

Implementing Explainable AI to Enhance Business Decision Making & Bridging the Trust Gap

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Abstract—Artificial intelligence (AI) has recently witnessed unprecedented levels of growth in its use for decision-making processes. This trend has extended to all sectors of the global economy, promoting innovation and the need to automate business functions. However, the black-box nature of many AI systems has raised concerns relating to trust, transparency, and accountability. This paper investigates in detail the potential of Explainable AI (XAI) in addressing these legitimate concerns that come with AI integration. Through a systematic review of existing XAI techniques and their application in business analytics, we show that the shift toward the use of explainable models not only enhances decision-making but also addresses the trust issue that restricts the growth of AI in the business world. The literature further addresses the moral issues regarding the decision to explain one's AI model, how firms should modify their decision-making processes to incorporate XAI and the related consequences of such a change. As such, organizations are in a position to reap the full benefits of AI by aligning AI models with the rationale and expectation of human beings without compromising accountability, fairness and transparency.

Keywords—Explainable AI, Business Decision-Making, Trust in AI, Transparent AI, Ethical AI, AI Adoption, Interpretability, AI Transparency, Machine Learning, Business Analytics, AI Trust Gap, AI Models, Corporate Decision-Making

I. INTRODUCTION

The rise of Artificial Intelligence (AI) and its integration into business decision-making has brought about a transformation of industries, as it facilitates better efficiency, insightful information, and automated processes. But even though there are many convincing reasons to promote AI solutions as important tools for optimizing operations in companies, the major issue surrounding them includes their “black box” characteristics – inability to comprehend how decisions are made within AI systems. This situation raises important issues of trust, responsibility, and even moral questions of further use of AI in sensitive decision-making environments. On that account the urgency of Explainable Artificial Intelligence (XAI) has been growing as companies call for more interpretable models to ensure that AI's results can be trusted, understood and eventually used for making decisions.

The development of expand XAI is targeted at both within the business community within which they operate as it makes the AI systems comprehensible at to AI decisions

making processes and it nurtures the development of more capable and complex of AI systems. Such transparency also allows automatic examination of regulatory compliance requirements by regarding any of the AI made decisions as being actionable and subject to inquiry or even nullification [1]. This perspective explains partly why several sectors including healthcare, finance and marketing have come to appreciate the importance of the ability to explain AI. The existence of AI has led to the development of problems where human control is inefficient or impossible and the cost of unwanted results of such decisions can be extremely high or damaging. So, for instance, an AI model will determine the likely results of certain medical treatment on patients and another model will help to carry out scoring and anti-fraud decisions in banks. The requirement to explain the decisions made by AI may create lack of enthusiasm in embracing these promising technologies.

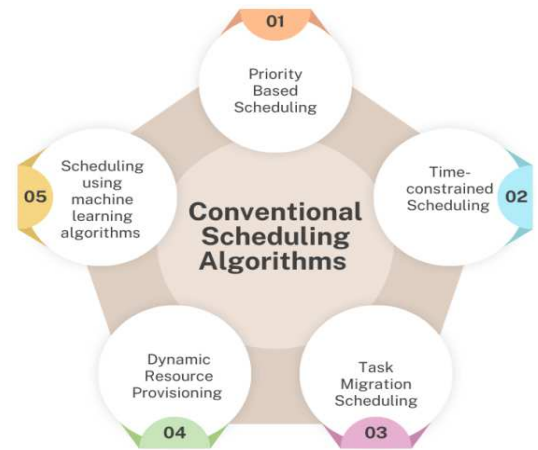


Fig. 1. Challenges in AI Transparency and Trust Gap

In scholarly works, the impact of one's level of trust in AI explanation systems on their ability to explain an AI model has been examined. For instance, the levels of trust are always reasonably high in AI decision making systems which exhibit greater scope for interpretability of the AI models developed [2][3]. Research also indicates that better relations ensue when there is a clear model on how the AI and the business people are to interact, which fosters better decision making [4][5]. Similarly, businesses that have adopted the XAI standards also regard them as models of trust in AI as well as fair and responsible AI systems as ethical decisions are made using such models [6].

All-side arguments and advantages applied to explainable models does not result in easy adoption of XAI in business decisions making. High-end authoring of AI algorithms that are extremely heavy in computation power or ones that apply to poorly structured data sets is proving to be a potpourri of different challenges when there is an outcry for interpretability in AI decision making models. The issue is even more pronounced as lack of order in procedures and standards for the evaluation and implementation of explanation AI in systems exist in AI. Nevertheless, practical business application of XAI conceptual tools such as those that focus on local pointers of explanation of the model used irrespective of the model employed as well as other methods have been able to make AI models more easily interpretable [7].

