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Literature Review: Designing for Explainability in Financial Credit Assessment: XAI Interaction Strategies for Non-expert Users

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Abstract

This review focuses on XAI interaction strategies for non-expert users in financial credit assessment. As AI models gain traction in finance, especially in credit scoring, explainability becomes crucial for trust, fairness, and user understanding. Regulatory, ethical, and practical needs drive XAI development. LIME and SHAP are key techniques for explaining complex models.

However, XAI's success in financial credit assessment relies on user - centered design. Principles like contextualization and interactivity are important for effective explanation experiences. User - centric evaluation methods are essential to gauge XAI's impact on users.

There are still challenges, such as balancing explanation complexity and user comprehension, and addressing ethical issues. Future research should focus on user - adaptive interfaces, causal explanations, and integrating XAI with financial education. Overall, XAI design in financial credit assessment is a human - centered problem. Optimizing user experience and following research directions can revolutionize financial credit assessment and build a more reliable financial future.

Keywords

Explainable Artificial Intelligence; Financial Credit Assessment; Non - expert Users; Interaction Strategies

Introduction : The Imperative of Explainable AI in Financial Credit Assessment for Non-expert Users

The integration of Artificial Intelligence (AI) achieving a result of being in connection with the financial sector, signifying a period of transformation possessing the characteristic of having promises including enhanced customer experiences that are of a formal nature, financial services that have the quality of being democratized, consumer protection that is improved in a formal sense and risk management that is significantly more effective in a formal way (as mentioned in accordance with the statements of Hadji Misheva et al., 2021； Nallakaruppan et al., 2024). And this technological revolution, which is impelled by

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machine learning (ML) models that are of an increasingly sophisticated kind, providing capabilities that are of an unprecedented nature in areas such as credit risk assessment which is a fundamental element of financial stability that is of a formal kind and inclusive economic growth that is of a formal nature. However, the very complexity which endows these advanced AI systems with power is presenting a challenge that is of a significant nature and has the feature of a lack of transparency and explainability in a formal context.In the case of easily obtainable computational power for the deployment of state - of - the - art ML models, the opaqueness of their decision - making processes constitutes a rather significant obstacle to their extensive adoption and acceptance. Regarding the area of sensitive nature, like financial credit assessment (Hadji Misheva et al., 2021； Lange et al., 2022； Nallakaruppan et al., 2024). The absence of transparency in a way undermines the trust in these technologies. It further gives rise to crucial ethical and regulatory concerns. When decisions have a direct impact on individuals' financial well - being and access to essential services.

In the financial credit assessment realm, the stakes' degree of significance attains a particularly high level. Credit scoring models, enabled via the application of AI, are being increasingly utilized for the ascertainment of loan eligibility, interest rates, and credit limits, having a direct influence exerted upon the financial opportunities of individuals and businesses (Bolarinwa et al., 2024; Jayanandini & Gautami, 2024; Kumbhar et al., 2024).This paper presents a practical example of how interpretable artificial intelligence (XAI) methods can be implemented in a banking environment to improve the interpretability and reliability of today's state-of-the-art AI models, and a method for analyzing the potential economic value of improved credit scoring models.It can be challenging for them to identify the factors that drive their decisions, and this opacity is particularly problematic when these models are applied to key decisions about one's financial life. This is especially true for non-expert users who may be in a state where they lack the technical expertise needed to understand the underlying algorithms and their output.

The need for explainability, commonly known as explainable artificial intelligence (XAI), has become a critical area of research in the field of artificial intelligence (AI) (Hadji Misheva et al., 2021; Jayanandini & Gautami, 2024; Lange et al., 2022; Nallakaruppan et al., 2024; Valdrighi et al., 2024). In high-risk areas of a financial nature, XAI strives to establish the link between the complexity of AI models and the need for human understanding. It also provides some insight into the ways in which these models achieve their predictions.Concerning non - expert users, who are those of financial credit assessment systems like loan applicants or small business proprietors, explainability is not merely a technical refinement. Instead, it is a fundamental prerequisite for trust, fairness, along with accountability. In the event of the situation where credit is refused to individuals or where unfavorable terms are offered to them by an AI - driven system, individuals possess a justifiable right to acquire understanding regarding the reasons that underlie these decisions.Moreover, in relation to the matter of ensuring compliance, mitigating risks, and promoting the adoption of responsible AI within the financial sector, regulators and financial institutions themselves are increasingly recognizing the significance of explainability (Lange et al., 2022; Nallakaruppan et al., 2024; Valdrighi et al., 2024).

This literature review undertakes an in - depth exploration of the crucial domain of the design with respect to explainability within the sphere of financial credit assessment. It specifically engages in focused attention upon XAI interaction strategies that are customized for non - expert users. The principal theme pertains to the optimization of user experience. It explores the manner in which to communicate in an effective fashion the internal operational mechanisms and decision - making procedures of intricate AI credit scoring models to those individuals who are bereft of technical proficiency in the fields of machine learning or finance. The review integrates extant research regarding XAI in the management of credit risk. It conducts an examination

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of diverse explanation techniques, interaction design tenets, and user - centered evaluation methodologies.It has the aim of the identification of the best practices and gives prominence to the directions of future research within this of utmost importance field, ultimately making a contribution to the development process of financial systems which are more transparent, trustworthy, and user - friendly and are driven by AI. The emphasis is not merely on the technical facets of XAI algorithms but instead on the challenges of human - computer interaction (HCI) regarding the conveyance of these explanations in an effective manner to non - expert users in a way that is meaningful and actionable. This perspective centered on the user is of supreme significance for the ensuring of the fact that XAI in financial credit assessment genuinely endows individuals with power and advances the adoption of responsible AI within the financial industry.

