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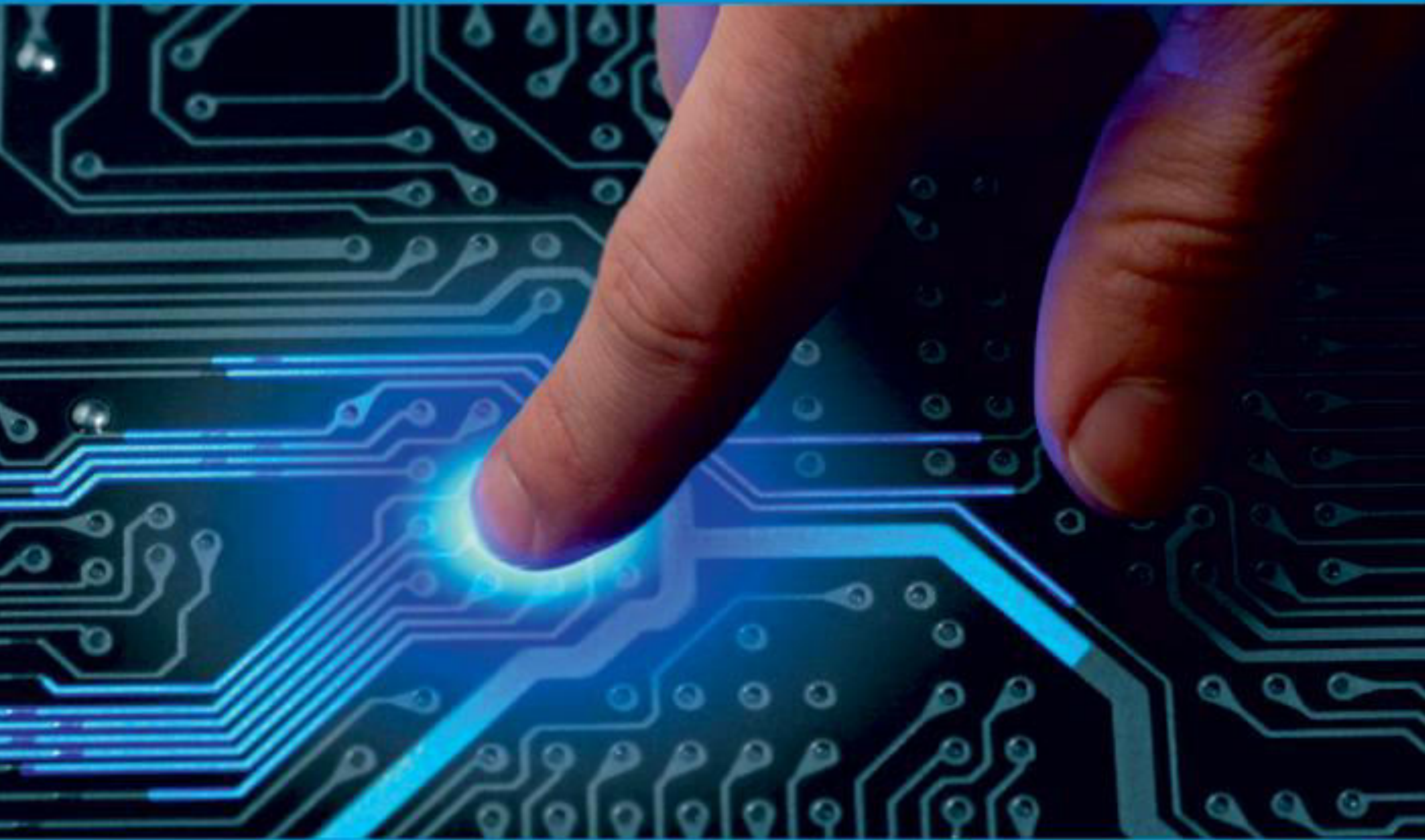

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Exploring the Landscape of Explainable Artificial Intelligence (XAI) in Finance: A Comprehensive Survey

