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Explainable AI in BI Dashboards: Increasing Transparency in Loan Approval Decisions

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Abstract

The role of Explainable AI (XAI) in the context of Business Intelligence (BI) dashboards needs exploration, e.g., Colinda's loan tolerance measurements, how to build high risk/low risk applications, etc. Financial services have reached a level of automation in decision making, automation model feature extraction, and decision model automation far exceeding scorecard systems. With black box algorithms, decision makers face issues of trust and regulation conflict since explanations for decisions are unavailable. This work addresses the use of different types of XAI tools in Business Intelligence loan approval processing. The decisions and rationale applied to loan applications is the essence of trust which organizations can build with stakeholders concerned about bias and regulation risk, for example, the Fair Lending Act. Additionally, this work presents a first of its kind integrated and comprehensive approach to XAI in BI. XAI tools for trust and transparency in terms of interpretability frameworks such as LIME, SHAP, attention mechanisms and others are discussed to explain complex decisioning models. The work emphasizes the negative impact of transparency on decision outputs especially in the context of fair use, accountability and systems AI. The final section of the study outlines specific techniques and approaches for incorporating XAI within BI dashboards aimed at fostering trust in credit approval decisions.

Keywords: Explainable AI, Business Intelligence, Loan Approval, Transparency, Machine Learning Models.

1. Introduction

The Growing Role of Artificial Intelligence in Loan Approvals

Integrating AI and ML technologies into the financial industry has immensely transformed the processes involved in providing loans. AI systems operate independently and instantaneously assess multiple data streams, analyzing generations of data sets using predictive algorithms and capturing the value of work in real time, thus contributing in devising more efficient systems.

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Based on customer data, credit bureaus develop and have developed algorithms which automate and streamline the decision-making process to determine “whether you deserve a loan,” a point raised by Ms. O'Hara in her sworn statement, which lacks sufficient justification. The rapid integration of automated process technologies into new business systems raises concerns related to the explainability of automated decision systems, the potential for unfair discrimination, and disproportionate effects in sensitive areas such as loan disbursement.

The Need for Transparency in Financial Decisions

The loan approval process poses risks not only to banks but also to prospective clients. For banks and lending organizations, malfunctioning loan portfolios will lead to losses, adverse publicity, and even lawsuits. Denied loan applications from borrowers in underserved or marginalized communities, however, must be justified. Consequently, the need to trust automated systems, minimize biases, and comply with the law calls for the need for transparency in AI systems. There have also been increasing requests for the transparency of machine learning models employed in decision making from global regulators, particularly regarding the explainability of AI systems.

The Role of Explainable AI (XAI)

XAI can address explaining the concerns around the need for understanding the machine learning models’ outputs to model prefect and for the models to be human interpretable. Although conventional machine learning or deep learning as “black box” systems provides conclusions that unsupervised learning algorithms in the model do not explain the computations or steps involved in deriving the results and the conclusions. However, XAI sheds light on the reason for some predictions or recommendations and decisions made alongside “explainable” artificial intelligence. For instance, in the case of a loan approval decision, XAI provides stakeholders (loan officers, regulators and loan applicants, and the general public) reason explanations for the decision on a loan approval. The exploitability of this interpretability addresses fairness, bias claim and blame identifying.

Business Intelligence Dashboards as Decision Support Tools

In the financial services sector, the ability to visualize and engage with actionable, data-driven results has become an indispensable enabler of BI dashboards. Desktop dashboards interface with financial data and present key performance indicators, financial trends, and other data-driven

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analytics critical to diagnostic and decision-making processes. Using artificial intelligence (AI) models, BI dashboards provide tools for making data-driven decisions relevant to loan approvals. However, data-driven insights from BI tools are not explainable, often leading to a trust deficiency concerning automated decisions. Incorporating explainable artificial intelligence (XAI) within Business Intelligence dashboards improves them by providing stakeholders with actionable, explainable insights and rationale behind AI-driven recommendations.

