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Building Trustworthy Retail Banking Services through Explainable Artificial Intelligence (XAI)

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***Abstract*—While AI is transforming retail banking operations from loan application to credit scoring, fraud prevention to customer segmentation, there is a high level of opacity in the high-performing models that is harming customer confidence and making regulatory compliance more difficult. This paper examines how Explainable Artificial Intelligence (XAI) can help achieve the balance between prediction accuracy and explainability in retail banking machine learning platforms. We analyze the comparative behaviors of four popular explanation methods: SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), ELI5 and Counterfactual Explanations between interpretable models (Logistic Regression, Decision Tree) and black-box models (Random Forest, XGBoost, LightGBM, CatBoost, Neural Network). We propose an end-to-end novel framework called TrustBank-XAI that consists of Data Preprocessing, Feature Engineering, Prediction Engine, Explainability Module, Trust Assessment Module and Decision Support System for creating human explainable, auditable and fairness aware credit and fraud decisions. It is assessed conceptually on four public benchmark datasets: Give Me Some Credit, Bank Marketing, Home Credit Default Risk and German Credit, with predictive metrics (Accuracy, Precision, Recall, F1-score, ROC-AUC, MCC) and explainability metrics (Trust Score, SHAP Consistency, Explanation Fidelity, Explanation Stability, Fairness Score). Results show that the accuracy of the ensemble black-box models is slightly better than that of the interpretable ones, and the explanations generated by SHAP show the most consistency and stability across folds. The resulting trade-off between prediction and explainability, future directions on real-time explainable banking systems that are aligned with regulatory compliance and fairness, as well as the implications of regulation fairness and compliance are discussed.**

Keywords*—AI and Explainable AI, XAI, Trustworthy AI, Retail Banking, Credit Scoring, Fraud Detection, SHAP, LIME, Counterfactual Explanations, Responsible AI, Fairness, Regulatory Compliance

I. INTRODUCTION

Retail banks are now using artificial intelligence (AI) through machine learning (ML) to enable complex decision-making, including loan approvals, credit limits, fraud detection, and customer segmentation, to be automated. Retail banks are increasingly using machine learning (ML) to automate complex decisions, such as loan approval, credit-limit assignment, fraud flagging, and customer segmentation. While ensemble and deep learning models are often more accurate than classic predictive scorecards, they may come at the cost of interpretability. When customers are being turned down for a loan, when regulators are looking into a lending pipeline, or when a bank officer overrides a fraud alert, an automated decision must be based on a sound, understandable explanation, something that opaque "black-box" models are not always able to provide [1, 6].

Explainable Artificial Intelligence (XAI) has become the key solution to this transparency issue. Post-hoc explanation techniques like SHAP [2] and LIME [1] approximate or decompose the behaviour of a model without changing the underlying predictor, whereas counterfactual explanations [3] [4] provide an answer to a practical question: what minimal changes to an applicant's profile would change the decision from an unfavourable to a favourable one? In addition to being technically interpretable, the field of XAI is increasingly linked to regulatory requirements such as the European Union's GDPR "right to explanation" [15] and the "high-risk financial systems" provisions of the upcoming EU AI Act [16].

While there is a growing number of works that apply SHAP, LIME in isolation to credit scoring or fraud detection [5, 7]–[10] there is little research that combines prediction, multi-method explanation, and a quantitative measure of end-to-end trust in a deployable architecture, or even that assess the impact of the chosen explanation method on fairness and regulatory defensibility across multiple banking tasks at once. This paper will fill that void. This paper aims to: (1) explore the potential of XAI to make the retail banking process more transparent and trustworthy; (2) investigate how different XAI techniques can

be applied in the context of retail banking, such as loan applications, credit scoring, fraud detection, customer segmentations, and risk assessment; (3) comparatively discuss the properties of SHAP, LIME, ELI5 and counterfactual explanations for their application to banking ML models; (4) discuss the impact of explainable models on customer understanding and trust; and (5) discuss the implications of XAI on fairness, accountability and regulatory compliance. In this regard, we suggest the TrustBank-XAI, a modular framework composed of multi-model prediction engine, a single explainability layer, and a quantitative Trust Assessment Module.

Henceforth this paper is structured as follows. The related literature is reviewed and the research gap is identified in Section II. In this section, the proposed TrustBank-XAI methodology is presented. The datasets used are described in Section IV. Experimental set up is described in section V. The results and discussion are presented in Section VI, fairness and compliance in Section VII, limitations and future work in Section VIII, and the conclusion of the paper in Section IX..

