

## ***Exploring Explainable AI And Data Visualization In Data Science For Improved Business Insights***

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### ***Abstract***

The increasing use of data-driven models in business analytics has amplified concerns regarding the transparency and interpretability of predictive systems. In response to these concerns, explainable artificial intelligence (XAI) has emerged as a critical approach for enhancing trust and understanding in machine learning-based decision support. This study investigates the integration of explainable artificial intelligence and data visualization within a data science framework to generate interpretable and actionable business insights, using customer churn prediction as an empirical context. A supervised learning model was developed to predict churn outcomes based on customer demographic, service, contractual, and billing attributes. To support interpretability, both model-intrinsic and post-hoc explainability techniques were applied, enabling examination of feature influence at global and local levels. Visual analytics were employed to translate explainability outputs into intuitive representations, facilitating interpretation across different analytical perspectives. The results demonstrate that churn behavior is influenced by a combination of service configuration, contractual commitment, and customer engagement characteristics, while explainability techniques provide clarity on how these factors contribute to individual predictions. The study highlights the value of combining interpretable modeling, explainable AI methods, and visualization to enhance the practical usability of data science models in business contexts. By emphasizing transparency alongside prediction, the proposed approach supports informed decision-making and contributes to the development of trustworthy analytics systems.

**Keywords:** Explainable Artificial Intelligence, Data Visualization, Customer Churn Prediction, Business Analytics, Interpretable Machine Learning.

### ***1. Introduction***

The growing use of data-driven methods in decision-making has changed how organizations study customer behavior, risk management, and strategic intervention design. Data science models and machine learning are now actively used in business to make predictions including customer churn, credit risk, and market demand. Although these models have in many cases shown great predictive power, their increasing complexity has cast a continuing challenge of transparency, interpretability and trust. Decision-makers in most operational contexts need a combination of precise predictions and a clear insight into the manner and rationale of making such predictions, especially when analytical outputs are used to make high-impact business decisions (Adadi and Berrada, 2018).

To address these apprehensions, explainable artificial intelligence (XAI) has become an important field of research in an attempt to improve the interpretability of machine learning models. According to recent systematic reviews and bibliometric analyses, the XAI research has grown at an impressive rate, and its scope of application and methodological approaches has become broad (Saranya and Subhashini, 2023; Sharma et al., 2024). This growth is part of a wider trend towards responsible and transparent AI practices, in which interpretability is being seen as a fundamental requirement, and not an optional addition.

Explainability is especially significant in applied and high-stakes areas like cybersecurity, healthcare, and large-scale enterprise systems. In such situations, the lack of transparency

in model decisions may destroy trust, restrict responsibility, and obstruct the successful human control (Capuano et al., 2022; Khan et al., 2025). The existing studies indicate that explainable models assist in enhancing the correspondence between automated systems and human judgment by allowing users to evaluate, challenge, and contextualize the outputs of algorithms (Charmet et al., 2022). In the dynamic XAI environment, data visualization has become a prominent auxiliary process of increasing interpretability. Visual analytics techniques allow users to interactively and intuitively explore the behavior of a model, facilitating sense-making in high-dimensional feature spaces and big data (Mills et al., 2024). Visualization can be used to provide a translation of numerical explanations into visual forms, allowing analytical insights to be communicated to technical experts and non-technical stakeholders, thereby increasing the practical value of explainable AI systems.

Customer churn prediction is a well-established but constantly difficult application field of business analytics. Although a lot of research has been conducted on the modeling of churn, recent reviews suggest that most of the existing methods focus on predictive accuracy and provide little information on the factors behind model decisions. Such a gap creates difficulties in the context of practical implementation, since organizations need interpretable insights to formulate specific retention strategies and defend data-driven interventions.

