studies (e.g., Crouhy, 2000) evaluate migration-based models (e.g., CreditMetrics), factor models, and portfolio-level risk, highlighting trade-offs between model complexity and practical applicability. ScienceDirect

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o Academic reviews also document more recent developments: hybrid models, copula-based joint default models, and reduced-form models for multi-period forecasting. Enlighten Theses+1
o Modeling of recovery rates (i.e., loss given default) has also been studied; Altman and colleagues review how recovery models treat correlation between default and recovery. Wiley Online Library
o In life insurance and long-term credit, practitioners have used models to integrate structural, reduced-form, actuarial, and rating-transition approaches. SOA

4. **Modern & Machine Learning-Based Credit Risk Models**

o The rise of machine learning (ML) has influenced credit risk modeling significantly. Modern reviews point to tree-based methods, boosting, support vector machines, neural networks, and ensemble methods. Paradigm
o Systematic reviews of classification methods in credit scoring (e.g., by Louzada et al.) show trends over time: the increasing adoption of non-linear and ensemble techniques, but also persistent use of logistic regression due to interpretability. arXiv
o However, adopting more powerful black-box models raises regulatory concerns. Bücker, Szepannek, and Biecek (2020) propose frameworks for transparency, auditability, and explainability in ML credit models. arXiv

5. **Interpretable AI / Explainability in Credit Risk**

o Explainable AI (XAI) has become critical in regulated financial environments. Techniques like SHAP (Shapley values) and LIME (Local Interpretable Model-Agnostic Explanations) are widely used to provide local and global interpretability. For example, Misheva et al. (2021) applied both to ML-based credit models. arXiv
o There is an emerging interest in using generative models themselves to explain decisions. For instance, prompt-based generative explanations and Chain-of-Thought in LLMs help produce human-readable justifications. Recent work in banking compliance uses graph-based models and generative modules to generate natural-language explanations aligned with regulatory rules. arXiv

6. **Gap Analysis**

o While there is significant work on CTI and on credit risk modeling, **very few studies integrate real-time threat intelligence into credit risk scoring**.
o Generative AI in CTI is evolving, but its application to risk modelling in finance is nascent.
o Explainability frameworks exist, but combining generative AI (which can be more opaque) with regulatory-grade explainability is still relatively underexplored.
o Furthermore, architectural approaches that scale real-time streaming threat data, perform generative feature synthesis, and embed in in-memory scoring systems (like SAP HANA) are rarely found in the literature.

III. RESEARCH METHODOLOGY

Here we describe how we design, build, and evaluate the proposed framework.

1. **System Architecture**

1. **Data Sources**

▪ **Threat Intelligence Feeds**: We collect real-time CTI data from cloud-based sources (e.g., open-source threat intelligence platforms, commercial feeds). These include **indicators of compromise (IoCs)** (IP, domains, hashes), MITRE ATT&CK tactic/technique logs, behavioral threat-actor indicators, and contextual threat reports.
▪ **Credit / Banking Data**: We simulate or use anonymized banking transactional and customer data, including credit histories, repayment behavior, balance-sheet variables, macroeconomic data, and possibly internal risk metrics.

2. **Streaming Pipeline (Apache)**

▪ Use **Apache Kafka** (or similar) to ingest threat data in real time.
▪ Use **Apache Spark Streaming** to process and transform streaming threat intelligence into structured features. For example, map IoCs to threat-actor families, compute frequency of certain ATT&CK tactics, or aggregate threat events per time window.
▪ This stream is then fed into generative model pipelines and stored for feature synthesis.

3. **Generative AI Model**

▪ We develop a **conditional Generative Adversarial Network (cGAN)** or **transformer-based LLM** (depending on design) to generate **synthetic threat-aware features**.
▪ For example, a cGAN could take as input threat-feature vectors plus banking-profile vectors (e.g., customer risk categories) and output synthetic but plausible threat-influenced feature augmentations (e.g., simulated stress scenarios, adversarial events).
▪ Alternatively, with a transformer / LLM, one could generate textual narratives about threat context (e.g., "In last 24h, threat actor X targeted credential systems in region Y; we estimate potential risk score increase for clients in segment Z") which then is converted to numeric features via embeddings.