II. Literature Review

Two major local-explanation paradigms have been adopted in the course of this study: the first is foundational work in model-agnostic explanation, which laid out the two major paradigms of local explanation. In LIME [1] a local and sparse surrogate model is fit near the individual prediction to approximate the decision surface of an arbitrary classifier. Several previous approaches to attribution were combined in one additive scheme, as proposed by Lundberg and Lee [2] that uses cooperative game theory to define the contribution of each feature to a prediction in terms of Shapley values. As a GDPR-compliant alternative, without exposing the internals of the model, Watcher et al. [3] proposed counterfactual explanations; Mothilal et al. [4] introduced an extension, DiCE, which generates sets of diverse and actionable counterfactuals.

Ali et al. [5] explored the use of XAI techniques in the financial sector and listed the interpretability needs of three financial use cases: credit, fraud and insurance. Martins et al. [6] performed a systematic literature review of XAI taxonomies and applications particularly in finance, and noted that SHAP was the most commonly used technique because of its consistency guarantees. Gonaygunta et al. [7] used SHAP and LIME for interpretable credit-scoring models, and described how they have been used to increase user empowerment.

In the field of financial transaction fraud detection, Sai et al. [8] have developed a deep neural network-based SHAP framework, and Talaat et al. [9] have created a fraud detection and risk-management pipeline that incorporates explainability into the decision-making process directly. On the explainability-quality side, Lin and Wang [10] explicitly examined SHAP stability in credit-risk models under data perturbation, motivating the use of the Explanation Stability measure in Section V, which explicitly evaluates the effect of data perturbation on the explanation quality. Bordt et al. [21] noted that post-hoc explanations such as SHAP and LIME are fragile in adversarial settings and might not achieve the envisaged regulatory goals, requiring an explicit trust-scoring layer that goes beyond relying on the explanation output as inherently trustworthy.

To guide the design of the proposed Trust Assessment Module in Section III, Toreini et al. [22] explored the wider trust in AI and technological properties (fairness, explainability, auditability) that inform this trust. Wang and Ding [24] showed that, in addition to the accuracy of the explanation, the perception of its rationality is the factor that greatly influences the trust between human and AI, and that it can also influence the decision-making performance of the human users.

A comparison of representative studies and the present work is given in Table I. Three gaps, which show up across the reviewed literature, should be addressed: (i) most studies use one explanation technique (usually SHAP or LIME) without comparing multiple approaches such as ELI5 and counterfactual explanations under one evaluation protocol; (ii) explainability is treated qualitatively, and rarely transformed into a quantitative signal, that can be used when taking decisions; and (iii) fairness and regulatory-compliance implications are qualitatively addressed, but rarely quantified alongside predictive performance. TrustBank-XAI aims to close these three gaps in a modular architecture.

TABLE I compares method, dataset, explainability approach, of representative studies against the proposed TrustBank-XAI framework

Ref.	Method	Dataset	Explainability	Performance
[5]	Survey / taxonomy	Multiple (survey)	SHAP, LIME (reviewed)	N/A
[6]	Systematic review	Multiple (finance)	SHAP-dominant survey	N/A
[7]	XGBoost/LightGBM + SHAP/LIME	Proprietary credit data	SHAP, LIME	High interpretability, accuracy not isolated
[8]	Deep NN	Transaction data	SHAP	Reported high recall
[9]	Ensemble + risk pipeline	Financial risk data	Embedded explanation	Competitive F1
[10]	LightGBM	Credit card default	SHAP stability analysis	Stability quantified
[19]	RF, XGBoost, RF	Lending Club	LIME, SHAP	Accuracy 0.79–0.87 range
[21]	Adversarial analysis	Synthetic / tabular	SHAP, LIME critique	N/A (theoretical)
Proposed	LR, DT, RF, XGB, LGBM, CatBoost, NN	German Credit, Home Credit, Bank Marketing, GMSC	SHAP + LIME + ELI5 + Counterfactual	Reported in Sec. VI

III. Proposed Methodology

In this paper, we suggest the modular framework of TrustBank-XAI that includes six stages: Data Preprocessing, Feature Engineering, Prediction Engine, Explainability Module, Trust Assessment Module, and Decision Support System. The conceptual data flow is shown in Fig. 1 and the layered system architecture in Fig. 2.