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ABSTRACT: This survey paper undertakes a comprehensive exploration of the integration of Explainable AI (XAI) within the financial sector. Acknowledging the transformative impact of AI on financial decision-making, the survey addresses the critical challenges arising from the opacity of AI models. With a focus on synthesizing existing research and developments, the paper delves into the multifaceted benefits that transparency, facilitated by XAI techniques, can bring to financial practices. By incorporating diverse perspectives, from regulators and financial institutions to consumers, the survey aims to illuminate the unique needs and concerns of each stakeholder in the context of XAI in finance. Additionally, it identifies key challenges, including the delicate balance between explainability and accuracy, designing user-centric explanations, and ensuring responsible use of XAI. Through this comprehensive analysis, the survey not only provides a panoramic view of the current landscape of XAI in finance but also serves as a foundation for guiding future research directions toward a more transparent, fair, and accountable financial ecosystem driven by explainable AI.

KEYWORDS*:* Explainable Artificial Intelligence, Financial Decision-Making, Transparency in Finance

I. INTRODUCTION

The advent of Artificial Intelligence (AI) in the financial sector has undeniably transformed the landscape of decision-making, enabling unparalleled capabilities in credit scoring, risk assessment, investment strategies, and various other financial processes. However, the opacity inherent in many AI models raises a critical question: while we observe the efficacy of AI, do we truly comprehend the mechanisms governing its decisions? This paper, titled "XAI in Finance," embarks on a comprehensive exploration of Explainable Artificial Intelligence (XAI) as a pivotal solution to this quandary. As financial institutions increasingly rely on complex algorithms for intricate tasks, the need to demystify these black box models becomes imperative to foster transparency, fairness, and trust in financial decision-making.

In this paper, we delve into the multifaceted realm of XAI, aiming to shed light on the inner workings of AI models deployed in finance. The objective is not merely technical; rather, it represents a paradigm shift towards elucidating the rationale behind AI decisions. We seek to unveil the discriminatory tendencies within algorithms, ensuring equitable outcomes in credit scoring, risk assessments, and investment opportunities. Furthermore, we examine how XAI can foster understanding and collaboration between AI and humans, thereby instilling confidence and trust in the financial system. The paper addresses the crucial aspect of accountability, clarifying responsibility for AI-driven outcomes and promoting ethical development to avert unjust consequences. Despite these promising prospects, the challenges of balancing explainability with accuracy, designing user-centric explanations for diverse audiences, and ensuring the responsible use of explanations are acknowledged and discussed.

This paper envisions a future where loan decisions are transparent, investment strategies are justified, and risk models undergo open scrutiny. The path to this future demands collaboration among developers, regulators, and financial institutions to craft and implement effective and ethical XAI solutions. While complex, this challenge is worth pursuing, as the benefits of explainable AI in finance extend far beyond the financial realm, shaping a more just and transparent society for all.

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II. LITERATURE SURVEY

The literature survey conducted for this paper delves into the realm of Explainable Artificial Intelligence (XAI) within the context of finance. In addressing the opacity inherent in AI models deployed in the financial sector, the survey explores concerns related to fairness, trust, and accountability. This survey has been informed by an array of scholarly contributions, each offering distinct perspectives and methodologies to tackle the challenges associated with black-box algorithms in financial decision-making.

The first set of papers [1],[2] undertakes the task of unraveling complexities in credit risk management using XAI techniques. These papers emphasize the significance of transparent AI models in promoting fair lending practices. Employing Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP), the authors reveal individual and global insights into the decision-making process, highlighting the impact on credit risk assessments. The results demonstrate the effectiveness of XAI in uncovering biases, thus underscoring the need for continuous monitoring and adjustments for ethical lending practices.

The subsequent papers [3],[4] expand the exploration of transparency in the financial sector by incorporating XAI into bank credit assessment. The authors acknowledge the superior accuracy of AI models in comparison to traditional statistical methods but emphasize the need for explainability. Through the application of LIME and SHAP, these papers aim to elucidate individual loan decisions and global model behavior, contributing to enhanced trust and transparency in credit assessments.

