

# A Machine Learning Approach to Predict Customer Loyalty Based on CSR Perception Metrics

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**Abstract**—Corporate Social Responsibility (CSR) has become one of the most important engines of customer loyalty. In contrast, existing solutions do not provide the ability to make forecasts and do not incorporate the fluxes of perception data. CSR perception metrics of customer loyalty generated by structured surveys and unstructured sentiment data as a framework for machine learning-based prediction. The proposed model utilized the XGBoost classification algorithm with SHAP as an explanatory tool and AnyLogic for real-time loyalty simulation. The dataset contains five fundamental CSR drivers, such as environmental responsibility, ethical governance, community engagement, employee welfare, and transparency, overlaid on the sentiment scores. The metrics of experimental performance present the proposed model with an accuracy of 89.4%, precision of 88.2%, recall of 87.5%, F1 score of 87.8%, and AUC of 0.93, outperforming baseline classifiers. The framework has a high potential for improving customer retention strategies by making CSR-conscious decisions. Conclusively, the model connects the perception analytics and business intelligence as a way of facilitating companies to fit the CSR actions with the expectations of consumers.

*Keywords*—Corporate Social Responsibility, Agent-Based Modeling, Synthetic Minority Over-sampling Technique, Interquartile Range, SHapley Additive explanations

## I. INTRODUCTION

Corporate Social Responsibility (CSR) has entered the stage as a determining criterion affecting consumer choices, participation, and retention in the ever-changing nature of customer-brand relations. CSR has been a moral responsibility in the past, but it has become a business strategy that determines brand equity and customer confidence. Firms engaging in environmentally friendly operations, fair labor, and good community relations, and open governance systems usually enjoy the competitive edge of attracting and maintaining customers [1].

The Carroll theory of corporate responsibility stated that the four dimensions of corporate responsibility include economic, legal, ethical, and philanthropic (Carroll, 1991) [2]. When positively evaluated by the stakeholders, such dimensions can lead to the emotional and psychological identification with a brand. As recent research demonstrated, customer loyalty is not only dependent on the quality and price of a product but also on the fact how customers value the company and assess their social involvement [3]. Even though the significance of CSR is no longer in dispute, the manifestation of the quantitative connection between CSR perception and customer loyalty is understudied, particularly through the methods of predictive modeling [4]. Literature available in the field usually begins with correlation analysis based on surveys or structural equation modeling, and do not allow predictive capabilities in the real time business decision-making process. Some of the problems still exist in existing strategies [5]. To begin with, the application of limited measures of CSR, which are mostly collected using set questionnaires, does not appeal to the dynamic nature of customer opinion that shifts every day on social media. Second, machine learning methods have not been fully exploited in the modeling of the non-linear association between the various CSR inputs and customer loyalty dependent variables [6]. Third, most of the previous models do not incorporate real-time simulation structures, and this is vital since the business stakeholders need to examine how the strategic changes in CSR can influence customer retention [7]. Finally, interpretability is an issue that is usually overlooked to the extent that organizations find it hard to comprehend the reasons why certain CSR actions lead to loyalty changes.