SHAP and LIME are post-hoc explainability methods, which have become popular in dealing with interpretability issues by offering a global and local explanation of model predictions (Gramegna and Giudici, 2021; Salih et al., 2025). These techniques allow studying both the effect of features at the population level and decision logic at the instance level. Simultaneously, the current research also emphasizes the necessity of strong and stable explanatory approaches, especially in complicated or decentralized analytical environments (Bogdanova et al., 2023). The recent landscape reviews also highlight the significance of combining explainability with the practical processes to facilitate the decision-making in the real world (Hamida et al., 2024). It is against this background that the current study examines how explainable artificial intelligence and data visualization can be integrated into a data science framework to analyze customer churn. The study aims to show how predictive models can be converted into transparent and actionable sources of business insight by integrating interpretable modeling, post-hoc explainability methods, and visual analytics. The study is guided by the following objectives:

- To develop an interpretable data science framework for customer churn prediction that balances predictive performance with explainability.
- To apply global and local explainable AI techniques in order to identify and interpret the key drivers influencing churn behavior.
- To examine the role of data visualization in enhancing the communication and practical usability of explainable model outputs for business decision-making.

## **2. Methodology**

### **2.1 Research Design**

The research design of the study is quantitative, data-driven in order to investigate the role of explainable artificial intelligence and data visualization in the creation of business insights based on customer churn data. The modeled churn behavior was done using a supervised machine learning framework and then explainability techniques were used to interpret model outputs both on a global and local scale. The methodological scheme combines predictive modeling and explainable AI to make results transparent and interpretable.

## **2.2 Dataset Description**

The analysis was performed on an open access customer churn data with 7,043 observations. The data includes demographic information, service subscription, contractual information, and billing features (Kleon, 2025). The target variable is the customer churn status, which is a binary outcome that shows whether a customer stopped using the service. The data is representative of a realistic business scenario and has enough variability to model and conduct interpretability analysis.

## **2.3 Data Preprocessing**

Primary data analysis was conducted to evaluate the type of variables, missing data, and the general quality of data. A number of variables had missing data, which were processed using a preprocessing plan. Binary indicator variables were formed to explicitly define missingness of features with incomplete values. Median values were used to impute numerical variables and an explicit category of Unknown was used to impute categorical variables. This method maintained the information related to missing data and retained the analytical completeness. One-hot encoding was then used to encode all categorical variables into numerical representations. The identifier variables were not included in the modeling to avoid information leakage.

## **2.4 Predictive Modeling**

The primary predictive algorithm was a logistic regression model because it is transparent and it is also suitable to explainable analytics. A stratified split was used to split the dataset into training and testing to preserve the original churn distribution. The training set was trained and predictive performance on the test set measured using standard classification measures, such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC). Logistic regression was an interpretable baseline, which allowed the direct analysis of the effects of features.

## **2.5 Global Explainability Analysis**

The first measure of global explainability was the coefficients of the logistic regression model. These coefficients gave information on the direction and the relative strength of the influence of each predictor on the results of churn at the population level. SHAP-based global importance analysis was performed to supplement model-intrinsic explanations by summing the absolute SHAP values across single predictions. This two-fold strategy allowed juxtaposing assumptions of structural models with predictive behavior that was observed throughout the dataset.

## **2.6 Local Explainability and Visualization**

SHAP-based instance-level analysis was used to analyze local explainability. The values of SHAP were calculated on each test observation in order to break down model predictions into feature-specific contributions. The effect of the positive and negative features was used to create a final churn prediction of a representative customer using a waterfall visualization. This method allowed the clear interpretation of personal choices and showed the way the global trends were reflected on the local level.

## **2.7 Visualization and Analytical Tools**

The Python-based analytical libraries, such as pandas, NumPy, scikit-learn, and SHAP, were used to perform data preprocessing, modeling, and analysis. Matplotlib was used to perform visualization to make it clear and reproducible. All analysis processes were performed based on standard and reproducible workflows and the results were produced directly out of the dataset without any human intervention.