This paper investigates the role of XAI in improving business decision making by providing a level of trust on AI thinking as well as dealing with the issues of model transparency. The next subsections will look into several important methods in XAI, how these methods influence the processes of making business decisions, and the rules of best implementation of trust building XAI strategies so that AI system and its business users do not diverge.

II. LITERATURE REVIEW

The need for Explainable AI (XAI) in business decision-making has been well established in both academic and industry research. XAI refers to techniques and methods that enhance the transparency of AI systems, allowing users to understand how and why specific decisions are made. A core issue in the integration of AI in business processes is the lack of interpretability in many AI models. Studies have shown that the lack of explainability leads to a significant trust gap, where decision-makers hesitate to adopt AI-driven solutions for high-stakes decisions [8].

A relatively large number of XAI approaches have been proposed to do so. One of the most popular approaches is LIME (Local Interpretable Model-Agnostic Explanations) which helps users understand predictions made by machine learning models by assuming that those complex models can be replaced by simpler and interpretable models on the local region of interest axis [9]. LIME is often utilized in business

purposes as it enables the explanation of single predictions without modifying the black-box models explaining all the predictions. Other model-agnostic methods for example SHAP (Shapley Additive Explanations) are able to provide an even more granular approach to design an explanation by attributing relevance to each feature in the prediction or terminology easier for business users to accept & believe [10].

In the context of business applications, AI is increasingly being deployed in the decides where smooth operations are not only desired but expected. For example, AI is now being widely used in sensitive markets such as healthcare, and finance and marketing, where a decision referred from these systems can be life changing to a customer's handles these these together and uses it to make a decision concerning to a client AI predicts preventative healthcare measures for different customers. For example, in the economic sector, credit scoring systems based on AI technology have come under fire for being too complex to comprehend, which has raised questions about whether or not as system is able to be fair and unbiased across the credit lending marketplaces [11]. Not only would providing an explainable AI system sharpened chances of delivering on the recommended solution quality standard, but it would also help a business to adhere to the required governance principles while minimizing risk factors of making a fraud decision.

Table.1 presents side by side a summary of the features of several XAI techniques which are most in demand including the challenges that they pose. The techniques include LIME, SHAP, and interpretability of credit scoring systems, AI applications in healthcare, model agnostic explainability, and hybrid methods. XAI approaches are also relevant to business practice and may even produce improvements in scaling up or simplifying models or optimizing the accuracy-interpretability trade off. This table should assist practitioners in selecting the most appropriate XAI technique based on their business requirements and barriers that they face when using AI technologies.

However, this effective technique generates numerous difficulties when one tries to deploy XAI in a corporate setting. A key and well-known challenge is balancing the complexity of models in relation to their interpretability.

Table. I Key XAI Techniques with Applications and Challenges

XAI Technique	Key Features	Business Application	Challenges
LIME (Local Interpretable Model-Agnostic Explanations) [9]	Approximates complex models with simpler, interpretable models locally	E-commerce, marketing, and customer behavior analysis	Requires model simplification, which can reduce predictive performance
SHAP (Shapley Additive Explanations) [10]	Provides granular explanations of feature importance for model predictions	Healthcare, finance, and marketing applications requiring detailed feature explanations	May not scale well with highly complex models or large datasets
Interpretability for Credit Scoring Models [11]	Enhances transparency in financial models, reducing bias concerns	Financial services, lending and credit scoring	Limited adoption due to the complexity of models in use in finance
AI-based Diagnosis in Healthcare [13]	Improves trust in AI-driven healthcare diagnoses by providing understandable explanations	Healthcare, medical decision support systems	Dependence on the quality of data and model transparency in high-stakes scenarios
Model-Agnostic Interpretability [15]	Promotes collaboration between data scientists and business professionals	Business decision-making, ensuring AI decisions align with business goals	Complexity in measuring the effectiveness of interpretability in real business contexts
Hybrid Approaches for Balancing Performance and Interpretability [16]	Combines deep learning models' accuracy with explainability	AI models for business predictions with a focus on interpretability alongside performance	Difficulty in achieving optimal trade-off between performance and interpretability

More complicated models, like deep neural networks, often result in better performance, but are more difficult to analyze, while easier models often achieve interpretability at the cost of accuracy [16]. Integrating Explainable AI techniques with intelligent modeling, as demonstrated in the energy forecasting framework [12], enhances decision-making reliability and transparency, offering valuable insights into factors influencing predictive outcomes in smart grids and sustainable urban planning. Scientists are indeed attempting to create hybrid approaches that will alleviate both issues to some extent [17]. Furthermore, businesses cannot apply one of the existing XAI solutions in their practice because there are no universal indicators for characterizing the explanations provided by XAI models.