The Landscape of Explainable AI in Credit Risk Management: Motivations, Techniques, and Applications

The utilization of Explainable AI (XAI) in the domain of credit risk management is experiencing a rapid upsurge in momentum. This phenomenon is propelled by a convergence of multiple factors, including regulatory compulsion, ethical contemplations, and the practical necessity for the establishment of trust and comprehension within AI - driven financial systems (Hadji Misheva et al., 2021; Lange et al., 2022; Nallakaruppan et al., 2024; Valdrighi et al., 2024). Regarding explainability for credit scoring models employed by banks and financial institutions, financial regulatory bodies are increasingly imposing requirements. Bias, discrimination, and the absence of accountability within opaque "black - box" AI systems are acknowledged by them in their potential existence (Lange et al., 2022; Valdrighi et al., 2024). Automated decision - making processes' fairness and transparency related ethical apprehensions are impelling the financial industry to embrace more responsible AI practices, with explainability as a fundamental cornerstone (Bolarinwa et al., 2024; Valdrighi et al., 2024). Regulatory and ethical imperatives' addition, explainability also confers tangible business advantages, enabling financial institutions to enhance their models' understanding, discern potential vulnerabilities, and refine their risk management strategies (Hadji Misheva et al., 2021; Lange et al., 2022; Nallakaruppan et al., 2024). For customers, understanding the factors that influence credit decisions gives them the ability to improve their financial position and increase access to credit, which can drive greater financial inclusion and equity (Bolarinwa et al., 2024; Jayanandini & Gautami, 2024; Kumbhar et al., 2024).

Several studies have explored the use of specific XAI techniques in credit risk management frameworks, showing all the potential of these techniques to improve the transparency and interpretability of complex ML models. Scholars Hadji Misheva et al., in 2021, and Nallakaruppan et al., in 2024, have investigated the use of two relatively well-known XAI methods of post-model agnosticism, which are locally explicable model agnosticism interpretation, namely LIME. And the additive interpretation of SHapley, or SHAP.These techniques are of a model - agnostic nature, which indicates that they can be made use of to provide an explanation for any ML model, without taking into account its underlying architectural structure, rendering them particularly of great value for the act of providing an explanation for complex "black - box" models that are commonly employed in credit scoring. LIME centers on the provision of local explanations, effectuating an approximation of the behavioral pattern of the complex model in the vicinity of a specific data instance by means of a simpler, interpretable model.This permits the comprehension of the reasons behind the approval or rejection of a particular loan application, emphasizing the features that exerted the most significant influence in that specific decision - making process (Hadji Misheva et al., 2021; Nallakaruppan et al., 2024). Instead, SHAP uses the principles of game theory to provide local and global explanations.

SHAP values quantify the contribution of each feature to the prediction of a particular instance, which is a local explanation, and SHAP values also provide relevant insights about the overall criticality of features across the model, which is a global explanation (Hadji Misheva et al., 2021; Lange et al., 2022; Nallakaruppan et al., 2024)..

Hadji Misheva et al. (2021) elaborated on a machine learning based credit scoring model using LIME and SHAP methods. The credit scoring model was trained on the Lending Club dataset, which is a publicly available dataset from a peer-to-peer lending platform in the United States. They apply these explainable artificial intelligence (XAI) technologies to models for predicting credit risk and document in detail the practical challenges associated with implementation, providing valuable insights for future research and practitioners. Their work emphasizes the importance of not only applying XAI methods, but also carefully considering their practical deployment in real-world financial applications. Similarly, Nallakaruppan et al. (2024) proposed an XAI model for credit risk management, which also utilizes SHAP values to generate artificial intelligence predictions based on key explanatory variables.They bring demonstration of the effectiveness of their approach through employment of decision tree and random forest models, attaining high accuracy levels and conducting further testing of the model's performance upon a larger dataset. Their study gives emphasis on the potential of XAI not merely for the purpose of enhancing transparency but also for the end of providing information for policy development within credit risk management, enabling regulators and financial institutions to fashion data-driven policies that guarantee fairness and establish trust.

Lange et al. (2022) focuses on explainable AI for credit assessment specifically in banks, addressing the regulatory requirement for explainability in banks' credit scoring models. They propose an XAI model combining a LightGBM model, a gradient boosting algorithm known for its high performance, with SHAP for interpretation. Using a unique dataset of unsecured consumer loans from a Norwegian bank, they demonstrate that the LightGBM model significantly outperforms the bank's existing logistic regression model in terms of predictive accuracy. Crucially, they leverage SHAP to interpret the LightGBM model, identifying the most important explanatory variables for predicting credit default, such as the volatility of utilized credit balance, remaining credit as a percentage of total credit, and the duration of the customer relationship. This paper presents a practical example of how interpretable artificial intelligence (XAI) methods can be implemented in a banking environment to improve the interpretability and reliability of today's state-of-the-art AI models, and a method for analyzing the potential economic value of improved credit scoring models.

These studies collectively demonstrate the increasing interest and practical application of XAI in the field of credit risk management. The attention paid to LIME and SHAP reflects their popularity and practical utility as explanatory techniques that do not rely on specific models. The application of real-world datasets, along with in-depth exploration of the challenges encountered in the implementation process, highlights the relevance between this research and the financial industry. However, even though these studies focus on the technical aspects involved in applying XAI methods, the key aspects of user interaction and the design of effective explanatory interfaces for non expert users still belong to a critical field that urgently needs further in-depth research. Merely relying on LIME or SHAP to generate explanations is insufficient; For individuals who may not have a background in data science or finance, explanations must be presented in an understandable, actionable, and trustworthy manner. This requires a deeper exploration of XAI's interactive strategies and user centered design principles in the field of financial credit assessment.

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Interaction Strategies for Non-expert Users: Design Principles and UI Considerations for XAI in Financial Credit Assessment

The effectiveness of Explainable AI (XAI) in the sphere of financial credit assessment hinges not only upon the accuracy and fidelity of the explanation methods, but also, and perhaps more significantly, upon the manner in which these explanations are presented and interacted with by non - expert users. Regarding individuals engaged in the act of seeking loans or the process of understanding their creditworthiness, complex technical explanations of the workings of AI models are unlikely to be of assistance or even comprehensible. In lieu, XAI systems must be designed adopting a user - centric approach, focusing on interaction strategies and user interface (UI) elements which facilitate understanding, build trust, and empower users to take meaningful actions founded upon the explanations provided (Bove et al., 2022; Cheng et al., 2019). This necessitates a shift from the mere act of generating explanations to the design of explanation experiences which are tailored to the cognitive abilities, information needs, and goals of non - expert users within the financial domain.