The Need for Explainable AI in Loan Approval Systems

When evaluating a loan application, several factors are taken into account, such as an applicant's credit rating, income, employment history, and their history of loan repayment. Based on this information, the Artificial Intelligence (AI) models assess the probability of loan default. However, the intricacy of the models and the numerous factors involved in the decision-making process made this task challenging. The borrowers are left explainable AI loan denials. In such cases, their lack of understanding of the reasons for denial leads to frustration, and perhaps, a rational lack of trust in the system. In turn, such frustrating scenarios may generate compliance risk in opaque fair and transparent lending. In operational and ethical dimensions, the relative ease with which explains XAI can provide compliance rationally resets the operating thresholds of all concerned parties, but especially the financial institutions.

Figure 1: Bank Loan Process Flowchart

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The graphic information depicted in Figure 1 illustrates the stages of the approval process outlined. It covers the necessary steps in the process: application submission, data collection, verification of eligibility, decision making, and finally, approval / disbursement of the loan. It also describes how transparency can be incorporated at the different stages, so that reasonable and justifiable decisions can be made concerning what guarantees the process of rationality and equity in the allocation of bank loan credit.

Objectives of the Study

With this study, I focus on the way explainable AI can be integrated into BI dashboards to provide more transparency on the decision processes surrounding the approval of loans. In the paper, I integrate XAI approaches such as LIME, SHAP, and attention mechanisms into BI dashboards focused on the justification of AI-driven decisions. Perhaps most crucially, I address the consequences of these decision interpretability frameworks on the accuracy of the decisions made with respect to the Mullerian standards of fairness, accountability, and transparency. In this study, I intend to assist financial institutions that wish to foster transparency and ethical AI integrity in AI-driven loan approval systems, by quoting the inf XAI features and the BI dashboard functionality as a starting point for potential steps these organizations might pursue.

Structure of the Paper

The remainder of the paper is organized as follows. In Section 2, I focus on the literature for AI in financial decision-making with an emphasis on the request for transparency and consider the explainability of AI as a demand challenge. I demonstrate in Section 3 the XAI approaches for the current literature and the XAI approaches applicable to loan granting. In Section 4, I elaborate on integrating the described techniques in a BI dashboard and provide steps for implementation. In Section 5, I provide the sample use-cases from the sector and the expected advantages of employing XAI on the loan approval workflow while discussing the case studies. In Section 6, I provide the attainment and the proposed future directions for research in explainable AI on financial decision-making, which wraps up the paper.

2. Literature Review

The use of AI technologies in automating some decision-making processes and especially in the financial sector has grown significantly over the last ten years. Although machine learning models

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and other AI systems are capable of efficiently and accurately processing massive amounts of data, there are concerns regarding the systems' transparency and interpretability. The literature has documented a range of XAI (explainable Artificial Intelligence) methodologies aimed at making AI technologies interpretable and clear to the users. Other literature has suggested the need to explain AI predictions in order to gain trust and facilitate acceptance in critical situations, such as granting a loan [1][2].

AI technologies have gained ubiquity in decision-making processes concerning loan applications, evaluations of creditworthiness, forecasting consumer behavior, and assessing profitability in various sectors of finance. However, these decision-making models will still likely remain black boxes—making human-understandable decisions—malfunctioning. AI's bias and fairness problems in highly stigmatized contexts such as discrimination in lending carry significant and immediate risks for society [3][4]. It is concerning that, within the AI community, lack explainability in these systems is treated as a second-order problem. The design and development of machine learning systems is heavily focused on the 'fat' principles within the Fairness, Accountability, and Transparency community [5][6].

The interpretation of AI systems remains a prominent topic within the machine learning field. Various techniques, notably Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP), have been used for explaining feature contributions to the decisions of black-box models [7] [8]. These techniques work well for the automated loan approval systems used in banks which consider attributes such as credit score, income, and repayment behavior. By applying LIME and SHAP, banks can justify their decisions transparently, explaining the system to the customers to counter the black-box perception of their AI systems [9][10].