### 3. Results

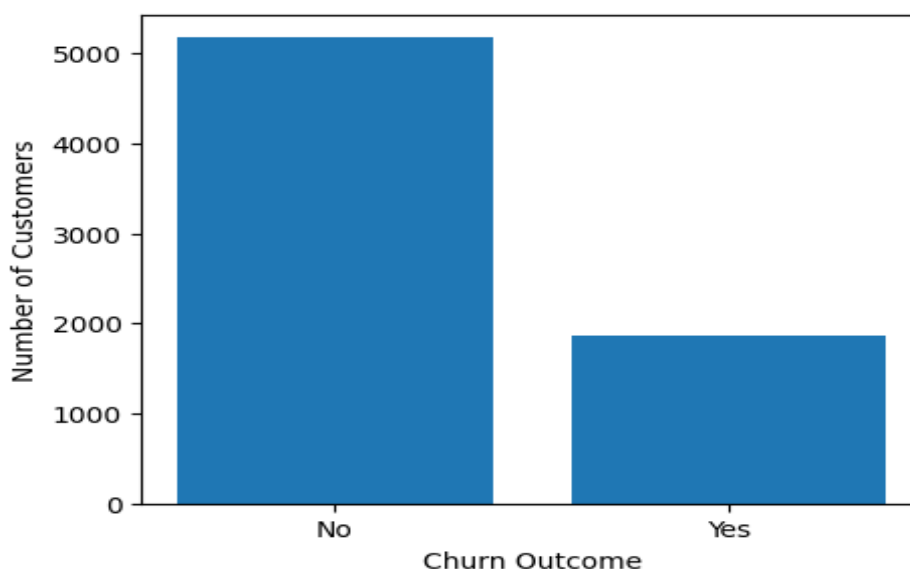
#### 3.1 Dataset Characteristics and Outcome Distribution

The resulting dataset comprised 7,043 observations of customers characterized by 40 coded predictor variables that included demographic features, service subscriptions, contractual terms, and billing features. After preprocessing, the data was ready and fit to be analyzed. The outcome variable showed that 73.46 percent of the customers were retained in the service and 26.54 percent of customers were churned. The distribution is in line with trends that are usually seen in customer retention scenarios. Table 1 presents descriptive statistics of the dataset and distribution of the outcome and Figure 1 demonstrates the visual representation of the churn outcomes.

**Table 1. Dataset characteristics and churn outcome distribution**

| Attribute                            | Description / Value                        |
|--------------------------------------|--------------------------------------------|
| Total observations                   | 7,043                                      |
| Predictor variables (after encoding) | 40                                         |
| Outcome variable                     | Customer churn                             |
| Non-churn customers                  | 5,174 (73.46%)                             |
| Churn customers                      | 1,869 (26.54%)                             |
| Missing values (post-preprocessing)  | None                                       |
| Data type composition                | Demographic, service, contractual, billing |

**Figure 1. Distribution of Customer Churn Outcomes**



#### 3.2 Predictive Performance of the Churn Classification Model

The model was tested on a held-out test set to assess the performance of the churn classification model using standard classification measures. Logistic regression had a total accuracy of about 79 percent and ROC-AUC of 0.83 which is a good separation between churn and non-churn customers. The model showed high recall among non-churn customers (0.89) and lower recall among churn customers (0.49), which is due to the fact that it is more difficult to identify churn behavior. These performance attributes

form a predictive baseline that is reliable and forms a basis of further explainability analysis. The results of the detailed classification are shown in Table 2.

**Table 2. Classification performance metrics for churn prediction**

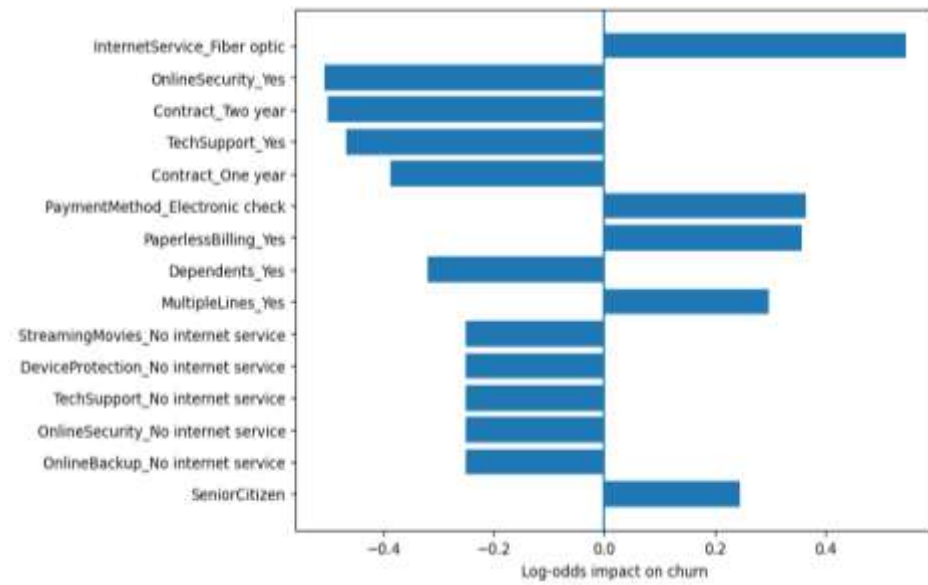
| Metric             | Non-Churn (Class 0) | Churn (Class 1) |
|--------------------|---------------------|-----------------|
| Precision          | 0.83                | 0.62            |
| Recall             | 0.89                | 0.49            |
| F1-score           | 0.86                | 0.55            |
| Support (test set) | 1,294               | 467             |