Cheng et al. (2019) directly undertakes the task of the challenge regarding the explanation of decision - making algorithms for non - expert stakeholders by means of the act of user interface design. They carried out an online experimental activity involving 199 participants, through the utilization of different explanation interfaces for the purpose of assisting users in the comprehension of an algorithm applicable to university admissions decisions. Despite not being specifically concentrated upon financial credit assessment, their research offers valuable understandings in relation to general design principles for explanation interfaces. They made a comparison of different explanation strategies, inclusive of interactive explanations and "white - box" explanations which have the effect of revealing the inner operational mechanisms of the algorithm. Their results demonstrate that both interactive and white - box explanations are capable of enhancing users' objective comprehension of the algorithm.Interestingly, they found that interactive explanations were more effective in the improvement of comprehension but accompanied by a trade - off entailing the requirement of more time from users. Furthermore, and somewhat surprisingly, their study disclosed that users' trust in algorithmic decisions was not significantly influenced by the explanation interface or their level of understanding of the algorithm. This indicates that despite the importance of understanding, other factors, like the perceived fairness or the perceived authority of the system, might also assume a crucial role in the formation of user trust.

Bove et al. (2022) places its specific focus upon the design of XAI systems for non - expert users. It puts forward generic XAI design principles for the contextualization and enabling of the exploration of local feature importance explanations. Their work has its basis in the context of an insurance scenario. This insurance scenario shares resemblances with financial credit assessment in relation to complexity and the necessity for user understanding. A controlled user study was carried out by them with 80 participants. Four different versions of their XAI system were compared, with each version embodying different combinations of contextualization and exploration principles. Contextualization principles have the aim of offering explanations that are relevant and meaningful to the specific situation of the user. Exploration principles enable users to actively conduct an investigation of the explanations and make a deeper delve into the reasoning of the model.

Their results' manifestation shows that the contextualization principles' enhancement of user satisfaction is significant, and their having of a near-significant impact on objective understanding occurs. The exploration principles' contribution to the improvement of user satisfaction also takes place. Nevertheless, their discovery

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indicates that the combination of contextualization and exploration principles does not inevitably result in additive improvements in both understanding and satisfaction, hinting at a possible trade-off or the requirement for meticulous design to balance these two facets.

Drawing upon these insights and considering the specific context of financial credit assessment, several key interaction strategies and UI design principles emerge as crucial for designing effective XAI systems for non-expert users:

1. Contextualization: Explanations ought to be furnished within a context characterized by meaningfulness and relevance vis - à - vis the user's financial situation and goals. For example, upon the occasion of explicating a credit rejection, the explanation should not merely enumerate the influential features but also establish a connection between them and the user's application as well as financial profile. This might entail engaging in a comparison of the user's profile with the typical profiles of approved applicants or emphasizing specific domains in which the user fails to meet the model's criteria. Contextualization may also involve the customization of the degree of detail within the explanation in accordance with the user's perceived level of financial literacy and their declared information requirements.

2. Simplification and Abstraction: The complex technical details of the AI model are required to be subjected to the act of abstraction. Attention ought to be directed towards the act of presenting explanations in a plain language form, which is characterized by being easily comprehensible to non - experts. Avoidance of technical jargon is necessary. The utilization of analogies or metaphors can be employed as a means to convey complex concepts in a more intuitive fashion. For instance, rather than engaging in a detailed explanation of SHAP values, the act of explanation could concentrate on the "importance" or "influence" of each factor with respect to the credit decision. Visual representations such as bar charts or feature importance rankings can be utilized to effectively convey this information.

3. Interactivity and Exploration: Providing of interactive elements within the explanation interface, this act of providing interactive elements can enable users to conduct an active exploration of the explanations and attain a more profound understanding. This engagement might involve the act of permitting users to delve into specific features, carry out an exploration of counterfactual scenarios (an analysis of alternative situations), or execute a comparison of different explanation perspectives. For instance, users could engage in interaction with a feature importance chart for the purpose of discerning how an alteration to a specific feature would exert an impact on the predicted credit score or the probability of loan approval. Interactive explanations are also capable of catering to different learning styles and information preferences, allowing users to embark on an exploration of the explanations at their own chosen pace and level of detail.

4. Visualizations and Visual Aids: Visual representations with a greater degree of formality in their descriptive terms are often more effective in terms of conveying complex information as compared to textual descriptions, specifically in relation to non - expert users. Visualizations, inclusive of bar charts, pie charts, and decision trees, are capable of being utilized to illustrate feature importance with more formalized expressions, decision paths with greater formality in their description, and model behavior in a manner that is more intuitive and engaging. For instance, a visual decision tree has the capacity to demonstrate the key decision points within the credit scoring process, with a highlighting of the factors that resulted in a particular outcome. Visualizations need to be meticulously designed so as to achieve clarity, conciseness, and to refrain from overburdening users with an excessive amount of information.

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5. Transparency and Trust Building: The explanation interface should be designed with the aim of the establishment of trust with regard to the AI system and the explanations provided. The achievement of this can be realized through several approaches. These involve the clear enunciation of the limitations of the model, the acknowledgment of uncertainty in the places where it occurs, and the presentation of evidence or rationale for the explanations. For example, the system could offer links to relevant data sources or documentation that provide support for the model's reasoning. Additionally, the interface ought to be crafted to attain transparency concerning the data employed, the model's goals, and the potential biases that might be present.Actively addressing these potential ethical issues can contribute to building trust in and acceptance of AI-driven financial systems.

6. Actionability and Guidance: Explanations are not merely required to have characteristics of description but also to display attributes of action, providing users with clear guidance in relation to the steps that can be carried out to improve their creditworthiness or challenge a credit decision. For example, if the explanation emphasizes "high debt - to - income ratio" as a crucial factor in a credit rejection, the system is able to provide practical suggestions with regard to the ways in which debt can be decreased or income can be increased. Actionable explanations grant users the capability to take control of their financial situations and make use of the explanations for their benefit.This is in line with the principle of "right of interpretation", which ensures that the user is not only informed of the relevant decisions, but also understands them, and may object to the decisions, or play a role in enhancing them.

By integrating these interaction strategies and UI design principles, this paper can make the XAI system for financial credit evaluation easier to access and understand, and at the same time bring greater benefits to non-expert users. The focus here should be on creating explanatory experiences that are not only effective in technical aspects. And by putting people at the core, it promotes user trust in the system, improves transparency in the system, and ultimately makes financial services fairer and more inclusive.Additional research is required to conduct an empirical evaluation of the effectiveness of diverse interaction strategies and UI designs within real - world financial contexts, encompassing diverse user populations and scenarios.