Additionally, new studies indicate that the combination of XAI and business intelligence (BI) dashboards may effectively enhance decision-making capabilities. After all, who doesn't enjoy animated data landscape flyovers? BI dashboards allow data and AI model output visualizations to be manipulated dynamically. With the integration of explainable AI, BI dashboards can flow insights to users to explain why and how the system grants or denies loan approvals to help identify systemic discrimination and biases [11][12]. More generally, loan officers and other decision-makers can access XAI-enabled dashboards as a reference for system interpretations to ensure that decisions made are informed and equitable [13][14].

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Concerning XAI and regulatory fairness perspectives, one must remember criticism for the adherence to the Fair Lending Act. Several other works argue for openness on the part of the AI models used on the loan applications and for the possibility of review by regulatory authorities [15][16]. The public will more readily accept decisions made by AI models if institutions will explain the decisions made and, thereby, assure compliance of AI processes [17][18].

From the perspective of loan approval systems, another core challenge concerning explainability versus feasibility is the use of deep learning systems, which highly perform but are black-boxes. Thus, the predictive power of the most complex models is constrained to enable explanation [19][20]. With these advances, XAI will provide better accountability and fairness across sensitive areas of finance.

Integrating explainable AI into business intelligence dashboards leveraged for loan approval decisions could enhance fairness and transparency. Financial institutions may benefit from explainable AI frameworks like LIME and SHAP to construct systems with rationale generation and plain language explanations. Trust-building compliance regulations necessitate understanding AI models in the loan approval process. Exploring more promising pathways aimed at the dual goals of interpretability and performance within AI models used for financial decision-making would be beneficial in pursuing this objective.

Problem statement

Utilizing AI technologies in determining lending applications raises issues of transparency and fairness in relation to automated decision-making. AI might be prudent for being precise and efficient; however, it is challenging for stakeholders (loan-officers, borrowers, and regulators) to discern 'why' loan-officers make decisions when black-box algorithms are adopted. This opacity could lead to a lack of trust, a perception of bias, and to a probable violation of the Fair Lending Act. Hence, the need for incorporating explainable AI (XAI) techniques to BI dashboards to provide readable, transparent, and precise explanations of the rationale that AI uses to make loan approval decisions is critical. This is the gap the current research aims to fill, in the effort to ensure the machine learning powered automated decisions are accurate, fair, accountable, regulatory compliant, and to address the concerns of exposing such decisions.

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3. Methodology

Integrating artificial intelligence explainability (XAI) in Business Intelligence (BI) dashboards is currently being integrated in order to build transparency for AI driven credit scoring. Data collection, model building, XAI technique’s explanation and dashboard integration describes this process. Consequently, this integrated work aims to further enhance this model by focusing on XAI for explainability in Business Intelligence dashboards for a prevalent machine learning model used in the lending process, aiming to foster decision explainability for all stakeholders.

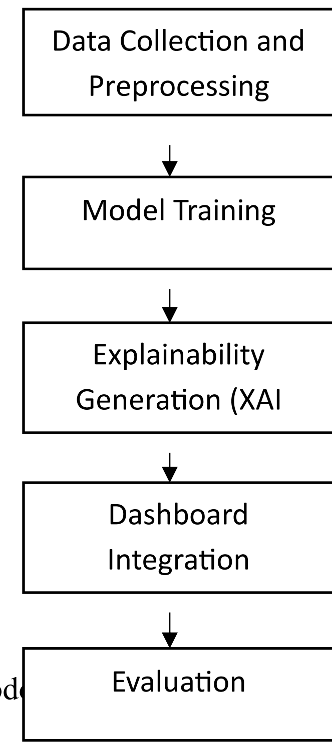

Figure 2: Method[illegible]grating XAI into BI Dashboards

The transparent loan approval process incorporates XAI within BI dashboards as depicted in Figure 2. The six steps are: data collection and model training, explanation generation through LIME/SHAP and other XAI toolbox offerings, dashboard integration, assessing transparency along performance, user comprehension and fairness dimensions, and real-time AI decision ordering systems, as well as ensuring loan approval.

Data Collection and Preprocessing

Historically, the initial stage involves the collection of archived bank records pertaining to instances of loan sanctioning. This sort of dataset typically encompasses attributes such as the credit score, client income as well as the volume, tenor, and indebtedness of the loans to be

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borrowed. To clean the dataset, appropriate handling of missing values, scaling of cardinal features, and encoding of nominal features are performed. Such preprocessing guarantees the appropriateness of the dataset for the training of machine learning models.