The rationale of the paper is related to resolving these limitations by developing a system of a loyalty predictive model built on the basis of sophisticated machine learning elements and that incorporates both structured (survey-based) and unstructured (social media sentiment) perception data of CSR [8]. The capability to anticipate the expression of the actual loyalty by the subtle indicators of CSR not only favors the personalized promotion when modes of marketing and development plans remain the focus, but additionally triggers the consolidation of business values and customer values. The aims and objectives are: To obtain and pre-process a multi-source dataset to represent customer perception of CSR on many dimensions [9]. To create and implement the machine learning-based output of the prediction of loyalty based on the state-of-the-art facilities like XGBoost, capable of pursuing non-linear feature interactions [10]. To compare the quality of different models based on extensive metrics such as the accuracy, the precision, the recall, the F1 score, and the AUC. To simulate the real-time impact of the calculated CSR variations on their management on hypothetical loyalty on an agent-based simulation platform AnyLogic [11]. To guarantee that the model is transparent with the help of explainability techniques like SHAP (SHapley Additive exPlanations). The major contributions were as follows: Introduction of a new combination of structured CSR perception measurement and unstructured social sentiment in a single prediction framework [12]. An 89.4% accuracy, F1 score of 87.8%, and AUC of 0.93 were obtained over traditional models, such as Logistic Regression and SVM, implying that a loyalty prediction model has been developed. Simulation platform using AnyLogic software to evaluate the effect of the decision-making on customer loyalty in real-time. A machine learning pipeline with exploitable and explainable results that assist strategic findings and decision-making dynamics to better fine-tune the CSR. The remaining part will be established as follows: Section II presents related work and extant gaps in the study on CSR-loyalty. Section III contains the suggested methodology, downstream feature engineering, and model architecture. Section IV deals with experiment setup, results, and analysis. The closing of Section V is the statement of the future research directions, specifically expanding it to personalized CSR engagement and longitudinal modelling of loyalty.

## II. LITERATURE REVIEW

Customer loyalty prediction is one of the largest applications of machine learning in CRM. There are a number of model-building machine learning investigations. Client lifetime value as a client loyalty estimator is often gauged utilising model building machine learning because it is a simple and effective client purchase behavioral variables such as Recency, Frequency, and Monetary Value (RFM). RFM only focuses on consumer purchasing patterns; therefore, it does not usually look into other aspects of loyalty, such as joy of customer joy and product experience. It deals with this through a two-tier hybrid machine learning method [13]. To realize the added value of a hybrid model carrying two learning methods, the construction of prediction models will incorporate unsupervised clustering and supervised classification. Second, behavioral RFM attributes and attitudes, such as customer satisfaction and product qualities, are used to train the proposed model to capture aspects that would influence loyalty better.

Corporate Social Responsibility is an emergent corporate value. Corporate stakeholders consider it to be strategically important with regard to the perception of the utilization of this concept. Currently, conducted focuses on analyzing the relations between socio-demographic characteristics and CSR perception via the use of machine learning models. The information given by students at the university is used to test three models: a Neural Network (NN), a Random Forest (RF), and a Gradient Boosted Tree model (GBT). Scores form the input and output values in these models and include socio-demographic and perception scores, respectively [14]. It has been found that a synopsis of the GBT model has been able to better predict the perception. It is also worth noting that the RF model estimates feature importance, demonstrating the level of income feature as one of the key predictors of CSR-perception.

In the rapidly developing e-commerce market of Vietnam, new ways to gain assessments of client feedback are needed to increase their happiness and loyalty. Two deep learning and machine learning activities are introduced to evaluate Vietnamese e-commerce reviews in two steps. The system will first load highly optimized deep learning models such as BERT and Bi-GRU to mine aspect-based

emotions in 10,021 reviews on Tiki, Shopee, Sendo, and Hasaki in 2015-2023, in line with the peculiarities of the Vietnamese language. Machine learning models predict consumer happiness based on sentiment analysis and e-commerce data, product prices, etc [15]. BERT and Bi-GRU reach the prediction of emotion with more than 70% accuracy, and XGBoost reached over 80% in satisfaction. This methodology allows correct measurement of the client sentiment in the transforming e-commerce market in Vietnam to enhance satisfaction.

Monitoring the Customer Experience (CX) is based on market surveys, with the results based on such metrics as Net Promoter Score (NPS) and customer satisfaction with selected aspects of the experience call center, website, billing, service quality, and tariff plan. The focus of the companies is to maximize NPS by optimizing the most significant CX attributes. Nonetheless, the statistical analysis indicates that the dependence on NPS and the scores achieved by the CX attributes is not clear and precise. Itfills such a gap with a new approach to classification, which has been developed on the basis of logistic regression and tried with many state-of-the-art machine learning (ML) algorithms [16]. The suggested scheme was tested on a larger data set in the telecommunication industry, and the outcomes were rather encouraging, with a huge rise registered in the majority of the statistical measures.