Specific XAI Methods and their Application in Credit Scoring: LIME and SHAP in Detail

As per the prior discussion, LIME (Local Interpretable Model - agnostic Explanations) along with SHAP (SHapley Additive exPlanations) stand as two preeminent post - hoc model - agnostic XAI techniques which have been extensively utilized within the sphere of credit risk management and financial applications (Hadji Misheva et al., 2021; Lange et al., 2022; Nallakaruppan et al., 2024). The model - agnostic character thereof renders them peculiarly appropriate for elucidating complex "black - box" models customarily employed in credit scoring, such as neural networks, gradient boosting machines, and random forests. Comprehending the specific mechanisms and characteristics of LIME and SHAP assumes critical importance for the effective application thereof in the design of XAI systems for non - expert users in financial credit assessment.

Local Interpretable Model-agnostic Explanations (LIME):

LIME, as the name put forward, centers upon the provision of local explanations for individual predictions carried out by a complex model. The core notion underlying LIME is the approximation of the complex model in the local area, in the proximity of a specific data instance, through employment of a simpler, interpretable model, like a linear model or a decision tree. This local approximation enables the comprehension of the behavior of the complex model for that specific instance, despite the global behavior

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of the model remaining unclear. The procedure of generating a LIME explanation usually encompasses the following steps:

1. **Perturbation:**Regarding the instance needing to be explained, LIME produces perturbed samples through the act of slightly modifying the feature values of the original instance. The perturbation type is reliant upon the data type (for example, the application of noise addition to numerical features, the implementation of word replacement in text data). These perturbed samples stand for the local neighborhood in the vicinity of the instance undergoing explanation.

2. **Prediction:** The utilization of the complex “black-box” model for the purpose of prediction of the outcome regarding each of the perturbed samples takes place. These predictions give reflection to the manner in which the complex model conducts itself within the local neighborhood.

3. **Weighting:** The samples which are in a perturbed state have weights assigned through the application of a process that is based upon the aspect of their proximity in relation to the original instance. Samples that possess a closer proximity to the original instance are provided with higher weights, with an emphasis being placed upon the local nature associated with the explanation. A distance metric, like Euclidean distance or cosine similarity, is utilized for the purpose of measuring the proximity.

4. **Local Model Fitting:** A model of simplicity and interpretability, such as linear regression or decision tree, undergoes the process of training upon the perturbed samples. Employment of the predictions sourced from the complex model as target values and the utilization of weights founded on proximity occur. This local model makes an approximation of the behavior demonstrated by the complex model within the local neighborhood's context.

5. **Explanation Generation:**The interpretable model trained in the proceeding step acts as the local explanation. Take for instance, a linear model being utilized, the coefficients of the linear model signify the feature importance regarding the instance undergoing explanation. These coefficients denote the direction and magnitude of the impact of each feature upon the prediction within the local neighborhood.

LIME explanations are typically presented in the form of feature importance scores, emphasizing those features that have the most positive or negative impact on predicting specific instances. These explanations have locality, meaning they are specific to the instance being explained and may not generalize to other instances. One key advantage of LIME is its model independent nature, which allows it to be applied to any type of machine learning model. However, LIME interpretation may be sensitive to the selection of perturbation methods, distance metrics, and the complexity of locally interpretable models. In addition, LIME provides explanations for individual instances, while generating global insights about model behavior requires interpreting a large number of instances and summarizing local explanations.

SHapley Additive exPlanations (SHAP):

SHAP, having its root in the area of game theory concept, offers both local and global explanations making use of Shapley values. Shapley values, initially formulated within the domain of cooperative game theory, assign a quantification to the contribution of each player (feature) towards the resultant outcome of a game (prediction). In the context domain of machine learning, SHAP values conduct a measurement of the

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contribution of each feature to the variance between the prediction for a specific instance and the average prediction throughout the dataset. SHAP has the objective to present a unified measurement of feature importance that is in a state of consistency and fairness. The key properties possessed by Shapley values consist of:

- **Local Accuracy:** The sum of the Shapley values for all features should equal the difference between the prediction for the instance and the average prediction.
- **Missingness:** Features that do not contribute to the prediction should have a Shapley value of zero.
- **Consistency:** If a feature's contribution increases or stays the same when another feature's contribution changes, its Shapley value should also increase or stay the same.
- **Additivity:** For linear models, Shapley values are simply the feature contributions.

Calculating of exact Shapley values has the potential to incur substantial computational costs, particularly in relation to complex models and large datasets. In consequence, a variety of approximation methods have been formulated for SHAP, inclusive of KernelSHAP and TreeSHAP. KernelSHAP, a model - agnostic approximation method, employs a kernel function for the purpose of estimating Shapley values. Conversely, TreeSHAP is expressly designed for tree - based models (for instance, decision trees, random forests, gradient boosting machines) and furnishes efficient and exact computation of Shapley values for these models.

SHAP explanations are typically presented in the form of feature importance plots of a nature that is highly formal and structured. These plots serve to display, in a manner befitting a formal setting, the Shapley values associated with each feature, be it for a specific set of instances or for the entirety of the dataset. The local explanations are furnished through the Shapley values corresponding to each individual instance. These values serve to denote, in a formal and precise manner, the contribution made by each feature to the prediction relevant to that particular instance. Global explanations are derived via the aggregation, executed in a highly formalized way, of the Shapley values across all instances. This aggregation provides, in a formal and rather disjointed fashion, insights into the overall importance of features and the direction of the effects of features, which pertains to the positive or negative impact on the prediction.

SHAP has several advantages over other explanatory methods, including its theoretical foundation based on game theory, its properties of consistency and fairness, and its ability to provide local and global explanations. However, SHAP interpretation may also have high-intensity features in terms of computation, especially for model independent approximation methods such as KernelSHAP. In addition, the interpretation of SHAP values requires a certain level of understanding of underlying concepts, and the effective communication of SHAP explanations to non professional users requires careful design of the interpretation interface and visualization.