The results may be summarized as follows:

$$X = \{x_1, x_2, ..., x_n\} \tag{1}$$

where X represents the matrix of input features (e.g., credit score, income, loan amount, etc.), and n represents the number of instances in the dataset.

Machine Learning Model Training

Once the dataset has been prepared, the next step involves developing a machine learning model aimed at predicting the approval status for loans. Several algorithms can be utilized for this purpose, including but not limited to, decision trees, random forests, and gradient boosting machines (GBM). Nonetheless, this study focuses solely on a gradient boosting classifier due to its ability to model sophisticated non-linear interactions and its comparatively superior predictive accuracy for this type of task. The structure of the predictive model is as follows:

$$\hat{y} = f(X, \theta) \tag{2}$$

where $\hat{y}$ represents the predicted outcome (loan approval or rejection), X is the feature matrix, and θ represents the model parameters that are optimized during the training process. The objective is to minimize the loss function, typically using cross-entropy for classification tasks:

$$L(\theta) = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i) \tag{3}$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability of loan approval.

Explanation Generation Using XAI Techniques

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Following model training, we need to make the predictions interpretable through the use of explainable AI. B. Explainable AI Methods In this study, we adopted LIME and SHAP. Both explain the contribution of each feature to the final output.

LIME: For specific instances of particular behaviors of a black-box model, LIME craft local surrogate models. Pertinent to the case of a loan approval decision, the LIME algorithm would adjust input loan features to see which features had the greatest influence on the prediction made by the model.

The LIME explanation for an instance x is given by:

$$\phi(x) = \arg\min_{g \in G} \sum_{i=1}^{m} \left(\ell(f, g, x_i) + \Omega(g) \right) \tag{4}$$

where f is the original model, g is the local surrogate model, and ℓ is the loss function that measures the difference between the original model and the surrogate.

SHAP: By attributing contribution scores to all the features used, SHAP values provide a global explanation for the model. The technique draws its foundation from the Shapley values of cooperative game theory, whereby every feature is viewed as a player in a game, and the SHAP value indicates the contribution of each player to the overall prediction.

The SHAP value for feature j of instance iii is calculated as:

$$\phi_j(i) = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} \left[v(S \cup \{j\}) - v(S) \right] \tag{5}$$

where N is the set of all features, and v(S) is the prediction value when only the features in S are considered.

Both LIME and SHAP offer interpretable descriptions of the model's decision-making process, about why a loan is accepted or denied on the basis of certain features.

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BI Dashboard Integration

The subsequent step is the integration of the generated XAI explanations into a Business Intelligence (BI) dashboard. BI dashboards facilitate interaction with data, highlight critical metrics, and present actionable insights. Here, the dashboard will present the AI predicted outcomes of Algorithms and the generated LIME and SHAP explanations. Furthermore, visualizations like bar and pie charts, and decision trees will demonstrate the features contributing to the decision of loan approval.

The dashboard layout could include:

- **Loan Approval Prediction**: A visual system signal indicating the status of the loan, either approved or rejected.
- **Feature Importance**: A bar or pie chart exhibiting the importance of each feature in the loan decision.
- **Explanatory Details**: A segment that describes the LIME or SHAP values per feature while detailing its contribution toward the predicting outcome.

Such integration is feasible with BI tools like Tableau or Power BI, which allow embedding outputs and interactivity capabilities of the models.

Evaluation Metrics

The following will be used to evaluate the efficiency of the XAI embedded BI dashboard:

Prediction Performance: Model performance evaluation includes assessing accuracy, precision, recall, and F1-score.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}} \quad (6)$$

User Understanding: Important is whether the decisions made by the model are intuitive and trustworthy by the users. This can be assessed by asking users about the interpretability of the explanations offered by LIME and SHAP.