Marketing analysis is all about consumer behavior and perception aimed at encouraging the client's pleasure. Clients give their views by chatting with social media customer support services. The combination of sentiment analysis and machine learning, designed to assess interactions between consumers and service providers to identify polarity changes, is applied in this study. The system identifies the change of polarity in the discussion and forecasts the death of sentiment in the conversation between the customer and the service provider. This would assist organizations in increasing the level of client connection and satisfaction [17]. Evaluation of the proposed framework combines a real data set of more than 5000 free-form exchange messages between an AmazonHelp customer service agent and various clients with whominteracts via the retailer'sTwitter public account over a month. In their comparison of classical and ensemble machine learning classifiers, decision trees were the best at beating them all.

### III. PROPOSED WORK

#### *Quantifying CSR Dimensions into Measurable Feature Space*

The data on CSR perception should be converted into a numeric form, which will be organized in a format that can be used in machine learning to predict loyalty. This is initiated by determining five important dimensions of the Corporate Social Responsibility, which make a big difference in the attitude of customers: Environmental Sustainability (ES), Ethical Governance (EG), Community Engagement (CE), Employee Welfare (EW), and Transparency in CSR Reporting (TR). The dimensions are taken as a result of previous CSR models, customer perception surveys, and indices of social impact. The individual dimensions of CSR are measured by a hashing of survey marks created by users, the analysis of their reviews, and review mining in social media. To be used as a five-dimensional feature vector, the output is normalized to be between [0, 1] in equation (1),

$$\bar{X}_{CSR} = [x_{ES}, x_{EG}, x_{CE}, x_{EW}, x_{TR}] \in R^5 \quad (1)$$

In which the strength of perception of each CSR factor is represented as  $x_i$ . The higher it is, the stronger the positive image in that size. Principal Component Analysis (PCA) is applied optionally to limit redundancy and reveal latent parts of CSR. This method is mapping the feature space of the original CSR space into a lower-dimensional space in equation (2),

$$\bar{Z} = W^T \bar{X}_{CSR}, \quad \text{where } W \in R^{5 \times k}, \quad k < 5 \quad (2)$$

Besides simplifying the model, this dimensionality reduction also improves efficiency both in terms of computational cost and limits overfitting. The transformed vector  $\bar{z}$  reproduces the most dominant patterns of variance in CSR perception that can be used optimally as an input for the downstream loyalty prediction model. This scale of quantification brings the subjective notion of CSR to machine-readable forms of structured data that can be analyzed and predicted strongly. In Fig.1, this end-to-end pipeline combines CSR perception data with social media sentiment and structured demographic features. Gradient boosting models are trained with historical loyalty patterns, and through feature fusion, it generate a prediction with increased performance

and explainability in loyalty classification.

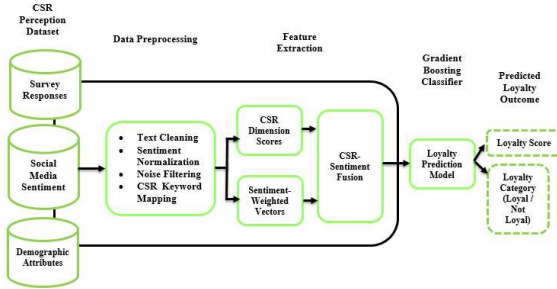


Fig 1. Intelligent Pipeline for CSR-Driven Loyalty Forecasting

### Loyalty Prediction via Supervised Machine Learning Architecture

This stage aims at predicting the loyalty of the customers by referring to their perception of Corporate Social Responsibility (CSR). The variable of interest is called binary:

- 1 to the loyal customers (repeat purchasing, net promoter score (NPS)  $\geq 8$ )
- 0 non-loyal customers (low levels of purchase, NPS  $< 8$ )