Application of LIME and SHAP in Credit Scoring:

Both LIME and SHAP have undergone utilization in the domain of credit scoring, with the objective of furnishing explanations regarding the predictions of diverse ML models. Hadji Misheva et al. (2021) as well as Nallakaruppan et al. (2024) both effectuate the utilization of LIME and SHAP, with the purpose of elucidating credit scoring models that have been trained upon the Lending Club dataset. They effectuate a demonstration of the manner in which LIME is capable of offering local explanations with respect to individual loan application decisions, placing emphasis upon the features that exerted the most substantial influence within each decision. SHAP, conversely, is made use of to provide both local and global explanations, thereby uncovering the importance of features for individual instances, as well as the overall

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importance of features across the entirety of the credit scoring model. Lange et al. (2022) specifically undertakes the employment of SHAP, for the purpose of explaining a LightGBM credit scoring model that has been trained upon a Norwegian bank dataset. They make use of SHAP values, with the intention of identifying the most crucial features for the prediction of credit default, thereby providing valuable insights with regard to both model interpretation and risk management.

In the designing context of XAI systems for non - expert users within the realm of financial credit assessment, both LIME and SHAP present valuable capabilities. The local explanations of LIME are utilizable for the provision of personalized explanations regarding individual credit decisions, facilitating users' comprehension of the reasons for the approval or rejection of their loan applications. The global explanations of SHAP are capable of furnishing a broader understanding with respect to the factors that commonly exert influence on credit scoring decisions, enabling users to understand the overall criteria employed by the model. Nevertheless, the effective communication of LIME and SHAP explanations to non - expert users necessitates meticulous consideration of interaction strategies and UI design. The mere presentation of raw LIME or SHAP values is improbable to be comprehensible to users lacking technical expertise. Instead, explanations should be transformed into plain language, effectively visualized, and contextualized to the user's specific situation.

For example, scores of feature importance derived from LIME or SHAP can be manifested in the form of bar charts, accompanied by labels and explanations that are clear in terms of what each feature represents within the framework of credit assessment. Elements of interactivity can be integrated to enable users to conduct further exploration of the explanations, such as delving into specific features or engaging in a comparison of explanations for different instances. The determination between LIME and SHAP, or a combination thereof, is contingent upon the specific objectives of the XAI system and the requirements of the target users. LIME might be more fitting for furnishing highly localized and instance - specific elucidations, whereas SHAP might be more proper for offering a more all - encompassing comprehension of both local and global model behaviors.

User-Centric Evaluation of XAI in Financial Applications: Metrics and Methodologies

The evaluation of the effectiveness of XAI systems, specifically in user - facing applications such as financial credit assessment, necessitates a transition from solely technical metrics (for example, explanation fidelity, computational efficiency) to user - centric evaluation methodologies. The ultimate objective of XAI for non - expert users is the enhancement of their understanding, satisfaction, trust, and the ability to reach well - informed decisions on the basis of the explanations presented. Consequently, evaluation metrics and methodologies must concentrate on the capture of these user - centered outcomes. A number of studies have utilized user studies and experiments for the evaluation of XAI systems, particularly within the context of explanation interfaces and interaction strategies (Bove et al., 2022; Cheng et al., 2019). These studies offer valuable insights regarding appropriate metrics and methodologies for the evaluation of XAI in financial applications.

User-Centric Evaluation Metrics:

Several metrics can be used to assess the effectiveness of XAI systems from a user perspective. These metrics can be broadly categorized into:

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1. **Objective Understanding:** The function of this indicator is to measure the user's accurate understanding of the underlying artificial intelligence model interpretation and decision-making process, and evaluate the user's objective understanding of the underlying artificial intelligence model interpretation and decision-making process, which can be achieved by various methods, such as:.

- **Comprehension Quizzes:** After users interact with the XAI system, the system will ask users some questions related to interpretation and model behavior, and the accuracy of users' answers to these questions can reflect their objective knowledge of the relevant content. In the study conducted by Cheng et al., 2019, and the study conducted by Bove et al., 2022, Cheng et al. Both use comprehension tests to measure the objective understanding of users.

- **Task Performance:** As mentioned in this paper, the tasks assigned to users require them to make use of explanations related to decision-making or problem solving in the field of artificial intelligence systems. When users use XAI systems, the task performance improves, which means that users have a better objective understanding of it. For example, in the scenario of credit evaluation, the task performance is improved. It may allow users to make predictions about creditworthiness based on explanations, or to identify factors that would improve a loan application.

2. **Trust:**In terms of user adoption and acceptance of artificial intelligence system, trust in the system and relevant explanations are very key factors. In a more sensitive field such as finance, the degree of trust can be measured by issuing questionnaires or conducting surveys. This means assessing how much trust users have in the accuracy, fairness, and reliability of the system. During the research, Cheng et al. (2019) unexpectedly found that trust was not greatly affected by the interpretive interface, which suggests that trust may be a more complex structure that can be affected by other factors besides the interpretive design.

3. **Perceived Usefulness:** This metric performs an evaluation on the aspect of users' perception in relation to the utility of the explanations so as to enable their attainment of goals or the making of well - informed decisions. The determination of perceived usefulness can be achieved through the utilization of questionnaires or surveys, with the stipulation that users rate the helpfulness of the explanations in various scenarios or tasks.Explanations that users find useful are more likely to be chosen and used in practice.

4. **Efficiency and Time on Task:** While understanding and satisfaction are the primary goals of the XAI system, the efficiency of the XAI system and the time it takes for users to interact with the system are also key aspects to be considered in practical applications.Excessive time expended in the process of understanding explanations or traversing complex interfaces can exert a negative influence on the user experience. Thus, the measurement of the time dedicated to specific explanation - related activities can offer insights regarding the usability and efficiency of the XAI system. Cheng et al. (2019) discovered that interactive explanations, during the process of enhancing comprehension, also necessitated more time on the part of users.

User-Centric Evaluation Methodologies:

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To effectively evaluate XAI systems using these metrics, various user-centric evaluation methodologies can be employed:

1. **Controlled User Studies:**Experiments that are under control, in the manner carried out by Cheng et al. (2019) as well as Bove et al. (2022), represent an approach that is characterized by rigor for the purpose of conducting an assessment regarding the influence exerted by distinct XAI design options upon user results. In a study that is under control, participants are assigned in a random manner to diverse conditions (for instance, distinct explanation interfaces, distinct XAI techniques), and the measurement of their performance along with their perceptions is accomplished through the utilization of the metrics that have been described previously. Studies that are under control permit the act of isolating the effects associated with specific design variables and the drawing of causal inferences concerning their influence upon user results.