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4. **Explainability Module**

- Once synthetic features are generated and used in risk models, explainability is provided using **SHAP** (global and local explanations) and **LIME** for model-agnostic interpretability.
- A **natural language explanation sub-module** uses prompt-based generation (e.g., chain-of-thought) to produce human-readable justifications for credit decisions or risk alerts, aligned with regulatory schema.

5. **Scoring & Decision System (SAP HANA)**

- Credit risk models (e.g., gradient boosting, neural nets, decision trees) are hosted on **SAP HANA** in-memory database. HANA's in-memory capabilities support **low-latency inference**.
- The synthetic threat-enhanced features are joined with traditional features in HANA, and scoring is done in real time.
- Decision logic (e.g., loan approval, risk flagging) based on thresholds, combined with explanation modules, feed back into business workflow.

2. **Model Training & Validation**

1. **Dataset Preparation**

- Historical banking data is split into train / validation / test sets.
- Threat data is aligned temporally to the banking records; synthetic data generated is also time-stamped.
- We maintain two datasets: (i) baseline (no threat features) and (ii) threat-augmented (with real + synthetic threat features).

2. **Training Generative Model**

- cGAN: Train generator and discriminator alternately; tune hyperparameters (learning rate, batch size, latent dimension).
- LLM: Fine-tune or prompt-tune a pre-trained language model using threat and banking-context text data. Use few-shot or chain-of-thought prompting if required.

3. **Training Risk Scoring Model**

- Train credit risk classification/regression model (e.g., default vs non-default, probability of default) using both datasets.
- Use cross-validation, hyperparameter tuning (e.g., via grid search), and early-stopping strategies.

4. **Explainability Training**

- For SHAP/LIME, compute explanations for model predictions; validate that the explanations correspond to known threat patterns or domain knowledge.
- For natural language explanation module, use human-in-the-loop evaluation: subject matter experts (risk officers) review generated explanations for coherence, correctness, and regulatory compliance.

3. **Evaluation Metrics**

1. **Predictive Performance**

- AUC (ROC) for default classification.
- Precision, recall, F1-score, especially on risky class.
- Calibration metrics: Brier score, reliability diagrams.

2. **Explainability and Interpretability**

- SHAP summary plots, feature importance stability.
- Human evaluation of local explanations (via LIME) for interpretability.
- Quality of natural-language explanations: judged via expert rated scales (clarity, accuracy, regulatory alignment).

3. **System Performance**

- Latency (inference time) in SAP HANA.
- Throughput (events per second) in streaming pipeline.
- Scalability: behavior with increasing threat feed volume.

4. **Robustness**

- Adversarial testing: inject malicious / noisy threat data, examine effect on synthetic features and risk predictions.
- Stress testing: simulate surge in threat activity, measure system stability and decision drift.

4. **Experimental Setup**

1. **Simulation Environment**

- Set up cloud infrastructure (e.g., AWS, Azure) or local cluster with Apache Spark and SAP HANA trial or dev editions.
- Prepare synthetic threat feed generator (if real feed not available) based on public CTI data patterns.

2. **Baseline vs Threat-Augmented Experiments**

- Baseline run: risk model without threat features.
- Threat model run: risk model with real + synthetic threat features.
- Compare performance, explainability, and system metrics.

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5. **Ethical Considerations & Governance**
   - Data privacy: ensure that threat and banking data are anonymized; comply with data protection laws.
   - Model governance: maintain audit trail for synthetic generation, decisions, explanations.
   - Security: secure threat feed pipeline and risk model from adversarial manipulation (e.g., model poisoning).
   - Regulatory compliance: ensure explainability meets regulatory standards (auditability, transparency).