Paper [5] critically examines the current status of XAI in various domains, including finance. By categorizing existing XAI techniques and proposing future directions, the authors underscore the gap between explaining individual predictions and understanding global model behavior. The paper advocates for user-centric, value-driven XAI development, combining local and global explanations and tailoring explanations to different user audiences for a comprehensive understanding.

Addressing the dynamic between benefits and concerns in powerful AI models in finance, paper [6] investigates the perspectives of banks and supervisory authorities. Through semi-structured interviews, the study uncovers a disparity in explainability needs between banks and regulators, emphasizing the importance of collaboration to balance AI benefits with transparency and accountability in the financial sector.

The survey also delves into the historical evolution of AI in finance [7]. This paper traces the transition from transparent statistical methods to opaque black-box models, emphasizing the need for XAI to responsibly unlock AI's potential. By championing XAI for trust-building, bias mitigation, and enhanced accountability, the paper envisions a future where AI benefits all stakeholders in finance.

Paper [8] extends the examination of XAI to insurance, addressing concerns about fairness, transparency, and accountability in AI models. Through the application of LIME and SHAP, the study sheds light on AI risk assessment and decision-making, emphasizing tailored explanations for different audiences. The findings indicate that incorporating XAI significantly improves transparency, accountability, and responsible risk assessment in the insurance industry.

In a systematic review of literature [9], the survey focuses on the applications of XAI in finance, encompassing credit scoring and fraud detection. The paper categorizes various XAI techniques and their applications, emphasizing the challenges in user-centricity and the importance of bias mitigation. It proposes future research directions that underscore the significance of regulatory compliance and the customization of XAI methods for different user groups.

In addressing the lack of transparency in AI-driven financial decisions, paper [10] introduces a conceptual framework for XAI. Emphasizing the demystification of models through techniques like LIME and SHAP, the framework advocates for tailored explanations and user-centric communication. This proposed framework lays the groundwork for a more transparent, accountable, and responsible financial sector powered by AI.

Another paper [11] presents a methodological and theoretical framework for implementing XAI in business applications. By leveraging XAI techniques to unveil the factors and logic behind AI decisions, and tailoring explanations for users, the framework aims to unlock the full potential of business AI. The results indicate that the proposed framework enhances transparency in business AI models, fostering trust, understanding, and responsible decision-making.

Paper [12] investigates the objectives, stakeholders, and future research opportunities in XAI. Identifying diverse stakeholders and mapping future research directions, the paper advocates for collaborative efforts among researchers, developers, and users. It serves as a strategic roadmap for advancing the development of trustworthy and responsible AI, emphasizing transparency, fairness, and accountability.

Addressing the challenges in financial market planning, paper [13] applies XAI models to elucidate the reasoning behind market predictions. Using techniques like Gradient Boosting and SHAP, the study demystifies financial AI models, providing individual case explanations and insights into overall behavior. The paper underscores the importance of tailored explanations for fostering trust and understanding among diverse stakeholders.

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Paper [14] focuses on understanding XAI challenges in finance from diverse stakeholder perspectives, including regulators, financial institutions, and consumers. By mapping concerns and potential benefits of XAI, the study highlights the importance of user-centric XAI solutions tailored to diverse stakeholder needs. Collaboration is emphasized as a key element, urging joint efforts by regulators, financial institutions, and developers to achieve ethical and transparent XAI implementation in finance.

The final paper [15] explores diverse perspectives on XAI in the finance sector, considering stakeholders such as regulators, financial institutions, and consumers. By mapping stakeholder perspectives, the study aims to guide the development and adoption of XAI, fostering a future where AI decisions in finance operate transparently and ethically, benefiting all stakeholders.

Collectively, these papers contribute to the ongoing discourse on XAI in finance, providing valuable insights, methodologies, and future research directions. By addressing the challenges of opacity, bias, and accountability in AI-driven financial decisions, the literature survey informs the development and implementation of responsible, transparent, and trustworthy XAI solutions in the financial sector.