### 3.3 Global Explainability Based on Logistic Regression Coefficients

The coefficients of the logistic regression model were used to analyze the global trends in churn prediction. The estimates of the coefficients show that the service configuration, the duration of the contract, and the features associated with the support have a significant impact on the churn results. Specifically, fiber-optic internet service and electronic check payment option were found to correlate with greater churn propensity, and longer contract terms, online security services, and technical support were found to be correlated with lower churn risk. These correlations indicate that the service experience and the commitment of the contract are significant in customer retention. The most significant predictors and the value of their coefficients are summarized in Table 3, and their directional effects are depicted in Figure 2.

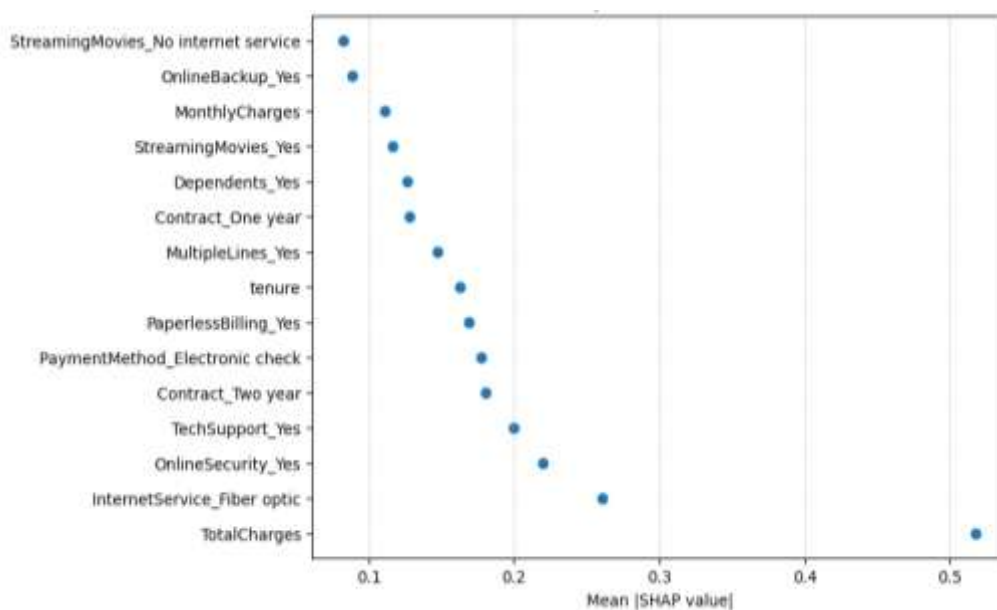
**Table 3. Most influential predictors of churn based on logistic regression coefficients**

| Rank | Predictor                      | Coefficient Direction | Interpretation                          |
|------|--------------------------------|-----------------------|-----------------------------------------|
| 1    | InternetService_Fiber optic    | Positive              | Associated with higher churn propensity |
| 2    | OnlineSecurity_Yes             | Negative              | Reduces likelihood of churn             |
| 3    | Contract_Two year              | Negative              | Strong retention effect                 |
| 4    | TechSupport_Yes                | Negative              | Service support lowers churn risk       |
| 5    | Contract_One year              | Negative              | Moderate retention effect               |
| 6    | PaymentMethod_Electronic check | Positive              | Higher churn risk associated            |
| 7    | PaperlessBilling_Yes           | Positive              | Linked to increased churn likelihood    |
| 8    | Dependents_Yes                 | Negative              | Family association reduces churn        |
| 9    | MultipleLines_Yes              | Positive              | Slight increase in churn risk           |
| 10   | SeniorCitizen                  | Positive              | Higher churn vulnerability observed     |