2. **Usability Testing:** Usability testing encompasses the act of conducting observations of users engaged in interaction with the XAI system within a scenario that attains a degree of realism, and further encompasses the process of pinpointing usability issues as well as areas that necessitate enhancement. The implementation of usability testing can be achieved through the utilization of diverse techniques, for instance, think - aloud protocols, wherein users give voice to their thoughts and actions during the utilization of the system, and eye - tracking, which undertakes the task of tracking the gaze patterns of users with the aim of discerning their attention and interaction with the interface. Usability testing holds a particularly significant value in relation to the identification of practical usability problems and the iterative refinement of the design of the XAI system.

3. **Surveys and Questionnaires:** Surveys and questionnaires are a way of cost - effectiveness that is characterized by being a means to gather user feedback in the form of a larger - scale implementation. Surveys have the potential to be utilized for the purpose of gauging subjective comprehension, satisfaction, trust, perceived utility, and other user - related perceptions. Questionnaires can be executed subsequent to users having engaged in interaction with the XAI system, or even in the time periods both prior to and subsequent to, for the intention of measuring alterations in user attitudes or knowledge. Surveys are capable of offering valuable data of a quantitative nature regarding user perceptions and preferences.

4. **Qualitative Data Analysis:** In addition to quantitative indicators, which have clear quantitative attributes, the category of qualitative data, such as user comments, open-ended survey responses, and specific methods such as voice thinking protocols, has the ability to provide rich insights into users' experience and cognition of explainable artificial intelligence (XAI) systems. The field of qualitative data analysis techniques, such as thematic analysis and content analysis, can be used in a more formal way to identify recurring themes, patterns, and user needs that may not be obtainable solely through quantitative indicators. Qualitative data can provide valuable background information and depth to the evaluation results.

5. **A/B Testing:**In real - world deployments, the employment of A/B testing can be utilized to effectuate a comparison between diverse versions of the XAI system or explanation interfaces within a live environment setting. The assignment of users to different versions is executed in a random manner. Subsequently, the tracking of their behavior and the resultant outcomes is carried out over a

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span of time. A/B testing enables the assessment of the real - world impact exerted by different XAI designs upon user engagement, user satisfaction, and business - related metrics.

In financial credit assessment context's domain, user - centric evaluation of a formal nature is of great significance. It is for the purpose of the ensuring act that XAI systems are in a state of not only technical soundness but also effective service - providing act to the needs of non - expert users. Evaluation studies should bring in users of a representative kind from the target population, like loan applicants of a formal nature, small business owners of a formal nature, or bank customers of a formal nature. The evaluation scenarios should be of a realistic nature and of a relevant nature to the financial domain, such as the act of understanding of a formal nature of credit decisions, the act of seeking of a formal nature of loan approvals, or the act of improving of a formal nature of creditworthiness. The choice of evaluation metrics and methodologies of a formal nature should be under the guidance of the specific goals of the XAI system and the research questions being dealt with in a formal way. A combination of quantitative and qualitative methods of a formal nature is often of the most effective kind for the act of providing of a comprehensive understanding of user experiences of a formal nature and the impact of XAI in financial applications of a formal nature.

Challenges and Future Directions in Designing XAI for Financial Credit Assessment

In the domain of Explainable AI (XAI) and its utilization in financial credit assessment field, with significant progress having been achieved, several challenges and open research topics continue to exist. Especially in the aspect of the design of XAI interaction strategies aimed at non - expert users. The handling of these challenges and the pursuit of future research orientations holds great importance for the achievement of the complete potential of XAI in the promotion of transparent, trustworthy, and user - friendly AI - driven financial systems.

Challenges in Designing XAI for Non-expert Users:

1. **Complexity of Explanations vs. User Comprehension:** The inherent trade - off that exists is between the complexity and fidelity of explanations, along with the ability of non - expert users for comprehending them. Explanations that are of a highly detailed and technically accurate nature may pose difficulty for users who are lacking in technical expertise to understand. On the other hand, explanations that are overly simplified may have a lack of crucial information or may be misleading. The act of finding the appropriate balance between the complexity of explanations and the comprehension of users is a design challenge of significant nature.

2. **Contextualization and Personalization:** Explanations, which are of a nature to be in a state of having a requirement for being contextualized and personalized in a manner that is characterized by the achievement of meaningfulness and actionability with regard to individual users. Generic explanations, having the property of not being tailored to the user's specific financial situation and goals, may exhibit a state of being less effective. The development of methods for the automatic contextualization and personalization of explanations, founded upon user profiles, application details, and financial history, is a task that is of a challenging nature.

3. **Trust and Transparency Trade-offs:** Transparency, as a key objective of explainable artificial intelligence (XAI), may inadvertently lead to a decrease in user trust by revealing too many details about the internal operations of complex AI models. Users may fall into an excessive burden due to

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technical details, or even when faced with explanations, they may still view the model as overly complex and opaque. Furthermore, due to considerations of proprietary information or model security, complete transparency is not always desirable or feasible. The balancing of transparency and trust in explainable artificial intelligence design is a complex challenge.

4. **Ethical Considerations and Bias Mitigation:** The XAI system is required not merely to possess interpretability, but also to maintain fairness and absence of bias. The act of providing explanations is capable of facilitating the identification and mitigation of potential biases within artificial intelligence models. Nevertheless, the design of XAI systems which actively foster fairness and ethical decision - making continues to pose a persistent challenge. It is of equivalent significance to guarantee that the explanation itself does not exhibit bias or possess the potential to mislead.Addressing the ethical issues associated with data privacy, algorithmic discrimination, and the responsible use of AI in financial credit assessments cannot rely on explainability alone, but requires an approach that takes all factors into account.

5. **Evaluation and Validation of User-Centered XAI:** The evaluation of the effectiveness of XAI systems in terms of a user perspective encounters difficulties. User understanding, satisfaction, and trust pertain to subjective and multifaceted constructs. The development of robust and reliable user - centered evaluation methodologies and metrics belongs to an ongoing research domain. The validation of the real - world influence of XAI systems on user behavior, financial results, and overall system effectiveness necessitates longitudinal investigations and field implementations.