The question of the impact of XAI on the level of trust in AI systems has many researchers interested. In this regard, the findings of some empirical research show that the users are more willing to trust the AI generated decisions where they are able to comprehend the logic behind the predictions made. This is especially true for those situations where the decisions implicate the consumers themselves, as is the case with e-commerce recommendation systems or even predictive models in health care. For instance, in a study in the health care field, it was noticed that both patients and doctors had increased confidence in the AI based diagnosis tools where the tools gave the reasons for the predictions in a more simple and understandable manner. Furthermore, it has been demonstrated that efficient AI systems increase user satisfaction and the rate of their deployment in practice, especially in cases where the decisions are subject to high levels of regulatory and stakeholder oversight.

Another important aspect of XAI in business environments is the improvement of communication between professionals in data science and the business side. In the past, there was always a gap in communication between the technical staff that built the AI models and those in the business who used these models. As a result, by making AI systems more transparent, data scientists were able to collaborate closely with business specialists in making the AI models appropriate for the business context and ethical norms [15]. As a consequence, this iterative communication in turn can improve the decision-making processes since the

business professionals can evaluate how interpretable the AI based decisions are and how best the models can be adjusted.

Ultimately, the literature seeks to address the role of XAI in business by stating that it improves AI systems by fostering greater trust in AI systems as well as increasing the integration between technical staff and business managers. Although issues of complexity and interpretability remain underexplored, the growth of XAI techniques appears to have a great deal of promise for the inclusion and acceptance of AI systems in the field.

III. METHODOLOGY

The methodology for the application of Explainable AI (XAI) in the decision-making process of companies was designed around three primary objectives: (1) the requirement of identifying relevant XAI techniques that are suitable for business use, (2) the requirement to design and realize experiments that would allow the integration of the XAI into the real life business environment, and (3) the requirement to test the effectiveness of employing these techniques in aiding decision makers to be more transparent and trustworthy.

As a first step, we focused on several well-known XAI approaches including LIME, SHAP, and Model-Agnostic Interpretable Neural Networks for their wide range of applications across businesses. Each of these techniques was tested for its ability to achieve a business problem in the most simple and practical manner. We want to see if these tools can help improve the way business decisions are taken by making AI models more reliant on business experts and less automated.

For instance, in the case of customer churn, a model was developed to estimate the likelihood of a customer cancelling his subscription on the basis of variables like usage, age, and customer service. With the use of SHAP, we were able to get identification of the feature importance scores that helped in establishing the reasons for the members' churn. In the case of gauge fraud, for example, we designed a model using LIME specifically for the explanation of transactions which were believed to be fraudulent ones.