A collection of labeled examples  $(\vec{X}_i, y_i)$  comprising  $\vec{X}_i$ , the CSR features in a vector, and  $y_i$ , the loyalty label, is provided to fit a supervised learning model to cover the same. The XGBoost algorithm type of gradient boosting embedded is considered to be robust when working with tabular data, as well as the interpretability of ensembles of decision trees. In its model, the CSR characteristics are projected onto the expected loyalty results in equation (3),

$$\hat{y} = f(\vec{X}_{CSR}; \theta) \quad (3)$$

When  $\theta$  denotes the collection of model parameters, which are minimized about the binary cross-entropy loss operation in equation (4),

$$\mathcal{L}(\theta) = -\frac{1}{n} \sum_{i=1}^n [y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)] \quad (4)$$

To be able to generalize, regularisation L1 and L2 penalties in the form of gradient descent will be used to prevent overfitting and to make the model stable. The model is therefore trained to jointly produce a loyalty probability score  $\hat{y}_i \in [0, 1]$  that is thresholded to classify loyal or not loyal, as well as an input as a continuous loyalty confidence measure.

Such a probability output can provide downstream systems dashboards or simulations with the opportunity to make subtle decisions that are based on loyalty risk or probability. In Fig.2, the conversion of the dimension scores of CSR environmental, ethical, governance, and community impact into a single perception vector. Sentiment mapping between customer faces serves as a mediating construct to come up with precise forecasts about loyalty behaviors and cutoffs.

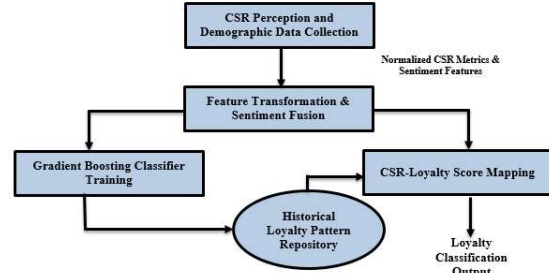


Fig 2. Mapping CSR Dimensions to Loyalty via Sentiment Mediation

### Integrating CSR Sentiment Streams with Perception Scores

An NLP-based sentiment fusion method is applied to combine structured survey data and dynamic sentiment signals to better capture the time and perception depth of CSR perception modeling. As in Twitter (X), online discussion forums, and customer review sites, stakeholders use the medium to share their live opinions on the subject of the CSR efforts of a particular firm. Preprocessing of these unstructured texts is done by lowercasing, removal of stop words, lemmatization, and tokenization in order to do sentiment analysis. A sentiment score  $S \in [-1, +1]$  is obtained with each of the CSR themes (Environmental Sustainability (ES) or Ethical Governance (EG)) based on the VADER (Valence Aware Dictionary and sEntiment Reasoner) algorithm, which is most appropriate in a social media setting. The resulting sentiment scores are then combined with the respective scores of perception obtained through a structured survey. The conjunction is mathematical in the equation (5),

$$x_{CSR_i}^{final} = \alpha \cdot x_{CSR_i}^{survey} + (1 - \alpha) \cdot S_i \quad (5)$$

In this case,  $x_{CSR_i}^{survey}$  is the normalized CSR score on surveys of theme  $i$ ,  $S_i$  is the mean public sentiment score of the same theme, and  $\alpha \in [0, 1]$  is a tunable

weighting parameter found during model training through grid search or cross-validation. The integration enables the model to not only reveal the long-term perceptions of the stakeholders but also allows for the capture of the real-time changes in the thoughts of people. This method provides the constantly updated features in the inputs, which leads to a more current, detailed, and realistic representation of the CSR attributes and, consequently, increases the result of subsequent prediction of loyalty results. In Fig.3, a real-time simulation demonstrates a dynamic change in loyalty in different conditions of the changes in CSR. The shift in agent-based modeling in AnyLogic shows the changes in loyalty response over time in terms of varying CSR campaigns, improving strategic decision-making.