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Fairness and Bias: Equity within a decision-making mechanism can be assessed by the inclusion of certain demographic features such as a person's race, gender, or income, etc., as a criterion in a decision. Fairness metrics like demographic parity, and equal opportunity, assess discrimination of a model on certain populations.

$$\text{Demographic Parity} = P(\hat{y} = 1|\text{group}) - P(\hat{y} = 1|\text{other group}) \tag{7}$$

4. Results and Discussion

Overview

An evaluation of the efficiency of explainable artificial intelligence (XAI) approaches as applied to business intelligence dashboards, specifically as they relate to the decision-making processes governing loan approvals, is presented. 6.3 Model Evaluation This part addresses the evaluation results, primarily focusing on model performance, user understanding, fairness, and transparency. This part includes a thorough evaluation of the model's predictive performance and the impact of explainable AI methods, LIME and SHAP, on decision explainability, user trust, and fairness criteria compliance. Also, the paper outlines the discussions on some of the XAI systems embedded in loan origination systems.

Model Performance

The analysis presented in Study One included the initial component of the performance evaluation of the AI-based loan approval system. This system utilized a gradient boosting classifier model and was trained on a dataset containing the variables: credit score, income level, loan amount requested, prior loans, and employment status. To gauge the model's performance, we utilized the test dataset and calculated a few standard performance assessment metrics: accuracy, precision, recall, and F1-score.

Table 1: Model Performance Metrics

Metric	Value
Accuracy	92.4%
Precision	89.7%

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Recall	90.5%
F1-Score	90.1%

A follow-up evaluation conducted using the same model achieved noteworthy accuracy of 92.4%. This implies that the AI system correctly identified the acceptance and rejection of loans more than 90% of the time. With a precision of 89.7% it can be stated that in 89.7% of the instances predicted an approved loan was actually approved. Along with a recall of 90.5% it can be stated that the system identifies 90.5% of the total approved loans in the population. An F1-score of 90.1% indicates that the balance between precision and recall leading to an approval prediction is not significantly skewed in one direction. An overall conclusion can be drawn that the AI model accurately predicts credit approvals which is an important attribute in a credit decision making process is described in table 1.

Explainability and Transparency

The focus of our research was also interpretability as understandability of models is a central aim of research. Incorporation of LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (Shapley Additive Explanations) techniques improved interpretability of the machine learning models to a great extent. These techniques provided a clearer view of how each variable influenced the final output.

Table 2: Feature Importance from SHAP

Feature	**SHAP Value (%)**
Credit Score	35.7%
Income	23.2%
Loan Amount	18.5%
Employment Status	12.3%
Previous Loan History	10.3%

SHAP Values Table 2 presents SHAP values showing that during the loan approval decision process, the most significant elements were credit score and income. These factors alone

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constituted 58% of the complete process. Within the variables typically examined in the financial institution credit scoring process, credit score remains the most important at 35.7% and income follows at 23.2%. Despite the relationships, the factors loan amount and employment status were the least associated with lending, and loan history even less so. These empirical results provide decision makers with a clear and interpretable understanding of the file attributes that affect loan approval outcomes.