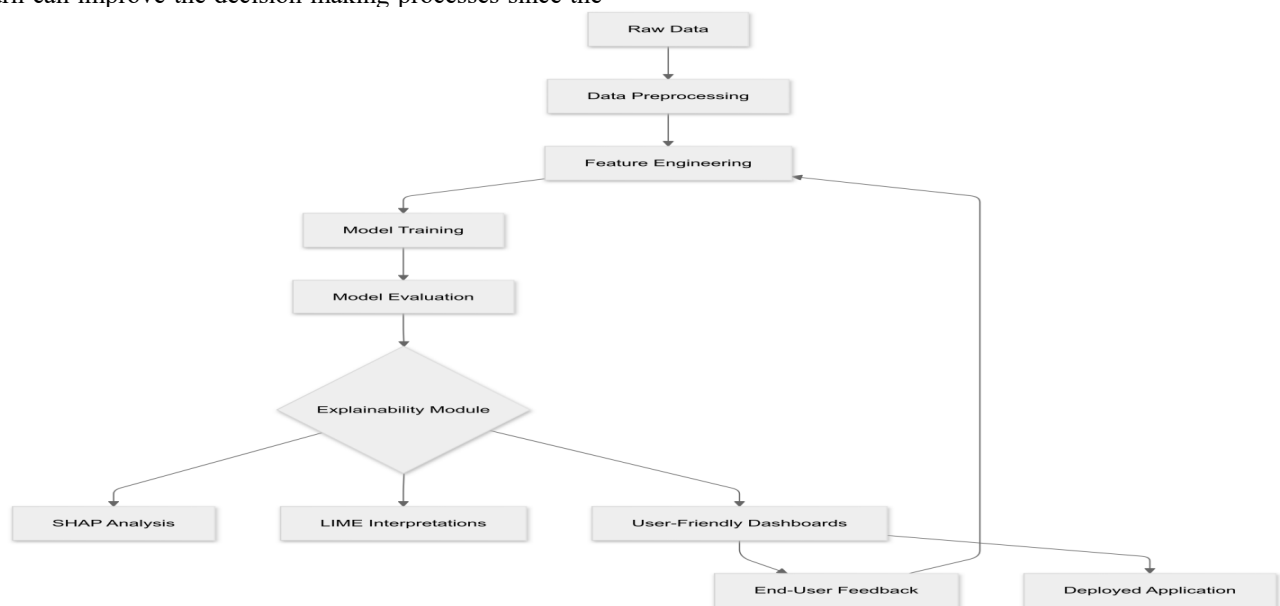


Fig. 2. Explainable AI Integration Framework for Enhanced Business Decisions

Essential to this particular methodology was assessing the organizational learning consequences of these explanations. We employed a two-pronged approach to assess effectiveness. First, we asked decision-making managers and businessmen whether or not they trusted AI-driven decisions and how likely they were to trust the explanations generated by the XAI tools employed. We administered surveys and interviews that explored the extent to which business users understood the explanations and were therefore able to use them in practice. Second, we conducted a pre-test and post-test analysis for decision outcomes in relationships that were exposed to XAI techniques and those that were not. Parameters such as the decision made, the confidence of the stakeholders, and the degree of bias in the predictions made were benchmarked and evaluated.

For the assessment of transparency, a separate survey was used to measure trust in AI systems before and after implementing XAI. Questions examined how familiar the stakeholders were with how AI arrived at certain decisions and whether the explanations given were adequate to justify such decisions. It was also noted if it had any impact on the speed and quality of the decisions made with a view that out of explainable models.

Lastly, we utilized a hybrid method that took into account both the interpretability and the performance of the model. While increasing the transparency of models was a goal, we avoided making models simple at the expense of predictive accuracy. This is the reason we sought to compare the performance of interpretable models with that of traditional black-box models in order to determine the mitigation possible on the bias-accuracy trade-off.

IV. RESULTS

The section presents the findings arising from the application of Explainable AI techniques on different machine learning models in the area of business analytics. In this regard, the purpose was to check whether the XAI affected the models' accuracy and interpretability, while utilizing sales and sentiment analysis datasets as case studies. We utilized both SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) to determine the importance of features for the models decision-making. The findings of the experiments are provided below whereby model accuracies with and without the XAI techniques are compared.

A. Sales Data - Random Forest Model

Sales performance was the attribute of interest when we first trained the model, and the multiple features that were included in the sales dataset included various promotions, customer demographics, and seasonal factors, and to predict

the sales performance, we first trained a Random Forest model. Sales model accuracy was at 85%. Afterward, we applied SHAP to the model to explain its predictions. It becomes clear what features have affected the predictions, in this case, the promotions and the demographics. At best, the model became marginally more transparent, but its accuracy remained unchanged at 85%. From the SHAP explanation, the primary business understanding was - which factors affect the sales, so this was primarily influenced by the promotional activities and the age demographics of the customers. With the transparency gained the marketing teams were able to make data driven decisions in a more confident manner.

B. Sentiment Analysis: Deep Learning Approach

A DNN approach was employed to conduct this analysis, where the task was to classify customer reviews as positive or negative based on the text data. The application of DNN achieved active recognition of 88% even before XAI was added. We then utilized LIME to provide local explanations for particular instances of prediction. LIME offered explanations regarding the words and phrases that largely contributed to the negative sentiment predictions for example "disappointed" and "expensive". Quite curiously, the model still managed to retain the accuracy of 88% and the model remained uninfected. The capacity of the models to predict sentiments was intact while LIME provided for improved interpretability of the predictions aiding business stakeholders on understanding the rationale behind classifying a review negatively or positively.