**Figure 2. Global Feature Effects on Churn Based on Logistic Regression Coefficients**

### 3.4 Visual Analytics of Global Feature Importance Using SHAP

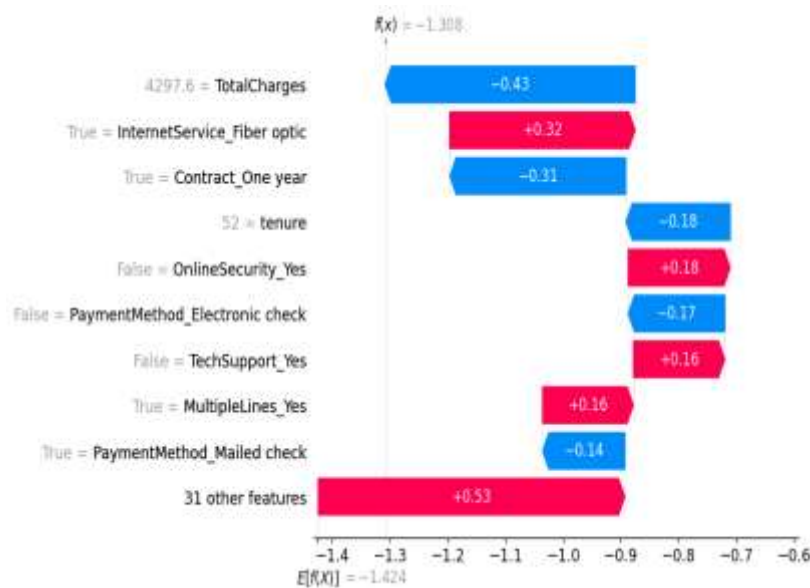
To further investigate the feature importance on the basis of predictive behavior, global explainability was evaluated through SHAP-based analysis. The SHAP values give an understanding of the comparative influence of features on model outputs on the customer population by summing up the local contributions of individual predictions. The analysis shows that total charges, type of internet services, duration of contract, and support services are significant predictors of churn, which supports the trends in the coefficient-based analysis. These effects can be viewed in a more visually differentiated way in the dot-based SHAP global importance visualization in Figure 3, which allows the intuitive interpretation of the magnitude of feature influence.

**Figure 3. Global Feature Importance Derived from SHAP Values**

### 3.5 Local Explainability Through Instance-Level SHAP Analysis

Besides the global trends, local explainability was also analyzed to provide the formation of individual churn predictions. A representative customer was analyzed at the instance-level SHAP analysis, which breaks down the prediction of the model into contributions of the features. The resulting waterfall plot shows that longer tenure and cumulative charges were associated with lower churn risk, whereas the use of fiber-optic services and lack of online security and technical support were associated with higher churn propensity. The last prediction is the effect of all these factors, which shows how the trends at the population level are reflected in the individual level. Figure 4 demonstrates the instance-level explanation.

**Figure 4. Instance-Level Explanation of Churn Prediction Using SHAP Waterfall Plot**



Collectively, the findings demonstrate that explainable AI approaches, with the help of the relevant visual analytics, can be used to interpret the churn behavior at various analytical levels. International studies show that there are structural forces of churn, whereas local explanations give an understanding of the specific decision outcomes. Visualization is critical in the transformation of complex model outputs into readable patterns that can help to understand predictive behavior in a transparent manner and make informed decisions in the business environment.

## 4. Discussion

The results of the current study indicate the importance of the combination of explainable artificial intelligence and data visualization in data science processes to support business decisions. The study also highlights the significance of interpretability in the interpretation of customer behavior by going beyond a single focus on predictive accuracy, especially in areas like churn management where strategic interventions rely on clear and reliable insights (Brasse et al., 2023). Predictively, the logistic regression model was found to have a good discrimination between churn and non-churn customers, which means that customer behavior can be well represented by a combination of demographic, service-related, contractual, and billing attributes. The imbalance in recall between churn and non-churn classes is in line with previous studies on churn prediction, which often indicate that it is more challenging to predict the customers who will leave than those who

will stay. Instead of being a weakness of the method, this asymmetry supports the applicability of explainable AI, since the interpretability is especially useful in the cases where the predictions are uncertain and trade-offs are involved.