Future Directions in XAI for Financial Credit Assessment:

1. **User-Adaptive Explanation Interfaces:** Future XAI systems should possess adaptability in relation to the individual user needs, preferences, and levels of expertise. Explanation interfaces are capable of effectuating dynamic adjustments to the complexity, level of detail, and presentation format of explanations through utilization of user interactions, feedback, and inferred understanding. User - adaptive explanations have the potential to undertake the personalization of the explanation experience and enhance user comprehension and satisfaction.

2. **Interactive and Explorable Explanations:** Moving beyond static explanations, future XAI systems should embrace interactiVe and an interpretable interface with exploratory features. Empowering users with the ability to actively explore explanations, delve into details, conduct "hypothetical scenario" analysis, and compare different interpretive perspectives can enhance user engagement, understanding, and trust. Interactive visualization and user-friendly exploration tools are crucial for enabling complex explanations to be accessible to non professional users.

3. **Causal and Counterfactual Explanations:** Explanations that exceed the importance of features and offer causal insights regarding the decision - making process of the model assume an increasingly elevated level of importance. Causal explanations have the capacity to assist users in comprehending the cause - and - effect connections between features and predictions. Conversely, counterfactual explanations (scenarios of alternative conditions) can proffer actionable guidance with respect to the means of altering outcomes. The development and the effective conveyance of causal and counterfactual explanations within the domain of financial credit assessment constitute a promising direction of research.

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4. **Integration of XAI with Financial Literacy Education:** The XAI system can integrate with financial literacy education initiatives to provide users with a better understanding of credit scoring, financial risk factors, and responsible financial behavior. Explanations can be used as educational tools to enhance users' financial knowledge and decision-making skills. The combination of XAI with educational resources and personalized financial advice can enhance the overall impact of XAI in promoting financial inclusion and well-being.

5. **Longitudinal Studies and Real-world Deployments:** Future research should focus on the performance of longitudinal studies and the real - world deployments of XAI systems in the area of financial credit assessment. Longitudinal studies possess the capacity to oversee the long - term impact exerted by XAI on user behavior, financial outcomes, and the trust in AI - driven financial systems. Real - world deployments have the capability to provide valuable viewpoints concerning the practical challenges and opportunities related to the implementation of XAI in operational financial environments.5. These studies need to take into account different user groups and different financial situations in order to ensure that the results obtained are generic and more robust.

6. **Ethical and Responsible XAI Frameworks:** Developing of comprehensive frameworks of ethics and responsibility for XAI in the field of financial credit assessment is of crucial significance. These frameworks ought to deal with matters including mitigation of bias, fairness, transparency, accountability, as well as privacy of data. They should offer guidelines and optimal practices for the design, development, and deployment of XAI systems in a manner that is ethical, responsible, and advantageous to all stakeholders. Collaboration among different disciplines between researchers of AI, ethicists, legal experts, and financial professionals is of essential importance for the development and implementation of such frameworks.

Through the act of the addressing of these challenges and the act of the pursuing of these future directions, the field of XAI within the domain of financial credit assessment has the potential for continuous advancement. This advancement leads to the development process of more transparent, trustworthy, and user - friendly AI - driven financial systems. These systems are of a nature that they confer empowerment upon individuals and promote the act of responsible AI adoption within the sphere of the financial industry. The focus ought to maintain its position on the optimization process of user experience. Ensuring is to be done that XAI systems are not merely of a technically sophisticated nature but are also of a human - centered nature and effectively serve the needs of non - expert users in the process of navigating the complexities of financial credit assessment in the era of AI.

Conclusion

This literature review has conducted an exploration of the critical domain of the design regarding explainability within the sphere of financial credit assessment. There is a specific focus on the XAI interaction strategies aimed at non - expert users. The growing dependence on intricate AI models in the realm of financial decision - making, especially in the area of credit scoring, gives rise to a concomitant emphasis on transparency and explainability so as to guarantee trust, fairness, and user comprehension. The review has accentuated the motivations for XAI under this circumstance, impelled by regulatory imperatives, ethical deliberations, and the practical necessity of fostering user confidence in AI - driven financial systems. Techniques such as LIME and SHAP have come to the fore as prominent instruments for elucidating complex models, providing both local and global perspectives on model behavior and the significance of features.

However, the review places emphasis upon the fact that the technical advancements within the realm of XAI algorithms constitute merely one component of the overall situation. The effectiveness regarding XAI in the domain of financial credit assessment ultimately relies upon the design of user - centered interaction strategies and user interfaces which engage in the act of effectively communicating explanations to non - expert users. Principles such as contextualization, simplification, interactivity, visualization, transparency, and actionability are of crucial significance for the purpose of designing explanation experiences that are of a nature to be understandable, trustworthy, and beneficial for those individuals who are engaged in the pursuit of understanding credit decisions and enhancing their financial standing. User - centric evaluation methodologies, inclusive of controlled studies, usability testing, and surveys, are of essential importance for the act of assessing the impact exerted by different XAI designs upon user understanding, satisfaction, trust, and the overall effectiveness of the system.

The progress that has been achieved notwithstanding, there remain significant challenges and future research directions. The act of achieving a balance between the complexity of explanations and the comprehension of users, the process of providing context and personalizing explanations, the act of navigating the trade - offs between trust and transparency, the addressing of ethical considerations, and the development of robust user - centric evaluation frameworks are areas of ongoing research. Future directions encompass user - adaptive explanation interfaces, interactive and explorable explanations, causal and counterfactual explanations, the integration of XAI with financial literacy education, longitudinal studies, and the development of ethical and responsible XAI frameworks for financial applications.

In conclusion, the design work with regard to explainability within the realm of financial credit assessment does not merely constitute a technical challenge matter but rather a human - centered design problem issue. The ultimate success state of XAI in this domain area is reliant upon our capacity ability to create explanation experience occurrences that endow non - expert user individuals with power, cultivate trust sentiment within AI - driven financial system entities, and promote more equitable and inclusive financial service provisions. Through the act of according priority to user experience optimization efforts and pursuing the future research direction guidelines that are outlined, the full potential possibility of XAI can be unlocked so as to effect transformation upon financial credit assessment processes and construct a more transparent and trustworthy financial future prospect.