III. XAI IN FINANCE MODELS

1. LIME (LOCAL INTERPRETABLE MODEL-AGNOSTIC EXPLANATIONS):

LIME, standing for Local Interpretable Model-Agnostic Explanations, stands out as a powerful tool in the realm of Explainable Artificial Intelligence (XAI). The core principle of LIME is rooted in the provision of local interpretability, particularly tailored for intricate and complex models. When applied in the context of credit scoring, LIME serves as a means to demystify the decision boundary of the underlying model within the proximity of a specific borrower's profile.

In the intricate landscape of credit scoring, where decisions hold significant financial implications, understanding the rationale behind each decision is paramount. LIME, by approximating the decision boundary, illuminates the critical features that exert substantial influence on the model's verdict—whether to approve or deny a loan. This localized interpretability ensures that stakeholders, including borrowers and regulatory bodies, gain nuanced insights into the factors steering the decision-making process.

Techniques:

The operational methodology of LIME involves a nuanced interplay of data perturbation and model observation. To unfold the decision-making process in credit scoring, LIME embarks on the journey of generating perturbed instances of the borrower's data. These instances represent slight variations of the original data, capturing the subtle nuances that might influence the model's output.

As these perturbed instances traverse through the model, LIME keenly observes the corresponding changes in the output. This observed data is then harnessed to construct a local, interpretable model. This local model, while simpler in structure, faithfully replicates the decision-making process of the original, more complex model but does so specifically for the chosen instance. The emphasis lies on illuminating the features that hold the most sway in determining the outcome, offering a transparent view into the inner workings of the credit scoring model for that particular borrower.

Challenges:

Despite its prowess, LIME is not without its set of challenges. One notable concern lies in the computational cost associated with its operation, particularly when grappling with large and intricate models. The generation of perturbed instances and subsequent model observations can be resource-intensive, potentially limiting the scalability of LIME in certain scenarios.

Moreover, the simplicity inherent in local models may pose challenges in capturing the intricate interactions between features. In credit scoring, where the relationships between various financial indicators are complex and multifaceted, the overly simplified nature of local models might fall short in encapsulating the true intricacies of the underlying decision process. Striking the delicate balance between simplicity and completeness remains an ongoing challenge for LIME, especially in contexts where feature interactions play a pivotal role in decision outcomes.

In essence, while LIME offers a compelling avenue for transparent and locally tailored explanations in credit scoring, the trade-offs between computational cost and interpretability complexity warrant careful consideration in its application within the financial domain.

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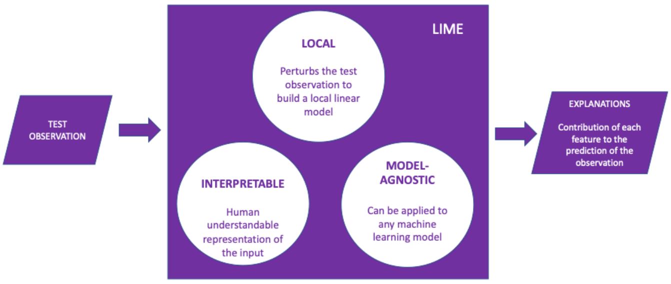

Fig 1 : LIME Architecture

2. SHAP (SHAPLEY ADDITIVE EXPLANATIONS):

SHAP, an acronym for SHapley Additive exPlanations, stands as a cornerstone in the pursuit of global interpretability within the realm of Explainable Artificial Intelligence (XAI). Unlike its local counterpart, SHAP adopts a holistic approach by assigning importance scores to features based on their collective contributions to predictions across an entire dataset. In the specific context of fraud detection, SHAP's role is pivotal in identifying features consistently wielding significant influence in differentiating between legitimate and fraudulent transactions.

In the intricate landscape of fraud detection, where the consequences of oversight can be severe, understanding the overarching patterns and key contributors to fraud alerts is paramount. SHAP, through its global interpretability lens, facilitates the identification of features that consistently play a significant role in the nuanced dance between legitimate and fraudulent transactions.