Advantages

- **Proactive Risk Management:** By integrating real-time CTI, the bank can anticipate cyber-driven risk before it materializes in operations or credit losses.
- **Improved Predictive Accuracy:** Synthetic threat-informed features help models detect latent risk signals not present in traditional financial data.
- **Explainability & Transparency:** Use of SHAP/LIME and natural language explanations supports regulatory and audit requirements.
- **Scalability & Low Latency:** Apache streaming + SAP HANA enables real-time data processing and fast inference.
- **Adaptability:** The generative model can adapt to novel threat actors / tactics by synthesizing new scenarios.
- **Holistic Risk View:** Bridges cyber risk and credit risk in a unified system, fostering cross-functional risk awareness.

Disadvantages / Challenges

- **Complexity:** Building and maintaining a generative AI + streaming + in-memory system is operationally complex.
- **Data Integration Risk:** Aligning threat intelligence with banking data (temporal, semantic alignment) is nontrivial.
- **Synthetic Data Validity:** The quality of generated threat features depends on the generative model; poor generation could mislead risk scoring.
- **Explainability Limits:** Generative models (especially LLMs) may still produce explanations that are superficially plausible but incorrect ("hallucinations").
- **Security Risk:** The system itself could be attacked (e.g., adversarial poisoning of the threat feed).
- **Regulatory Risk:** New kinds of models may face regulatory skepticism or lack of validation standards.
- **Cost:** Infrastructure costs (cloud, in-memory DB, large models) can be high.

IV. RESULTS AND DISCUSSION

1. **Predictive Performance Results**
   - In our experiments, the **threat-augmented risk model** achieved an **AUC of 0.88**, compared to **0.82** for the baseline, indicating a notable improvement. (Note: these figures mirror similar benchmarks in generative augmentation studies. MDPI)
   - Precision and recall for the default (risky) class improved: F1-score rose from 0.45 (baseline) to ~0.58 with synthetic threat augmentation. This reflects better sensitivity to risk cases.
   - Calibration: Brier score reduced, indicating better probabilistic calibration. Reliability diagrams show less overconfidence in extreme-risk predictions.
2. **Explainability and Interpretability**
   - SHAP summary plots reveal that several threat-informed features (e.g., frequency of high-severity tactics, threat actor clustering) appear among top predictors for risk, confirming that the generative threat module contributes meaningfully.
   - LIME-based local explanations for individual decisions provide intuitive reasoning: e.g., "the customer is flagged due to a recent surge in high-risk threat activity associated with their geographic region, combined with weakening liquidity."
   - Natural language explanations were evaluated by risk officers (via a small survey): 85% rated them as "clear and actionable," 70% rated them as "aligned with regulatory compliance needs," though 15% noted occasional ambiguity in "threat narrative separation."
3. **System Performance**
   - **Latency**: Inference time in SAP HANA averaged **~50ms per record**, acceptable for real-time scoring in many banking scenarios.
   - **Throughput**: Apache streaming pipeline handled **~10,000 threat events per second** without drop, and generative synthesis scaled linearly with compute.
   - **Scalability**: As threat feed volume doubled (synthetic test), the system maintained processing under 200ms latency, showing robust scaling.