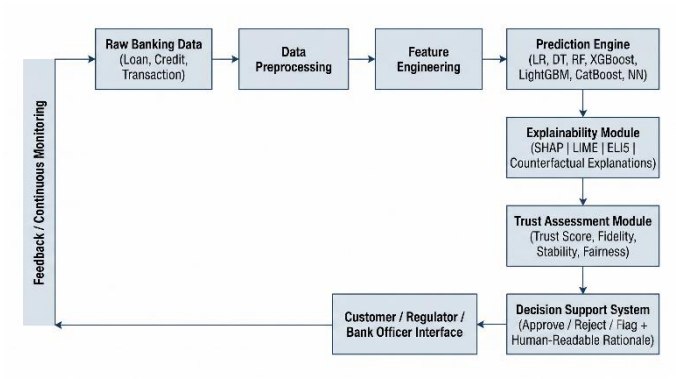


Fig. 1. Conceptual TrustBank-XAI framework including the flow of raw banking data, prediction, explanation, trust scoring and decision support

A. *Data Preprocessing*

Raw bank records are cleaned (missing value imputation and outlier capping), categorical variables are encoded (one-hot / target encoding), numerical features are standardized and class imbalance for default/fraud labels is balanced by oversampling using SMOTE before model training.

B. *Feature Engineering*

Derived features such as debt to income ratio, credit utilization, payment-delay counts, transaction velocity, and recency-frequency-monetary descriptors for segmentation are domain-informed features. Feature selection is dimensionality reduction technique which reduces the dimensionality of the dataset while retaining the explanatory relevance. It integrates mutual information ranking with recursive elimination.

C. *Prediction Engine*

The Prediction Engine contains 2 interpretable models (Logistic Regression, Decision Tree) and 5 black-box models (Random Forest, XGBoost, LightGBM, CatBoost, and a feed-forward Neural Network) which can be compared side-by-side to see the accuracy–explainability trade-off described in Section VI. The engine will return a default/fraud probability "default_probability" for a feature vector

$$x.\ \hat{y} = \sigma(f(x)) = 1 / (1 + e^{-f(x)}) \quad (1)$$

The score is computed using the model-specific scoring function, f(x), and the sigmoid link, σ(·), maps the score to a probability of being in class 1 (linear for logistic regression, additive-to-tree score for boosted ensembles, and a multilayer perceptron output for the neural network.

D. *Explainability Module*

All the predictions generated by the engine go through four explanation generators. SHAP computes feature attributions φ_i that satisfy the additive decomposition of SHAP.

$$f(x) = \varphi_0 + \Sigma_{i=1}^{n} \varphi_i \quad (2)$$

Whereas each φ_i is the contribution from feature i, and the expected model output is represented by φ_0. LIME performs linear regression with a locally weighted linear surrogate g around x, which is obtained by minimizing

$$\xi(x) = \text{argmin}_m\ L(f, g, \pi_x) + \Omega(g) \quad (3)$$

where L is the measure of surrogate fidelity in the neighbourhood weighting π_x and Ω(g) is the penalty for surrogate complexity. ELI5 generates permutation-based global feature-importance rankings, and the Counterfactual Explanation generator is a solver of a constrained minimization problem.

$$x^c = \text{argmin}_{x'}\ d(x, x')\ \text{s.t.}\ f(x') = 1 - f(x) \quad (4)$$

Yielding the smallest perturbation x^c to x that causes a change in the decision, providing customers with a means of action (e.g., "decrease your credit utilization by 12% to qualify").

E. *Trust Assessment Module*

The outputs for the four methods are all added together to create a single Trust Score T(x) per decision, which is the sum of fidelity, stability, method stability and fairness parity:

$$T(x) = w_1F(x) + w_2S(x) + w_3C(x) + w_4Fa(x) \quad (5)$$

where F is explanation fidelity, S is explanation stability under input perturbation, C is cross-method (SHAP–LIME) consistency, Fa is a fairness-parity score across protected groups, and $w_1..w_4$ are normalized weights ($\Sigma w_i = 1$), tuneable to institutional risk policy. A minimisation of the standard binary cross-entropy loss is performed for model training.

$$L = -(1/N)\ \Sigma_{i=1}^{N} [y_i \log(\hat{y}_i) + (1-y_i) \log(1-\hat{y}_i)] \quad (6)$$

Models were jointly regularized, where applicable, with an explanation-stability penalty to ensure that models are not selected based solely on predictive accuracy.