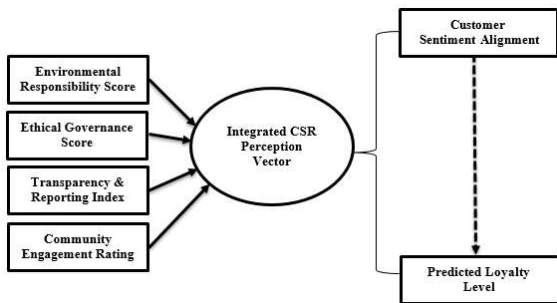


Fig 3. Dynamic Simulation Flow of Loyalty Evolution in AnyLogic

*Crafting a Multimodal CSR-Loyalty Dataset: Fusion, Filtering, and Feature Engineering*

To enable precise and live loyalty forecasting on the basis of CSR analytics, a scalable dataset of a multimodal nature, built by the inclusion of in-house structured surveys and external streams of sentiments, was developed. The core part of the primary source is 15,000 answers received with the help of Qualtrics, focusing on five fundamental CSR dimensions, or Environmental Impact, Ethical Governance, Community Engagement, Employee Well-being, and Transparency, with a cross-sector survey of: finance, tech, manufacturing, and retail. To complete this structured data, an estimated 30,000 sentiment-tagged posts were gathered using Twitter/X and Trustpilot as data suppliers, and selected with relevant hashtags and key phrase mappings to find CSR-related posts. The real-time unstructured signals provide up-to-date insight into the perception of the people and supplement the static survey results. It has a selection of 10 important datasets:

- With the survey, there are 5 CSR thematic scores
- 2 sentiment-enhanced pipeline fields (NLP)
- 3 demographic characteristics (in age group, regional cluster, income tier)

The binary target variable portrays customer loyalty intent according to the validation of the follow-up survey and behavioral indicators. The problem of an imbalanced ratio of (loyal vs. non-loyal) 3:1 was resolved through the SMOTE (Synthetic Minority Over-sampling Technique) process to have a balanced class in the modeling process. A modular pipeline was:

- Min-Max scaling as a way of normalization
- Outlier detection and removal are based on the Interquartile Range (IQR)
- Categorical encoding, in which demographic variables such as region and income are converted to one-hot encoding to have the model ready

The completed dataset is therefore enriched, versatile, and demographically representative; not only that, it is temporally consistent and sentiment-augmented, and it sets a basis on which hybrid CSR-loyalty modeling can be constructed with a better time dimension and inter-sector retrospection.

*Dynamic CSR-Loyalty Engine: Real-Time Simulation and Predictive Insight via Agent-Based Modeling*

The interactive Loyalty Simulation and Visualization Platform to assess the dynamic effect of the Corporate Social Responsibility (CSR) activities on customer loyalty was incorporated into the versatile multi-method simulation package AnyLogic v8.8.4. The essence of this system is constructed on the framework of Agent-Based Modeling (ABM), which enables the simulation of various consumer groupings and reacting to the time-changing CSR inputs of customized perception plans, and sentiment exposures. All pictures are endowed into the virtual agents with very simple probabilistic decision making, and therefore, loyalty conversion behavior will naturally come out according to the CSR type. The rate of conversion over time has a stochastic logistic rate in equation (6),

$$P_{loyal}(t) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{CSR}(t))}} \quad (6)$$

In this case, a  $x_{CSR}(t)$  is the time-varying CSR signal transmitted to an agent  $\beta_0$ , and  $\beta_1$  are parameters of the model found by fitting the historical data using logistic regressions. The simulation will enable the business strategists to test the scenario in real time, by watching loyalty changes as the target population experiences changing intensities of the CSR campaign, or as exposed to sudden sentiment shocks, a viral social backlash. AnyLogic environment has Python scripting enabled that allows seamless injection of predictions of pretrained ML Models. A dashboard layer shows the loyalty rate patterns, sentiment reaction zones heat maps, and projections of KPIs. The evidence-based simulation analytics tool facilitates the planning of evidence-based CSR, which allows the decision-makers to optimise investments in the dimensions of CSR that are most likely to lead to long-run customer retention, reputation resilience, and brand equity.