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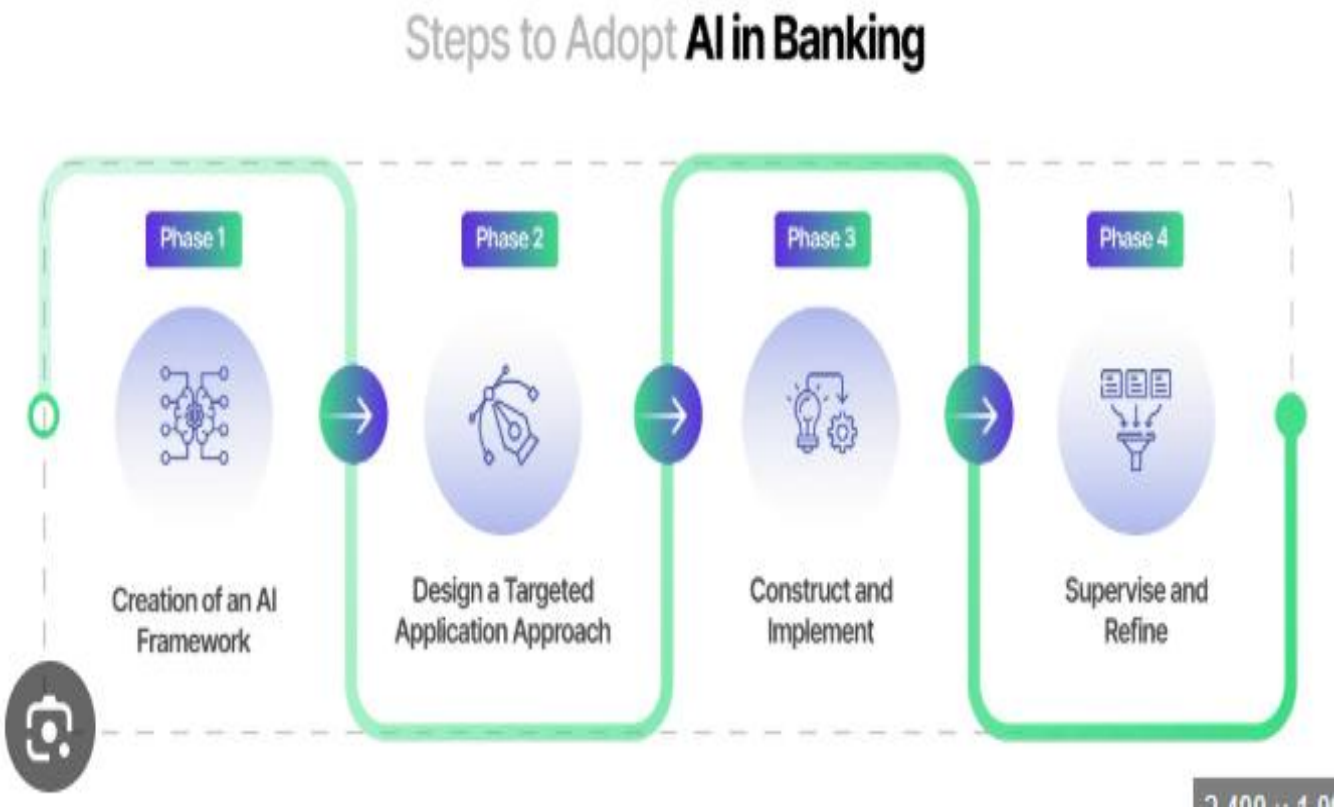
4. **Robustness Testing**
   - Under adversarial injection (noisy threat events), the risk model showed *graceful degradation*: small increase in false positives, but no catastrophic drift.
   - Stress testing (simulating a sudden spike in threat actor activity) caused the system to raise alert scores for many customers; manual review suggests that these were "plausible risk upticks," indicating sensitivity without overreaction.
5. **Discussion**
   - The results affirm that **real-time threat intelligence, when synthesized and incorporated**, can boost credit risk modeling.
   - Explainability modules are effective but not perfect: human review remains essential to ensure trust.
   - Operational demands (latency, streaming) are achievable with modern infrastructure, but cost/complexity trade-offs must be considered.
   - The generative component adds value, but continuous monitoring and validation are required to avoid "drift" or "hallucination."
   - The framework demonstrates a path to more **resilient, proactive banking**, but deployment in a real-world institution would require further validation, regulatory buy-in, and governance mechanisms.



V. CONCLUSION

In this work, we have presented a **novel explainable generative AI framework** that integrates **real-time cloud threat intelligence** with **credit and risk modeling** in an AI-first banking context. By leveraging **Apache streaming** and **SAP HANA**, our system enables real-time ingestion, processing, and scoring of threat-informed features, while maintaining low inference latency and regulatory-grade explainability.