The global explainability analysis gives an understanding of the structural factors of churn on the population level. Service configuration and contractual commitment became the key predictors of churn propensity, where premium service offerings like fiber-optic internet were linked to higher churn risk and longer contract terms and value-added services like online security and technical support were found to stabilize churn propensity. These trends are generally in line with the current literature on customer retention, which highlights the quality-of-service expectations and contractual lock-in in the formation of customer loyalty (Chaudhary et al., 2025). The overlap of model-intrinsic explanations based on the logistic regression coefficients with post-hoc SHAP-based importance measures indicates that the model is able to capture meaningful relationships and not spurious correlations.

Notably, the SHAP-based global analysis contributes to the coefficient-based results by showing the extent to which features actually affect predictions by heterogeneous customer profiles. Whereas coefficients characterize the average directional effects when the model assumes that the effects are average, SHAP values sum up actual contributions found in individual predictions, and thus characterize variability and interaction effects found in the data. The fact that these two explainability perspectives are aligned reinforces the belief in the strength of the identified churn drivers and proves the complementary nature of intrinsic and post-hoc explainability approaches (Asif et al., 2025). At the individual level, the local explainability analysis demonstrates that churn risk is caused by the combination of various factors and not single predictors. The instance-level SHAP waterfall analysis demonstrates that the long-term engagement indicators, including longer tenure and cumulative charges, can help to eliminate the churn risk despite the risk-promoting factors, such as the type of service or the lack of support features. This subtle perception brings out the contingent and contextualized nature of churn behavior, which is usually lost in aggregate analyses. These localized accounts are especially useful in an operational context, where retention policies are implemented at the customer level and not at the population level (Imani et al., 2025).

One of the contributions of this study is the role of data visualization in increasing interpretability. Explainability outputs are represented visually and can be used to support cognitive processing and make complex model behavior easier to understand by the stakeholders. Through the use of varying visual representations of different levels of explanation including coefficient plots to SHAP-based global and local visualisations this paper has shown how visualisation can aid the layered interpretation of predictive models. Such visual distinction does not only enhance interpretability, but also minimizes the possibility of misinterpretation, particularly by non-technical decision-makers (Kucher et al., 2025). In a wider sense, the research will add to the current debate on the responsible and transparent application of artificial intelligence in business analytics. As organizations are becoming more and more dependent on data-driven systems to make strategic decisions, there is an increasing need to have models which are not only accurate but also interpretable. The results indicate that explainable AI systems can help reduce the divide between the technical model creation and the real business implementation, allowing organizations to extract practical information without losing trust and accountability (Leichtmann et al., 2023).

In general, the discussion supports the idea that explainability is an essential part of data science practice, but not a secondary functionality. The study combines interpretable modeling, post hoc explainability methods and visual analytics to offer a holistic framework of generating business insights that are analytically sound and practically

meaningful. This method is consistent with the current trends in explainable AI research and provides a way of making decisions in a more transparent and informed way in a complex business setting.

### **5. Conclusion**

The growing usage of data-driven models in business analytics has increased the pressure on the approaches that would incorporate both predictive and interpretable capabilities. In this framework, the current study examined the incorporation of explainable artificial intelligence and data visualization in assisting transparent and meaningful business insights out of customer churn data. The analysis demonstrates that the churn behavior is influenced by a set of service-related factors, contractual provisions, and customer interaction patterns. Although predictive modeling offers an effective tool to define the customers at risk of churn, explainable AI methods allow a more in-depth view of the mechanism of forming such predictions. Global explainability provides understanding of the drivers at the population level that are used to make strategic decisions, but local explanations clarify how individual predictions are the result of interacting factors, which underlies more focused and context-specific interventions. Visualization comes out as a particularly significant part of the process of converting the results of intricate analytical tasks into an easy-to-understand form. Through the use of specific visual forms that are consistent with various levels of explanation, the study illustrates how data visualization can be used to improve the understanding of model behavior among various stakeholders. This integration enhances increased transparency, trust in analytical systems, and the ease of use of the data science results in the operational environment. In general, the results indicate that explainability needs to be incorporated as an essential part of the business analytics processes instead of a secondary feature. Interpretable modeling, explainable AI techniques, and visual analytics give a systematic way of producing insights that are not based solely on prediction. This approach has practical value to organizations aiming to achieve a balance between analytical performance and transparency and informed decision-making within more complex data environments.

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