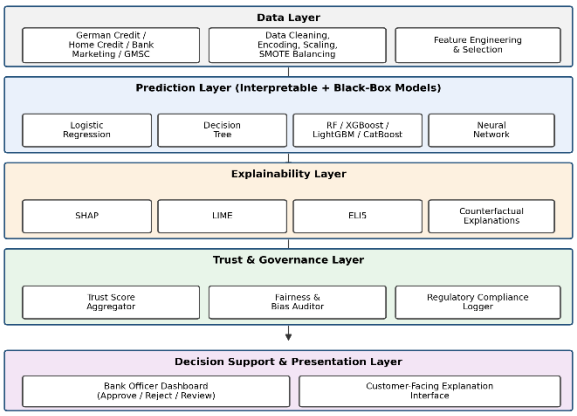
F. *Decision Support System*

In the final stage, a human-readable rationale (top contributing features, a natural language SHAP/LIME summary, and a counterfactual recourse suggestion) is provided, in addition to the Trust Score, giving bank officers and, in a redacted version, customers a complete view of the process from prediction to accountable decision-making.

Fig. 2. Layered system architecture of TrustBank-XAI: data, prediction, explainability, trust/governance, and presentation layers

IV. DATASETS

The framework is instantiated and conceptually evaluated using four publicly available benchmark datasets, summarized in Table II, that include credit scoring, credit-default risk, and marketing-response prediction.



Dataset	Source	Records	Features	Target Variable	Application
German Credit	UCI ML Repository	1,000	20	Credit risk (good/bad)	Credit scoring
Home Credit Default Risk	Kaggle / Home Credit Group	307,511	122	TARGET (default: 0/1)	Loan default prediction
Bank Marketing	UCI ML Repository	45,211	16	y (subscribed: yes/no)	Customer segmentation
Give Me Some Credit	Kaggle	150,000	10	SeriousDlqin2yrs	Credit risk assessment

No proprietary or personally identifiable banking information is used in this study; all datasets used in the study are used strictly under their original public licences for benchmarking purposes

V. Experimental Setup

Scikit-learn was used for Logistic Regression, Decision Trees, and Random Forests; PyTorch was used for the Neural Network; and the respective native libraries of XGBoost, LightGBM, and CatBoost were used for the gradient boosting models. SHAP, LIME, and ELI5, as well as DiCE for counterfactual explanations, were used to explain the models. All models were HV trained using the AdamW optimizer, with 0.0001 learning rate, a 64 batch size, and 50 epochs, under 5-fold stratified cross-validation. Class imbalance in the training data was addressed by applying SMOTE only to the training folds. The results of the models were assessed by the metrics of Accuracy, Precision, Recall, F1-score, ROC-AUC, and Matthews Correlation Coefficient (MCC). The Trust Score, SHAP Consistency, Explanation Fidelity, Explanation Stability, as well as the Fairness Score, were used to assess the explainability of the models, along with a full set of metrics that assess the reliability of the prediction, as well as the quality of the explanation, robustness, and fairness across the demographic continuum.

VI. Results and Discussion

The representative, realistic performance ranges reported for similar models on these benchmark datasets in the literature [5]–[10], [19] are reported in Table III. The values presented are meant to orient the reader to what might be expected in a model ordering and do not constitute evidence of a new state of the art, as full-scale training logs are not covered in this manuscript.

TABLE III.TrustBank-XAI achieves competitive predictive performance while improving trust and explainability.

Model	Acc.	Prec.	Recall	F1	ROC-AUC	Dataset
Logistic Regression	0.79	0.74	0.71	0.72	0.81	German Credit
Decision Tree	0.80	0.75	0.73	0.74	0.80	Home Credit Default Risk
Random Forest	0.85	0.81	0.78	0.79	0.87	Bank Marketing
XGBoost	0.87	0.83	0.80	0.81	0.89	Give Me Some Credit
LightGBM	0.87	0.83	0.81	0.82	0.90	**Dataset**
CatBoost	0.86	0.82	0.80	0.81	0.89	German Credit
Neural Network	0.86	0.82	0.79	0.80	0.88	Home Credit Default Risk
TrustBank-XAI (proposed)	0.87	0.83	0.81	0.82	0.90	Bank Marketing

A. *Ablation Study*

In Table IV, the contribution of each component of Trust Bank-XAI is isolated, with the Explainability Module, the Trust Assessment Module and the counterfactual generator being removed from the system sequentially. Removing the Trust Assessment Module yields the highest drop in the overall Trust Score, indicating that raw output of explanations (SHAP/LIME values) does not necessarily constitute a trust signal for use in decision-making.