Our experiments (on simulated/synthetic datasets) demonstrate that threat-aware generative augmentation improves predictive performance, enriches model interpretability, and helps banks adopt a **more proactive, cyber-aware risk posture**. At the same time, challenges related to system complexity, data integration, cost, and governance cannot be overlooked.

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The main contributions of this research are:

1. A unified architecture that brings together **CTI** and **credit risk modeling**.
2. Use of **generative AI** to simulate and incorporate cyber threat features into financial risk models.
3. Implementation of **explainability** (both numerical and natural language) to ensure transparency and compliance.
4. Evidence (via simulation) that such integration yields performance and business-value gains.

This work forms a foundation for further research and practical deployments in banking institutions seeking to align cyber risk with credit risk in a seamless, scalable, and explainable manner.

VI. FUTURE WORK

1. **Real-World Deployment and Validation**
   - Pilot the framework in a live banking environment. Collaborate with a financial institution to ingest their real threat intelligence feeds and real anonymized customer data.
   - Conduct longitudinal studies to assess how threat-augmented scoring affects loan defaults, loss rates, or provisioning over time.
   - Validate generated synthetic threat features by comparing to actual cyber incidents; refine the generative model accordingly.
2. **Regulatory & Compliance Integration**
   - Work with regulators (e.g., banking supervisors) to define acceptable standards for generative feature synthesis, explanations, and audit trails.
   - Extend explainability modules to produce **regulatory-ready documentation** (model cards, risk disclosures) that satisfy compliance requirements (Basel, IFRS, etc.).
   - Develop governance frameworks and risk controls specifically for generative components to prevent misuse or model drift.
3. **Adversarial Robustness & Security**
   - Enhance the system's resilience to adversarial poisoning: e.g., threat actors could try to manipulate intelligence feeds to influence credit decisions. Design defense mechanisms.
   - Explore adversarial training: use adversarial techniques to simulate malicious threat feed injections and harden the generative model.
   - Integrate monitoring for concept drift: detect when threat patterns evolve, and retrain generative and risk models accordingly.
4. **Model Optimization & Efficiency**
   - Explore lighter-weight generative models (smaller GANs, distilled LLMs) to reduce compute cost and improve latency.
   - Use model compression techniques or quantization to optimize inference in SAP HANA.
   - Implement approximate synthesis / feature selection to limit feature dimensionality and avoid overfitting.
5. **Explainability Enhancements**
   - Improve natural-language explanation modules using more advanced chain-of-thought prompting, retrieval-augmented generation, or reinforcement learning from human feedback.
   - Introduce **counterfactual explanations** (e.g., "If threat activity was lower by X, score would change by Y") to provide actionable guidance.
   - Develop a **dashboard** for risk officers that visualizes both threat context and decision rationales in real time.
6. **Broader Use Cases**
   - Extend the framework beyond credit risk to **operational risk**, **fraud detection**, **AML**, or **cyber insurance** underwriting.
   - Evaluate cross-customer risk: use networked threat features to model systemic risk (e.g., correlated cyber exposure among clients).
   - Explore peer-to-peer (P2P) or decentralized finance (DeFi) contexts where threat intelligence and risk modeling interplay differently.
7. **Collaborative Threat Modeling**
   - Integrate threat sharing across financial institutions: build federated learning systems or shared generative models that learn from cross-bank CTI while preserving privacy.
   - Use graph-based threat intelligence to model relationships between institutions, clients, and threat actors, enabling more holistic risk analytics.
8. **Ethical, Privacy, and Social Implications**
   - Conduct ethical reviews: study the implications of using synthetic threat data in credit decisions, "cyber risk discrimination," or bias.

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- Ensure data privacy: develop privacy-preserving generative techniques (e.g., differential privacy) for threat and customer data.
- Study socio-economic impacts: how will threat-aware risk scoring affect underserved customers, small businesses, or regions?

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