Techniques:

At the heart of SHAP lies the concept of Shapley values, a concept borrowed from cooperative game theory. These values form the bedrock of SHAP's methodology, distributing the "credit" for a model's prediction among its features. This distribution provides a nuanced understanding of each feature's impact on the model's overall prediction. In the context of fraud detection, this translates into the identification of features crucial in triggering fraud alerts.

The cooperative game theory underpinning SHAP ensures a fair distribution of importance among features, avoiding biases that might arise from the interplay of multiple contributors. This approach empowers stakeholders to unravel the intricate web of relationships between features and predictions, ultimately aiding in the development of targeted preventive measures against fraudulent activities.

Challenges:

While SHAP offers a robust methodology for global interpretability, it is not exempt from challenges. One notable concern is the computational cost associated with SHAP, especially when dealing with large datasets. The calculation of Shapley values across diverse instances in a dataset can be resource-intensive, potentially limiting the scalability of SHAP in scenarios with voluminous data.

Moreover, the interpretability of SHAP outputs may pose a challenge for non-technical stakeholders. Understanding the nuanced distribution of importance scores requires a certain level of technical expertise, potentially creating a barrier for individuals who are not well-versed in the intricacies of cooperative game theory and machine learning.

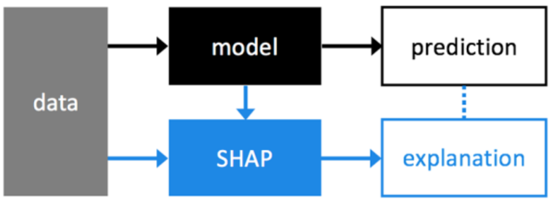

Fig 2 : SHAP Architecture

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IV. APPLICATIONS

1. Credit Scoring and Loan Underwriting with Explainable AI (XAI):

In the realm of credit scoring and loan underwriting, the advent of Explainable AI (XAI) heralds a transformative era for decision-making processes within lending institutions. The integration of transparent models not only modernizes these processes but also brings about a paradigm shift by providing borrowers with elucidating insights into the rationale behind loan approvals or denials. This transparency serves a dual purpose by not only reducing biases in credit decisions but also fostering a heightened sense of trust among borrowers in the overall lending system. Regulatory bodies stand to gain significantly from this transparency, as it assures them of the fairness of credit decisions and aids in ensuring compliance with anti-discrimination laws [1].

Implementing XAI in credit scoring involves the application of advanced techniques, with notable examples being Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) [1]. These techniques function as interpretive tools, allowing for the detailed analysis of individual loan decisions and the identification of the key factors influencing credit outcomes. The datasets employed in such studies are intentionally diverse, encompassing a wide array of borrower profiles. This diversity ensures that the model is exposed to various scenarios, thus facilitating a comprehensive understanding of its decision-making rationale.

However, the implementation of XAI in credit scoring is not without its challenges. Striking the right balance between simplicity and completeness in explanations is a delicate task. Overly simplified explanations, while more accessible, run the risk of failing to capture the full complexity of the underlying model. This raises concerns about the adequacy of the explanations provided to borrowers. Moreover, the disclosure of sensitive data points used in scoring introduces privacy considerations that necessitate careful attention and ethical considerations [1].

In summary, while XAI in credit scoring and loan underwriting brings about significant advancements, it is crucial to navigate the intricate balance between transparency and complexity, ensuring that the benefits of reduced bias and enhanced trust are achieved without compromising the privacy and security of sensitive information. This careful approach contributes to the ongoing evolution of fair, accountable, and transparent lending practices in the financial landscape.

2. Fraud Detection Empowered by Explainable AI (XAI):

The integration of Explainable AI (XAI) into fraud detection mechanisms stands as a pivotal advancement in fortifying the resilience of financial systems against illicit activities. XAI's role in this context is indispensable, offering a nuanced understanding of features and patterns utilized by fraudsters. This understanding not only facilitates the development of targeted preventive measures but also elevates the accuracy in distinguishing genuine transactions from fraudulent ones. Consequently, financial systems incorporating XAI models contribute significantly to creating a more secure and trustworthy environment by demystifying the rationale behind fraud alerts [2].