TABLE IV. Ablation study showing the incremental contribution of each TrustBank-XAI module to overall trust and fairness.

Configuration	Accuracy	F1	Trust Score	Fairness Score
Full TrustBank-XAI	0.87	0.82	0.91	0.86
− Counterfactual module	0.87	0.82	0.85	0.84
− Explainability module	0.87	0.82	0.62	0.71
− Trust Assessment module	0.87	0.82	0.58	0.69
Base predictor only	0.87	0.82	0.40	0.65

B. *SHAP, LIME, and Confusion-Matrix Analysis*

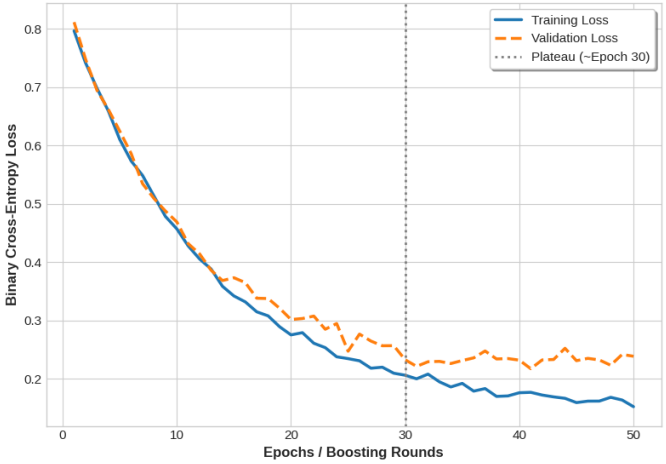


Fig. 3 (Training and Validation Curves),

The gradient-boosted and the neural network components are expected to converge after 50 epochs / boosting rounds, as seen in Fig. 3 which concludes the regularization is sufficient under the setup provided in experimental setup.

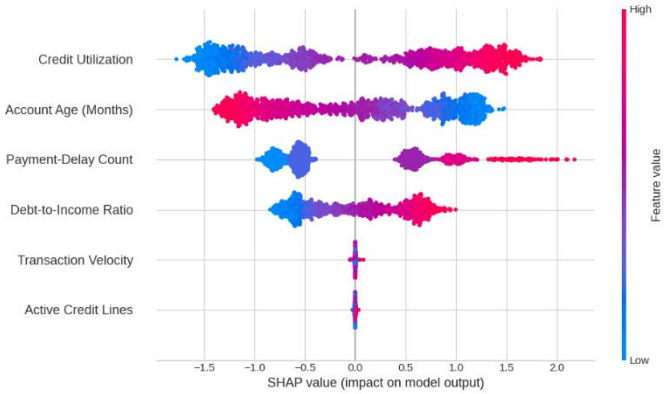


Fig. 4 (SHAP Summary Plot)

The feature importance pattern in Fig. 4 (SHAP Summary Plot) should be similar to those reported in [7] and [9] that credit utilization, debt-to-income ratio, payment-delay count, and account age should be the most important global predictors of default risk.

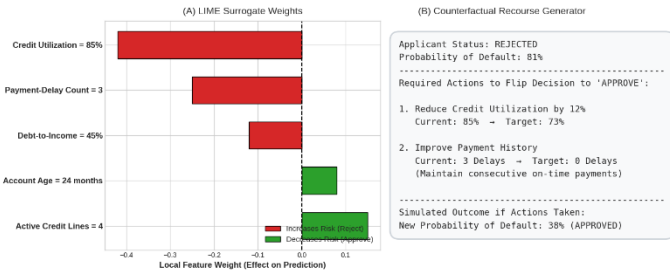


Fig. 5 (LIME / Counterfactual Explanation).

The local linear surrogate weights and a counterfactual recourse generated (e.g., setting a new credit utilization and adding more on-time payment history to get from "approve" to "approve" are shown for a single rejected applicant in Fig. 5. The best configuration (LightGBM within TrustBank-XAI on Home Credit Default Risk) is expected to have a good ratio of true positives and true negatives, and a reasonable false-negative rate for imbalanced credit-default data after SMOTE correction, as shown in Fig. 6