References

Bolarinwa, D. A., Ewim, C. P.-M., & Igwe, A. N. (2024). Designing a machine learning-based lending model to enhance access to capital for small and medium enterprises. *Computer Science &Amp; IT Research Journal*, *5*(11), 2539–2561. https://doi.org/10.51594/csitrj.v5i11.1707

Bove, C., Aigrain, J., Lesot, M.-J., Tijus, C., & Detyniecki, M. (2022). Contextualization and exploration of local feature importance explanations to improve understanding and satisfaction of non-expert users. *27th International Conference on Intelligent User Interfaces*, 807–819. https://doi.org/10.1145/3490099.3511139

Cheng, H.-F., Wang, R., Zhang, Z., O'Connell, F., Gray, T., Harper, F. M., & Zhu, H. (2019). Explaining decision-making algorithms through UI: Strategies to help non-expert stakeholders. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3290605.3300789

Drosos, I., Sarkar, A., Xu, X., Negreanu, C., Rintel, S., & Tankelevitch, L. (2024). "It's like a rubber duck that talks back": Understanding generative AI-assisted data analysis workflows through a participatory

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prompting study. *Proceedings of the 3rd Annual Meeting of the Symposium on Human-Computer Interaction for Work*, 1–21. https://doi.org/10.1145/3663384.3663389

Gicić, A., & Đonko, D. (2024). Leveraging time sequence deep learning models: Impact of hidden layers on AI model performance in credit scoring. *2024 IEEE International Conference on Future Machine Learning and Data Science (FMLDS)*, 344–349. https://doi.org/10.1109/fmlds63805.2024.00068

Hadji Misheva, B., Hirsa, A., Osterrieder, J., Kulkarni, O., & Fung Lin, S. (2021). Explainable AI in credit risk management. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3795322

Jayanandini, S., & Gautami, S. (2024). Adapting credit risk management for SMBs: Integrating behavioral economics and machine learning. *Nanotechnology Perceptions*. https://doi.org/10.62441/nano-ntp.vi.3977

Joseph, A. W., & Murugesh, R. (2020). Potential eye tracking metrics and indicators to measure cognitive load in human-computer interaction research. *Journal of Scientific Research*, *64*(01), 168–175. https://doi.org/10.37398/jsr.2020.640137

Kalyanathaya, K. P., & K, K. P. (2024). A framework for generating explanations of machine learning models in fintech industry. *The Scientific Temper*, *15*(02), 2207–2215. https://doi.org/10.58414/scientifictemper.2024.15.2.33

Kleinberg, J., Mullainathan, S., & Raghavan, M. (2022). The challenge of understanding what users want: Inconsistent preferences and engagement optimization. *Proceedings of the 23rd ACM Conference on Economics and Computation*. https://doi.org/10.1145/3490486.3538365

Kruschitz, C., & Hitz, M. (2010). Are human-computer interaction design patterns really used? *Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries*, 711–714. https://doi.org/10.1145/1868914.1869011

Kumbhar, T., Agrawal, D., Saldanha, L., & Koshti, D. (2024). AI-driven credit scoring and credit line solution for the unreserved and self-employed. *2024 Second International Conference on Inventive Computing and Informatics (ICICI)*, 178–184. https://doi.org/10.1109/icici62254.2024.00039

Lange, P. E. de, Melsom, B., Vennerød, C. B., & Westgaard, S. (2022). Explainable AI for credit assessment in banks. *Journal of Risk and Financial Management*, *15*(12), 556. https://doi.org/10.3390/jrfm15120556

Li, X., Zheng, H., Chen, J., Zong, Y., & Yu, L. (2024). User interaction interface design and innovation based on artificial intelligence technology. *Journal of Theory and Practice of Engineering Science*, *4*(03), 1–8. https://doi.org/10.53469/jtpes.2024.04(03).01

Nallakaruppan, M. K., Chaturvedi, H., Grover, V., Balusamy, B., Jaraut, P., Bahadur, J., Meena, V. P., & Hameed, I. A. (2024). Credit risk assessment and financial decision support using explainable artificial intelligence. *Risks*, *12*(10), 164. https://doi.org/10.3390/risks12100164

Rapp, A. (2020). In search for design elements: A new perspective for employing ethnography in human-computer interaction design research. *International Journal of Human–Computer Interaction*, *37*(8), 783–802. https://doi.org/10.1080/10447318.2020.1843296

Rayo Cantón, S., Lara Rubio, J., & Camino Blasco, D. (2010). Un modelo de credit scoring para instituciones de microfinanzas en el marco de basilea II. *Cuadernos de Difusión*, *15*(28), 89–124. https://doi.org/10.46631/jefas.2010.v15n28.04

Rheu, M. (MJ)., Dai, Y. (Nancy)., Meng, J., & Peng, W. (2024). When a chatbot disappoints you: Expectancy violation in human-chatbot interaction in a social support context. *Communication Research*, *51*(7), 782–814. https://doi.org/10.1177/00936502231221669

Sutton, S. J., Foulkes, P., Kirk, D., & Lawson, S. (2019). Voice as a design material: Sociophonetic inspired design strategies in human-computer interaction. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3290605.3300833

Valdrighi, G., Ribeiro, A. M., Pereira, J. S. B., Guardieiro, V., Hendricks, A., Filho, D. M., Garcia, J. D. N., Bocca, F. F., Veronese, T. B., Wanner, L., & Raimundo, M. M. (2024). *Best practices for responsible machine learning in credit scoring*. arXiv. https://doi.org/10.48550/ARXIV.2409.20536

Vinerean, S., Dabija, D.-C., & Dominici, G. (2024). Does experience matter? Unraveling the drivers of expert and non-expert mobile consumers. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(2), 958–974. https://doi.org/10.3390/jtaer19020050

Wen, H., Yi, X., Yao, T., Tang, J., Hong, L., & Chi, E. H. (2022). Distributionally-robust recommendations for improving worst-case user experience. *Proceedings of the ACM Web Conference 2022*. https://doi.org/10.1145/3485447.3512255

Yang, X., & Chen, G. (2009). Human-computer interaction design in product design. *2009 First International Workshop on Education Technology and Computer Science*, 437–439. https://doi.org/10.1109/etcs.2009.359