In the landscape of fraud detection, XAI techniques such as SHapley Additive exPlanations (SHAP) values and feature importance analysis are commonly employed [2]. These techniques serve the critical purpose of shedding light on the factors that contribute to fraud predictions, thereby assisting in the formulation of robust preventive measures. The datasets utilized for training these models are intentionally diverse, encompassing a wide array of transactional data. This inclusivity ensures that the models are exposed to a comprehensive range of patterns, capturing both legitimate and fraudulent activities for a more accurate predictive capability.

Despite the evident advantages, the disclosure of specific triggers for fraud alerts introduces a delicate concern. The transparency offered by XAI, while enhancing the understanding of model decisions, raises the issue of potential vulnerabilities in the system. The detailed knowledge of triggers that could lead to a fraud alert may be exploited by criminal entities to refine their fraudulent activities. This poses a substantial challenge to maintaining the security and integrity of financial systems [2].

In conclusion, while XAI significantly bolsters fraud detection capabilities, the balance between transparency and security must be carefully navigated. Striking this balance ensures that the benefits of accurate fraud detection are realized without inadvertently providing tools for malicious entities to exploit vulnerabilities. The incorporation of XAI into fraud detection mechanisms is a testament to the ongoing commitment to creating robust, secure, and transparent financial ecosystems.

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3. Transparent Horizons: Explainable AI in Risk Assessment and Pricing

The infusion of Explainable AI (XAI) into risk assessment and pricing practices within the financial sector marks a transformative shift towards transparency and fairness. This application of XAI yields numerous advantages, including the provision of clearer justifications for risk scores and insurance premiums. This newfound clarity enables personalized adjustments based on individual profiles, fostering trust between insurers and policyholders and thereby enhancing the overall dynamics of their relationship [3].

Within the realm of risk assessment and pricing, the implementation of XAI involves the utilization of techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) [3]. These techniques play a pivotal role in demystifying the intricate workings of complex models, unraveling both individualized risk factors and broader trends. The datasets employed in these studies are deliberately diverse, encompassing a wide array of risk profiles. This inclusivity ensures that the models are exposed to a comprehensive range of scenarios, enhancing their adaptability and robustness.

Nonetheless, challenges emerge in this domain, particularly concerning the risk of over-reliance on individual explanations. While personalized justifications offer valuable insights, maintaining a holistic understanding of the broader risk landscape is imperative for a comprehensive assessment. Furthermore, concerns loom over the disclosure of specific factors influencing pricing decisions, as this transparency could potentially expose financial institutions to competitive disadvantages [3].

In conclusion, this work adeptly navigates the intricacies of XAI's impact on risk assessment and pricing, shedding light on its transformative potential and the challenges it introduces. By exploring the nuances of the models employed and the datasets utilized, this work contributes significantly to the understanding of the role XAI plays in reshaping critical facets of the financial landscape. Readers are equipped with a comprehensive overview, allowing them to appreciate the multifaceted nature of XAI's influence on risk evaluation and pricing in the financial sector.

V. CONCLUSION

In conclusion, the integration of Explainable Artificial Intelligence (XAI) into the financial sector has emerged as a transformative force, reshaping critical processes such as credit scoring, fraud detection, and risk assessment and pricing. The adoption of transparent models, facilitated by XAI, introduces a new era of accountability and understanding in lending institutions. Borrowers now benefit from clear insights into the rationale behind loan decisions, fostering trust and mitigating biases. Regulatory bodies, equipped with the visibility provided by XAI, can ensure compliance with anti-discrimination laws, ensuring a fair and just financial landscape.