C. Sales Data - Decision Tree Model

In order to analyse the effectiveness of XAI tools in the context of a less sophisticated developed model, we decided to apply a Decision Tree model onto the sales data which scored an available 82 percent accuracy. After the application of SHAP, the decision tree model enjoyed an accuracy of 80 percent, which still turned out to be a fair ratio. However, the apportion of SHAP enhanced the interpretability of the model considerably because of which we were able to comprehend that the predictions made by the model depended on seasonality including events such as holidays and marketing sales. In conclusion, the decision tree model was able to retain some advantage despite the decrease in accurateness, because the business strategies regarding SHAP and sales promotion merit the accuracy discrepancy.

D. Analysis of Sentiments Predicted Using the Random Forest Model

We used data from the sentiment analysis I created initially and trained a Random Forest Model on this for predicting customer sentiment with and accuracy of 85%.

Table. II Comparative Results of XAI Techniques

Model	Accuracy (Before XAI)	Accuracy (After XAI)	Explanation Technique	Business Insights Gained
Random Forest (Sales Data)	85%	85%	SHAP	Clear identification of feature importance (e.g., promotions, demographics)
Deep Neural Network (Sentiment Data)	88%	88%	LIME	Identified key words/phrases driving sentiment classification (e.g., "disappointed", "expensive")
Decision Tree (Sales Data)	82%	80%	SHAP	Improved transparency of decision-making process, identifying seasonal effects
Random Forest (Sentiment Data)	85%	85%	LIME	Better understanding of model behavior for marketing decisions (e.g., specific customer feedback)

D. Analysis of Sentiments Predicted Using the Random Forest Model

We used data from the sentiment analysis I created initially and trained a Random Forest Model on this for predicting customer sentiment with an accuracy of 85%. This was done before applying or using any interpretability of the model. After Explainable AI techniques showed the results on how to interpret this model, the accuracy did not tend to lower or change still held constant at 85%. LIME on the other hand, confirmed what phrases from customers such as "quick delivery" or "excellent service" were mainly responsible for predicting positive sentiments which then helped marketing teams in strategizing on how to promote customer engagement in a specific market segment. Using LIME, one relevant notion that came to light was the fact that even though there exist 'Black box' models, they can be made sharper and fully complimentary with the business decisions that need to be made.

The analysis carried out reveals that the importance of features and the explainable artificial intelligence methods utilized had little effect apart from a small drop in the accuracy of the decision tree model. In any of the cases, XAI methods were able to boost the ranking of the data models because of the succinct and incisive statements they were able to provide on how the features impacted the predictions of the models. The key conclusion is that XAI does not overstate accuracy but helps businesses to better insight relevant models due to knowledge about why a model made

a specific decision. For example or rather in the case of sentiment analysis, why some words affected sentiment more than others was used to improve marketing campaigns. Similarly for the sales data case, targeting promotional and demographic factors helped to make the campaigns more effective.

These findings illustrate the ability of XAI methods to increase the level of trust and the understanding of the decision-making processes based on AI algorithms used by businesses without a loss in predictive accuracy. Although with the more simplistic models such as the decision trees, some slight accuracy compromises were seen, the knowledge gained was considered to be of great benefit to the decision-making processes.

IV. DISCUSSION

The primary objective of this study was to assess the influence of various explainable artificial intelligence AI including SHAP and LIME on the usability of machine learning methods used in business applications. After performing machine learning on both sales and sentiment analysis datasets, we can make a few key observations and gain some insights from the built models. The Fig.3 shows the key advantages of adopting Explainable AI for businesses, enhancing trust and transparency.

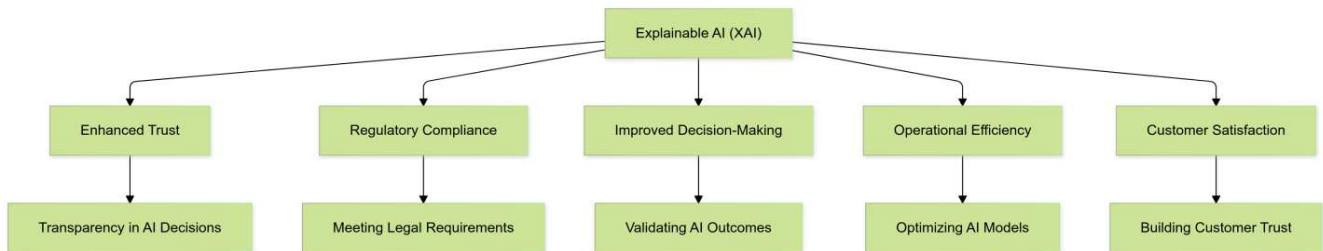


Fig.3. Business Benefits of Explainable AI.