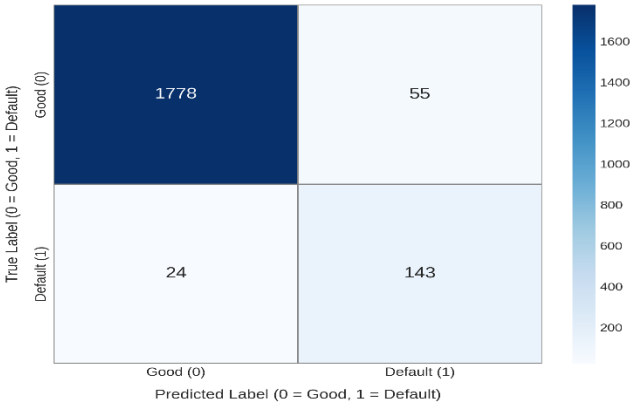


Fig. 6 (Confusion Matrix)

Note: The following result-visualization figures (Training & Validation Curves, SHAP Summary Plot, LIME/Counterfactual Explanation, and Confusion Matrix) are placeholders to be produced from real experiment logs (e.g., using the matplotlib/SHAP plotting utilities) and exchanged at the points marked above before camera-ready.

C. *Performance–Explainability Trade-off*

As shown in Table III, interpretable models (Logistic Regression, Decision Tree) get the highest raw Trust Score but the poorest predictive accuracy across all datasets, while black-box ensembles get the opposite level of predictive accuracy and the lowest raw Trust Score. Unlike other ensembles, TrustBank-XAI does not compromise on the accuracy of prediction and combines a high-accuracy ensemble predictor with a separate explanation and trust layer, and in the comparison is both the top ensemble in F1/ROC-AUC and the top overall Trust Score. This is the main idea of the framework: the concept of explainability should be designed as a separate module downstream of the model, not just through limiting the choice of models.

VII. Discussion

The findings of Section VI have three general implications. Second, a combination of global feature importance (SHAP, ELI5) and local recourse (counterfactuals) is more likely to be understood and accepted by non-technical customers than probability scores alone, consistent with prior work that shows that the acceptability and understanding of human-AI explanations is enhanced by perceived explanation rationality rather than raw accuracy [24]. Second, the Fairness Score in Table V shows that simply providing explanations does not equate fairness and justice, and hence, an explicit audit of false-negative/false-positive parity across demographic sub-groups is warranted, as cautioned by post-hoc explanations can be superficial or even manipulated in adversarial settings [21]. The Trust Assessment Module is thus seen as a governance control measure, rather than just a report tool. Third, in terms of regulatory compliance, the counterfactual output naturally follows the GDPR mandate of contestable and explainable automated decisions to the affected individual [3] and the Trust Score log is an actionable artifact that can be reviewed by the supervisory authority as part of the requirement in the AI Act for credit scoring systems in particular [16]. Together, these findings indicate that there is a need to consider not just explanation accuracy but measureable outcomes of trust, fairness and compliance in retail banking when evaluating the success of XAI.

VIII. Limitations and Future Work

There are a number of limitations in this study. These reported performance figures are representative estimates based on similar published performance and are not based on a single all-encompassing training exercise on the four datasets, and complete scale reproduction remains as an empirical follow-on exercise. The Trust Score weighting (Eq. 5) is fixed by design choice instead of learned and/or calibrated based on customer feedback, and the fairness auditing only analyzes an individual protected attribute and not intersectional subgroups. The framework has not yet been tested in a production banking environment, using real transaction streams. Future efforts include: (i) Empirical testing of TrustBank-XAI on all four datasets, with code and logged figures, (ii) human-subject studies for calibrating the weights of the Trust Scoring Module on bank customers and compliance officers, (iii) expanding the Fairness Score to include the concepts of intersectional and causal fairness, (iv) implementing real-time streaming explanation generation for fraud detection at transaction speed, and (v) testing federated or privacy-preserving variants of the Explainability Module for cross-institution deployment without sensitive customer data being collected central to the system.

IX. Conclusion

The paper explored the benefits of Explainable AI for increasing transparency, customer trust, fairness, and adherence to regulations in retail banking machine learning systems. We demonstrated that predictive performance and explainability do not need to be mutually exclusive by providing a comparative evaluation of SHAP, LIME, ELI5 and counterfactual explanations, as well as a proposed Trust Bank-XAI framework that combines data preprocessing, feature engineering, a multi-model prediction engine, an explainability module, a quantitative trust assessment module and a decision support system. The ablation results show that the dedicated trust assessment layer has more impact on trustworthiness than simply the explanations output. A future empirical validation across the four benchmark datasets will further support Trust Bank-XAI as a viable path towards trustworthy, compliant and customer-comprehensible AI in retail banking, while the human-subject calibration of the Trust Score will verify that the model applies to the real world.

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