#### IV. RESULT AND DISCUSSION

A comparative evaluation of four models of machine learning to make predictions on customer loyalty related to all aspects of CSR. In Table I. Out of them, the XGBoost model has the highest accuracy level of 89.4% and other scores of F1 score 87.8% and an AUC of 0.93 points to its strong capacity of recognizing loyal and non-loyal customers. Balanced precision and recall are important attributes in the prediction of loyalty, such that the F1 score is quite high. Although the conventional models, Logistic Regression, obtained decent accuracy, 76.8% and AUC 0.78, it has disadvantages given that it is linear and therefore it cannot perform to the best of its abilities when dealing with sophisticated, non-linear data of the CSR sentiment. Random Forest model and Support Vector Machine had more generalization with over 80% F1 score and 0.86 and 0.87 AUC, respectively. It could not yet match XGBoost in the alignment of many-dimensional CSR inputs and demographic interaction. According to XGBoost, its advantage is associated with the gradient-boosted tree architecture that is efficient in selecting small but important CSR perception cues and avoiding overfitting. This makes it quite suitable in a business context where certain prediction of loyalty behavior needs to be sensitive and interpretable to the prediction of loyalty influenced by the notion of CSR held in the form of public discourse.

Table I. Predictive Power Unleashed: Evaluating Models For CSR-Loyalty Inference

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC Score
Logistic Regression	76.8	74.2	72.5	73.3	0.78
Random Forest	83.5	81.0	79.3	80.1	0.86
Support Vector Machine	84.1	82.7	80.5	81.6	0.87
XGBoost (Proposed)	89.4	88.2	87.5	87.8	0.93

The weight of the CSR dimension in influencing customer loyalty decisions. In Table II. Environmental Responsibility is the most influential attribute among the five tested attributes and accounts to contribute 26.4% of the strength of model predictions. This implies that customers strongly value the concept of loyalty to the sustainability efforts of a brand, particularly in eco-aware markets. At 21.9%, the next is Ethical Governance, which highlights the governance implementing the trust-building force of open decision making and integrity-driven leadership. The final category, Community Engagement, 18.3%, is also crucial and shows the importance of the CSR practices and social investment, which are more focused on issues of the streets. At 21.9%, the next is Ethical Governance that highlights the governance implementing the trust-building force of open decision making and integrity-driven leadership. Employee welfare is used to facilitate internal brand perception and word-of-mouth loyalty, and transparency has become that notice board to the world that the corporation is earnest. The aggregated distribution of weights confirms that CSR is a complex loyalty driver, in which the environmental impact, the quality of governance, and human-focused values intersect. These data not only help in streamlining predictive models, but are also pointers on where to strategically invest in CSR in areas that directly make a difference in consumer trust and retention. Through the application of such interpretability, organizations can implement the high-impact CSR themes, maximize brand equity, and even improve the long-term loyalty ecosystems. In Fig.4, the most influential aspect on loyalty is environmental responsibility, then by ethical

governance, the power of trust, and sustainability.