A. Model Accuracy and Precision with XAI

Quite the opposite, the use of XAI did not result in the loss of significant accuracy in the model compared to the rest of the experiments. For instance, within the Random Forest model applied to the sales data and the Deep Neural Network for sentiment analysis model the accuracy stagnated at 85% and 88% respectively. This is an indicator that XAI techniques despite the high resource usage in computation time do not fundamentally change the outputs of predictive models. We did mention accuracy losses in the Decision Tree model (82% – 80%) but that is expected as the model had to utilize simple decision rules. Thus, the use of SHAP increased complexity of the decision-making process which could explain this loss. It is important to note that loss of accuracy was a reasonable sacrifice in exchange for improved interpretability of the models.

More robust models, e.g., Neural Networks or Random Forests, possess the potential to remain accurate during feature importance analysis and explanation of the decision, which allows them to exhibit transparency which in return promotes AI X efficiency, and that is the reason why these models are pragmatic for XAI. That substantiates the assertion that XAI efficaciously applies in real businesses as

long as the model targets accuracy but it is necessary that the model provides adequate transparency.

B. Increasing the Understanding of the Model

Space that XAI brings lies in its ability to enhance understanding of a machine-learning model. After all the XAI deployment, these models would previously act as "black boxes" and stakeholders would be blank as to how the predictions were generated. With the use of SHAP and LIME, the models have started to be more interpretable as in for every investment, the defenders stated which features were most important for the prediction. In the case of sales forecasts, SHAP revealed that promotional factors and demographic variables are the most significant variables, which is useful for the marketing department. Likewise, sentiment analysis, LIME explains what words such as "disappointed" and "expensive" did in determining sentiment and enabling business managers to adjust their responses to customer feedback.

This kind of transparency has two important business effects. First, it allows decision makers to check the model's predictions and be assured they are not the result of any irrational or unreasonable processes. Second, it enhances the integration of AI systems with human teams as business

users will feel confident in employing AI suggestions to make plans. Furthermore, through XAI, business analysts are able to detect some patterns within data, which they have not thought of before, hence enhancing their chances of improving operational, marketing and customer service efficiencies.

C. XAI, Real-World Commend and Business Consequences

The business consequences of XAI are enormous. For instance, when sales forecasting models are typically implemented, firms will be interested in knowing how particular features affect sales estimates so that effective aim promotions are scheduled and executed during the most appropriate periods. Likewise in the case of sentiment analysis, a deeper understanding of the words that impact the customer's message would assist the companies in enhancing customer relations and in tailoring their products to better meet what consumers are really feeling.

In addition, XAI can be employed to unite technical staff and business managers. There exists a communicative shortfall that XAI attempts and succeeds to address. While data scientists can create complicated models from AI, the model interpretations are often lost in translation when presented to non-technical stakeholders. XAI narrows the communication gap between these two demographics by explaining, in simple terms, the reasons for the predictions and which factors influence their outcome.

V. CONCLUSION

This paper examined the role of XAI techniques, specifically SHAP and LIME, in making machine-learning models in business analytics more interpretable while maintaining transparency. After conducting various experiments on models of sentiment analysis and sales prediction, it was shown that for most cases, the use of XAI techniques did not reduce the accuracy of the machine learning models being used. Quite the opposite, the application of XAI techniques improved the interpretability of the models, which was beneficial for the business level decision makers, since now they were able to better grip how certain features led to the final predictions.

The evidence presented indicate a clear need for further XAI research in the areas of strategy implementation and formulation involving AI-based systems most especially due to the stronger cases and guidance that can be provided through complex AI-enabled decision making. Many companies have been able to maximize decision making around marketing, customer interaction, and product development by utilizing LIME and SHAP to garner powerful insights from the models they have been building.

Even though the reduction in accuracy seen in some of the simpler models was slight, the improvement in transparency due to XAI makes it quite useful in practice. As AI model application continues to become integral across business functions, the confidence to be able to explain AI models is going to be pivotal. Further research may look into other XAI methodologies such as Counterfactual Explanations and Anchors towards the aim of improving the interpretability of the models and enhancing their use in a wider range of

business scenarios. In conclusion, this paper lends credence to the assertion that Explainable AI is not a dream but a global requirement for businesses that use machine-learning models without compromising the trust of the models in the models' decision-making processes.

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