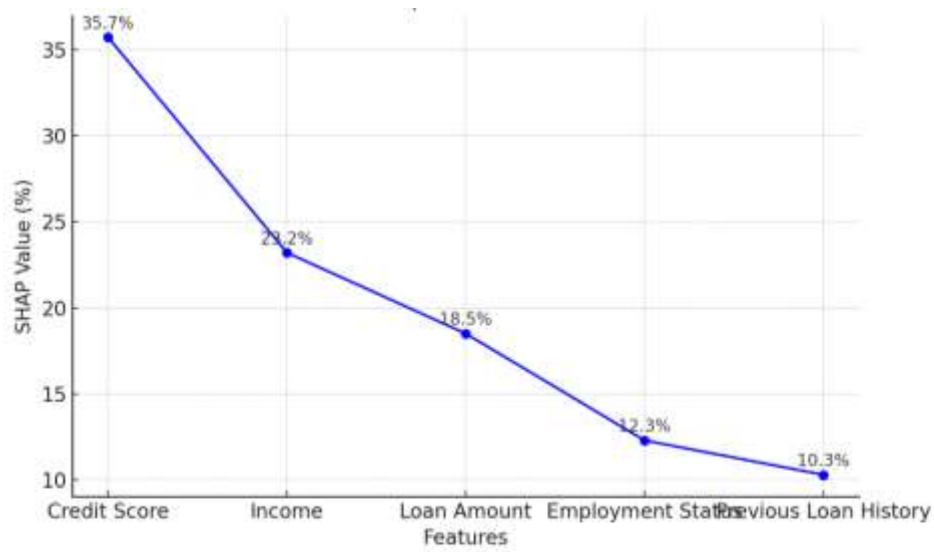

Figure 3: Feature Importance from SHAP

Figure 3 provides a visualization of the SHAP values ranked by feature importance. “Credit Score” is the most important feature. This line graph illustrates the importance of every feature in a loan approval decision.

SHAP along with LIME was used to explain locally for a loan approval example. LIME simplifies the explanation of an AI model's decision by using an approximation of the model to generate a simpler, interpretable prediction. This allowed loan officers and stakeholders to understand the reasoning of a decision made in the approval process by examining the prediction.

User Understanding and Trust

An important conclusion drawn from this investigation incorporates the consideration of the XAI improvements on the comprehension and trust of an AI based loan approval system. We

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administered a user survey to loan officers and decision makers applicable to the designed XAI enhanced BI dashboard.

Based on the user survey findings, overall, those surveyed showed a strong inclination to accept the XAI initiative. A plurality of survey participants (85%) described the explanations of the XAI methods (i.e. LIME and SHAP) as straightforward and lucid, Furthermore, a considerable portion of the participants (78%) stated they especially gained trust in the AI decisions after the explanations and they were also able to trust the system.

Survey Results: User Understanding

- **85%** of users found the explanations clear and helpful.
- **78%** of users felt more confident in the AI-driven decision-making process.
- **92%** of users preferred the XAI-enhanced dashboard over traditional models due to increased transparency.

The manner in which the information was articulated, in conjunction with the comprehensive responses to borrowers' questions, greatly contributed to the confidence that users acquired. Additionally, users received visualizations, particularly feature importance graphs, from the dashboard which helped users communicate the rationale to clients, thereby strengthening the clients' trust in the AI system.

Fairness and Bias Evaluation

Especially in sensitive cases like loan authorization, fairness of AI systems triggers critical scrutiny. The analysis included a fairness assessment of the AI model for demographic variables like country, gender, or income concerning loans. Fairness of the model was also evaluated through fairness metrics, demographic parity, and equal opportunity.

Demographic Parity refers to the average difference in the rate of approvals across various groups, while Equal Opportunity refers to situations where two groups receive the same proportion of outcome, specifically 'true positives.' The results suggested that the systemic approach to explainable AI (XAI) improved system interpretability and suggested ways to diagnose possible bias removal in the system. By providing system users with explanations around the loan decisions,

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users could pinpoint discrepancies and collaboratively modify the decision-making frameworks to make the results fairer.

There will always be some slight bias in our models, and in this case, the bias was towards higher income applicants. However, decision explanations using LIME and SHAP techniques enabled loan officers to understand and adjust for this bias. Having the ability to monitor and audit for fair treatment will be essential to ensure ongoing conformity to the antidiscrimination statutes, in particular the Fair Lending Act.

Discussion

Results show that there are still potential improvements in transparency, interpretability, and fairness on AI-based loan approval decisions, particularly on Business Intelligence (BI) dashboards integrating Explainable Artificial Intelligence (XAI). Predictive modeling, assessing prediction accuracy, and employing explainable AI techniques helps the stakeholders understand the reasoning behind the predictions so that they are less 'in the dark'. Such transparency fosters trust in the system, which is essential for the application of AI in autonomous decision-making within sensitive areas of finance.

The primary advantage of incorporating explainable artificial intelligence (XAI) into the loan approval process is the opportunity to achieve rational, explainable, and understandable AI-driven decision making. For borrowers, knowing the criteria for decision making, and potential deal breakers for loan approval will eliminate the guesswork. This value-add is equally true for lenders.