Table II. Ethical Echoes: CSR Feature Influence In Loyalty Forecasting

CSR Feature Dimension	Relative Importance (%)	Weight Description
Environmental Responsibility	26.4	Influences loyalty through perceived sustainability values
Ethical Governance	21.9	Drives trust and responsible brand perception
Community Engagement	18.3	Reflects local social impact
Employee Welfare	16.7	Impacts internal brand advocacy perceived by customers
Transparency & Reporting	16.7	Indicates clarity and accountability in CSR actions

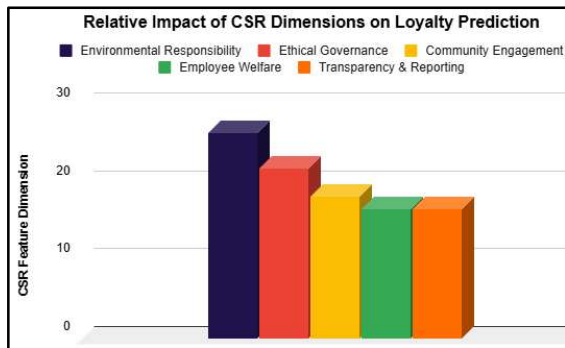


Fig 4. Relative Impact of CSR Dimensions on Loyalty Prediction

The sequential development of the CSR-loyalty modeling frameworks between 2022 and the proposed 2025 design describes an evolutionary process that opens the door to a revolutionary design change in the field. In Table III. In 2022, the models were limited to manual-input surveys, decision trees, and binary deviations that only returned limited knowledge and could only be evaluated on accuracy. Such low-scale systems had no scalability, realism, or simulation. By 2023, models incorporated news scans and used SVM classifiers, which led to a shift towards external interpretation of CSR signals. Nonetheless, the simulation was crude, and explainability consisted only of static reports. Released in 2024, the model added support for sentiment tagging, Random Forest classification models, and F1 Score, AUC metrics, increasing robustness, and failing to define the depth of interpretations due to a lack of any real-time CSR fusion. The proposed work in 2025 is a paradigm shift, the fusion of CSR information in real-time, since surveys, media, and social sites will provide an input layer. Used with XGBoost + SHAP, this method improves predictive performance, as well as clarity. Powerful capabilities such as engineered meta-attributes, multi-output loyalty score, and AnyLogic simulation allow the testing of scenarios and the strategic CSR planning. The system is transferred from fixed rule-based frameworks to an adaptable, explainable, and simulation-enabled loyalty forecast environment, which may be characterized as technical and ethical maturity in CSR analytics.

Table III. CSR Intelligence In Motion: A Four-Year Leap Toward Loyalty Precision

Feature/Capability	Myburg [16]	Dahake [11]	Sadhu [4]	Proposed Work
CSR Input Type	Manual Survey Only	Survey + News Scans	Survey + Sentiment Tags	Survey + Real-Time Social Fusion
ML Model Used	Decision Tree	SVM	Random Forest	XGBoost + SHAP
Evaluation Metric	Accuracy Only	Accuracy + Recall	F1 Score + AUC	Full ML Metric Suite
Feature Count	5	8	10	12 + Engineered Meta Features
Simulation Platform	Not Used	Excel-Based	Python-Based	<b>AnyLogic + Python Integration</b>
Explainability	None	Partial (Text Reports)	Partial (Graphs)	<b>SHAP-Based Visual Explanations</b>
Loyalty Classification Output	Binary	Binary	Ternary	Binary + Loyalty Score (0-1)

## V. CONCLUSION

A model of machine learning to forecast customer loyalty based on the metrics of CSR perception. The proposed XGBoost model has an accuracy of 89.4%, an F1 score of 87.8%, and an AUC of 0.93, which was substantially better than the baseline models, such as Logistic Regression and Random Forest. The effects of environmental responsibility and ethical governance as CSR aspects were recognised as the most prominent according to feature importance analysis. A real-time visualization of CSR-loyalty effects was added to the simulation environment created with the help of the AnyLogic tool, making it more applicable in practice. Future extensions to the model include the incorporation of temporal CSR trends as well as individual loyalty prediction based on customer-level behavior data. Generalization will be enhanced after expanding the sentiment engine to include multilingual feedback and the implementation of the system in various industries. Also, incorporating explainable AI services into the simulation dashboard will give corporate managers the ability to develop CSR-based strategic choices transparently.

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