However, this paradigm shift is not without its challenges. The delicate balance between transparency and complexity in explanations poses a constant tension. While local interpretability models like LIME offer a clear view of individual decisions, concerns linger about their ability to capture intricate feature interactions. Global interpretability models, exemplified by SHAP, provide a broader understanding but grapple with computational costs and potential interpretability barriers for non-technical stakeholders. Navigating these challenges requires a nuanced approach that considers the specific needs of each financial application.

As we move forward, it is imperative to address these challenges collaboratively. Future research should focus on refining XAI models, making them more accessible and efficient for widespread adoption. The financial industry stands at the cusp of a new era—one where transparency, accountability, and understanding converge to redefine the dynamics between institutions, regulators, and consumers. Embracing this transformation will not only fortify the integrity of financial systems but also pave the way for a more inclusive and equitable future.

REFERENCES

[1] B. Hadji Misheva, "EXPLAINABLE AI IN CREDIT RISK MANAGEMENT A PREPRINT," arXiv preprint arXiv:2203.14602, 2022.
[2] P. E. de Lange, B. Melsom, C. B. Vennerød, and S. Westgaard, "Explainable AI for Credit Assessment in Banks," in 2021 IEEE 31st International Conference on Artificial Intelligence and Pattern Recognition (AI*31), 2021, pp. 12212-12219.
[3] P. Gohel, P. Singh, and M. Mohanty, "Explainable AI: current status and future directions," arXiv preprint arXiv:2301.04911, 2023.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | A Monthly Peer Reviewed & Referred Journal |

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| DOI: 10.15680/IJIRCCE.2024.1201055 |

[4] O. Kuiper, M. van den Berg, J. van der Burgt, and S. Leijnen, "Exploring Explainable AI in the Financial Sector:Perspectives of Banks and Supervisory Authorities," arXiv preprint arXiv:2211.10509, 2022.
[5] B. Quinn, "Explaining AI in Finance: Past, Present, Prospects," arXiv preprint arXiv:2203.08477, 2022.
[6] M. Torky, I. Gad, A. E. Hassanien, and A. A. A. Elngar, "Explainable AI Model for Recognizing Financial Crisis Roots Based on Pigeon Optimization and Gradient Boosting Model," IEEE Access, vol. 10, pp. 46332-46344, 2022.
[7] S. Sandeep, "Machine Learning Based Explainable Financial Forecasting," in 2022 IEEE 23rd International Conference on Information Reuse and Its Applications (ICIRA), 2022, pp. 238-244.
[8] E. Owens, B. Sheehan, M. Mullins, M. Cunneen, J. Ressel, and G. Castignani, "Explainable Artificial Intelligence (XAI) in Insurance," arXiv preprint arXiv:2207.06255, 2022.
[9] P. Weber, K. V. Carl, and O. Hinz, "Applications of Explainable Artificial Intelligence in Finance—a systematic review of Finance, Information Systems, and Computer Science literature," arXiv preprint arXiv:2205.14487, 2022.
[10] S. Abdallah and A.-F. A. Elngar, "A CONCEPTUAL FRAMEWORK FOR EXPLAINABLE AI (XAI) IN THE FINANCIAL SECTOR," arXiv preprint arXiv:2202.07580, 2022.
[11] R. A. Al-Shafi, "XAI in the Financial Sector. A Conceptual Framework for Explainable AI (XAI)," arXiv preprint arXiv:2301.07172, 2023.
[12] D. Tchuente, J. Lonlac, and B. Kamsu-Foguem, "A methodological and theoretical framework for implementing explainable artificial intelligence (XAI) in business applications," arXiv preprint arXiv:2301.03629, 2023.
[13] C. Meske, E. Bunde, J. Schneider, and M. Gersch, "Explainable Artificial Intelligence: Objectives, Stakeholders, and Future Research Opportunities," arXiv preprint arXiv:2107.09658, 2021.
[14] E. Benhamou, J. J. Ohana, D. Saltiel, B. Guez, and S. Ohana, "Explainable AI (XAI) models applied to planning in financial markets," arXiv preprint arXiv:2210.09134, 2022.
[15] Perspectives on Explainable AI in the Finance Sector

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