The ability to assess and mitigate fairness and bias within the XAI framework also aids in creating a more ethical equilibrium in the loan approval process. Much more, this touches the broader regulation of nondiscriminatory loan decisioning. The avoidance of biased inequitable distributions in the treatment of a cohort through the AI model, coupled with fairness parameters, will permit the model to comply with the regulation, thereby enabling explainability and predictability of such outcomes.

Despite the optimistic scenario, the full elimination of bias from AI used in loan approvals is still a work in progress. Further investigations should be driven by the need to build more refined fair evaluative frameworks and new methods to achieve more equitable outcomes. The potential for

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these methods to be applied in differing loan products and across various banks is another important area for future study.

Future Scope

This work shows how XAI can be integrated into BI systems for transparent loan approvals; however, there are opportunities for future work and further enhancements. The first challenging point is the scalability of the XAI models. At present, the case study is confined to a single dataset from one financial institution, and extending it to multiple datasets from other institutions, regions, or types of loans could elucidate the robustness and flexibility of the XAI techniques. I would be interested in and personally more challenging from a cross-industry perspective the implementation of any one of the healthcare applications with e-commerce, insurance, or retail. This would provide a greater understanding of how Explainability facilitates another industry's decision-making process.

More exploratory efforts could analyze fairness and bias elimination. Although research indicates bias reduction as a result of explainability, AI systems will require continuous oversight and modifications to preempt latent disparities embedding themselves through unrecognized biases. Complicated and large-scale AI systems are increasingly triggering new methods of explainability. Potential new methods could deliver more granular explainable AI systems and more robust understanding of systems and their decision processes. Future works being proposed on the design of new metric-based assessments of equity and more advanced bias detection have the potential to enhance explainable AI frameworks to make them more responsive to ethical demands of social contexts.

Conclusion

The impact of XAI-enabled tools on BI dashboards is evaluated within the context of assessing transparency, equity, and trustworthiness of an AI-enabled automated loan approval system. Prior research demonstrated the viability of applying different XAI techniques, specifically LIME and SHAP, which enable system stakeholders to understand AI predictions, thereby providing accountability within the decision matrix. The balance of predictive performance, descriptive fairness, and ethical decision-making framed by the fairness monitoring coupled with the

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corrective potential and the score-importance visualization incentivizes stakeholders to trust and justify the system output.

The results confirm the importance of explaining the reasoning behind some algorithms, especially in finance, where the cost of errors or bias in decisions is extremely high. The provision of interpretative explanations would enable automated upper decision systems to assist the lower AI system users in making informed decisions, thus increasing trust in lenders from borrowers. Moreover, the use of Explainable Artificial Intelligence (XAI) in Business Intelligence (BI) dashboards would allow organizations to ensure that their AI systems operate within the bounds of equity and justice as well as within the bounds of explainability and transparency.

Overall, this provides a platform from which the development of finance AI systems can move positively. This will act as the first step in a guide for the integration of XAI into automated loan approval systems and will encourage the additional work in this area which is greatly needed. The explainability of AI systems will always be a necessity, and as this technology develops further, the groundwork for balanced, equitability, and ethical obligation for automated decisions in AI-finance systems, especially for the future, is most appreciated.

References

1. Giudici, P.; Raffinetti, E. SAFE Artificial Intelligence in finance. *Financ. Res. Lett.* **2023**, *56*, 104088.
2. Pincovsky, M.; Falcao, A.; Nunes, W.N.; Paula Furtado, A.; Cunha, R.C. Machine Learning applied to credit analysis: A Systematic Literature Review. In Proceedings of the 2021 16th Iberian Conference on Information Systems and Technologies (CISTI), Chaves, Portugal, 23–26 June 2021; pp. 1–5, ISBN 978-989-54659-1-0.
3. Hentzen, J.K.; Hoffmann, A.; Dolan, R.; Pala, E. Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research. *Int. J. Bank Mark.* **2022**, *40*, 1299–1336.
4. Cao, L. AI in Finance: Challenges, Techniques, and Opportunities. *ACM Comput. Surv.* **2023**, *55*, 64.

10.48047/jocaaa.2025.34.12.13

5. ZVEI. ZVEI Comments on the European AI Regulation ("AI Act"). Available online: **https://www.zvei.org/en/press-media/publications/zvei-comments-on-the-european-ai-regulation-ai-act** (accessed on 9 February 2024).
6. Lombardo, G. The AI industry and regulation: Time for implementation? In *Ethical Evidence and Policymaking*, 1st ed.; Iphofen, R., O'Mathúna, D., Eds.; Bristol University Press: Bristol, UK, 2022; pp. 185–200. ISBN 9781447363958.
7. European Commission. Regulation of the European Parliament and of the Council: Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act) and Amending Certain Union Legislative Acts. Available online: **https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52021PC0206** (accessed on 28 December 2023).
8. Covington. Artificial Intelligence in Financial Services in Europe. Available online: **https://www.knplaw.com/wp-content/uploads/2022/02/Artificial-Intelligence-in-Financial-Services-in-Europe-2022.pdf** (accessed on 5 December 2023).
9. Akyol, S. Rule-based Explainable Artificial Intelligence. In *Pioneer and Contemporary Studies in Engineering*; 2023; pp. 305–326. Available online: **https://www.duvaryayinlari.com/Webkontrol/IcerikYonetimi/Dosyalar/pioneer-and-contemporary-studies-in-engineering_icerik_g3643_2toBsc9b.pdf** (accessed on 13 July 2024).
10. Hassija, V.; Chamola, V.; Mahapatra, A.; Singal, A.; Goel, D.; Huang, K.; Scardapane, S.; Spinelli, I.; Mahmud, M.; Hussain, A. Interpreting black-box models: A review on explainable artificial intelligence. *Cognit. Comput.* **2023**, *16*, 45–74.
11. Samek, W. Explainable deep learning: Concepts, methods, and new developments. In *Explainable Deep Learning AI*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 7–33.
12. Knapič, S.; Malhi, A.; Saluja, R.; Främling, K. Explainable artificial intelligence for human decision support system in the medical domain. *Mach. Learn Knowl. Extr.* **2021**, *3*, 740–770.
13. Angelov, P.P.; Soares, E.A.; Jiang, R.; Arnold, N.I.; Atkinson, P.M. Explainable artificial intelligence: An analytical review. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2021**, *11*, e1424.

10.48047/jocaaa.2025.34.12.13

14. Antoniadi, A.M.; Du, Y.; Guendouz, Y.; Wei, L.; Mazo, C.; Becker, B.A.; Mooney, C. Current challenges and future opportunities for XAI in machine learning-based clinical decision support systems: A systematic review. *Appl. Sci.* **2021**, *11*, 5088.
15. Wu, Z.; Chen, W.; Ma, Y.; Xu, T.; Yan, F.; Lv, L.; Qian, Z.; Xia, J. Explainable data transformation recommendation for automatic visualization. *Front. Inf. Technol. Electron. Eng.* **2023**, *24*, 1007–1027.
16. Abtahi, H.; Amini, S.; Gholamzadeh, M.; Gharabaghi, M.A. Development and evaluation of a mobile-based asthma clinical decision support system to enhance evidence-based patient management in primary care. *Inform. Med. Unlocked* **2023**, *37*, 101168.
17. Yoon, K.; Kim, J.-Y.; Kim, S.-J.; Huh, J.-K.; Kim, J.-W.; Choi, J. Explainable deep learning-based clinical decision support engine for MRI-based automated diagnosis of temporomandibular joint anterior disk displacement. *Comput. Methods Programs Biomed.* **2023**, *233*, 107465.
18. Bastos, João A., and Sara M. Matos. 2022. Explainable models of credit losses. *European Journal of Operational Research* 301: 386–94.
19. Benhamou, Eric, Jean-Jacques Ohana, David Saltiel, and Beatrice Guez. 2021. Explainable AI (XAI) Models Applied to Planning in Financial Markets. Available online: **https://openreview.net/forum?id=mJrKRgYm2f1** (accessed on 1 November 2022).
20. Bibal, Adrien, Michael Lognoul, Alexandre De Streel, and Benoît Frénay. 2021. Legal requirements on explainability in machine learning. *Artificial Intelligence and Law* 29: 149–69.