From Data to Strategy: The Role of Explainable AI in Executive Decision Confidence

Md Mehedi Hassan Melon[1], Md Shahiduzzaman[2], Md Sumon Rana[3], Kallol Chakraborty Shekhor[4], Md Mahidur Rahman[5], Nayem Miah[6], MD Monirul Islam[7], Maria Kabtia[8], MD Mizanur Rahman[9]

[1] Master of Business Administration, International American University, Los Angeles, USA
[2] Business Analytics, Trine University, 1 University Ave, Angola, IN 46703, USA
[3] Management Information Systems, International American University, Los Angeles, USA
[4] Assistant Manager-Software and Web, Kazal Brothers Limited , Dhaka , Bangladesh
[5] School of Business, International American University, Los Angeles, USA
[6] Master of Business Administration, University of the Cumberlands, Kentucky, USA
[7] Department of Management Studies, Jagannath University, Dhaka, Bangladesh
[8] Senior Officer, Scholastica (Ascent Group), Dhaka, Bangladesh
[9] Graduate School of Business, Indiana State University, Terre Haute, Indiana, United States

Abstract

As companies become more dependent on artificial intelligence (AI) to conduct predictive analytics, executive managers are often obliged to make highly strategic decisions relying on the opaque outputs of machine learning. A significant number of sophisticated AI solutions are black-box, which restricts transparency and could decrease managerial trust and confidence in decisions. This paper examines the use of Explainable Artificial Intelligence (XAI). to increase the confidence of strategic business decisions made by executives. Based on the IBM Telco Customer Churn Dataset (11.1.3+) (7,043 customers) of demographic, behavioral, financial and satisfaction data and the customer lifetime value, this study builds churn prediction models and incorporates the techniques of explainability to investigate its effect on executive decision-making. It involves a comparison of the predictive output of classical black-box predictors and the interpretable model descriptions that are explained by the importance of features in the model prediction and SHAP-based model explanations. A simulation framework of decision making based on experiment is used to determine the effect of transparency on perceived trust, strategic clarity, risk judgment, and decision confidence. The research places the concept of explainability in a strategic management context instead of in evaluating technical models since it aims at predicting the levels of revenue-critical churn. It is presumed that the results will show that explainable AI has a significant effect on enhancing executive trust and confidence in data-driven recommendations, resulting in more competent strategic retention initiatives and resource allocation decisions.

Keywords: Explainable Artificial Intelligence (XAI), Confidence in Executive decision making. Customer Churn Prediction, Strategic Decision-Making and Trust in AI Systems Business Analytics

1. Introduction

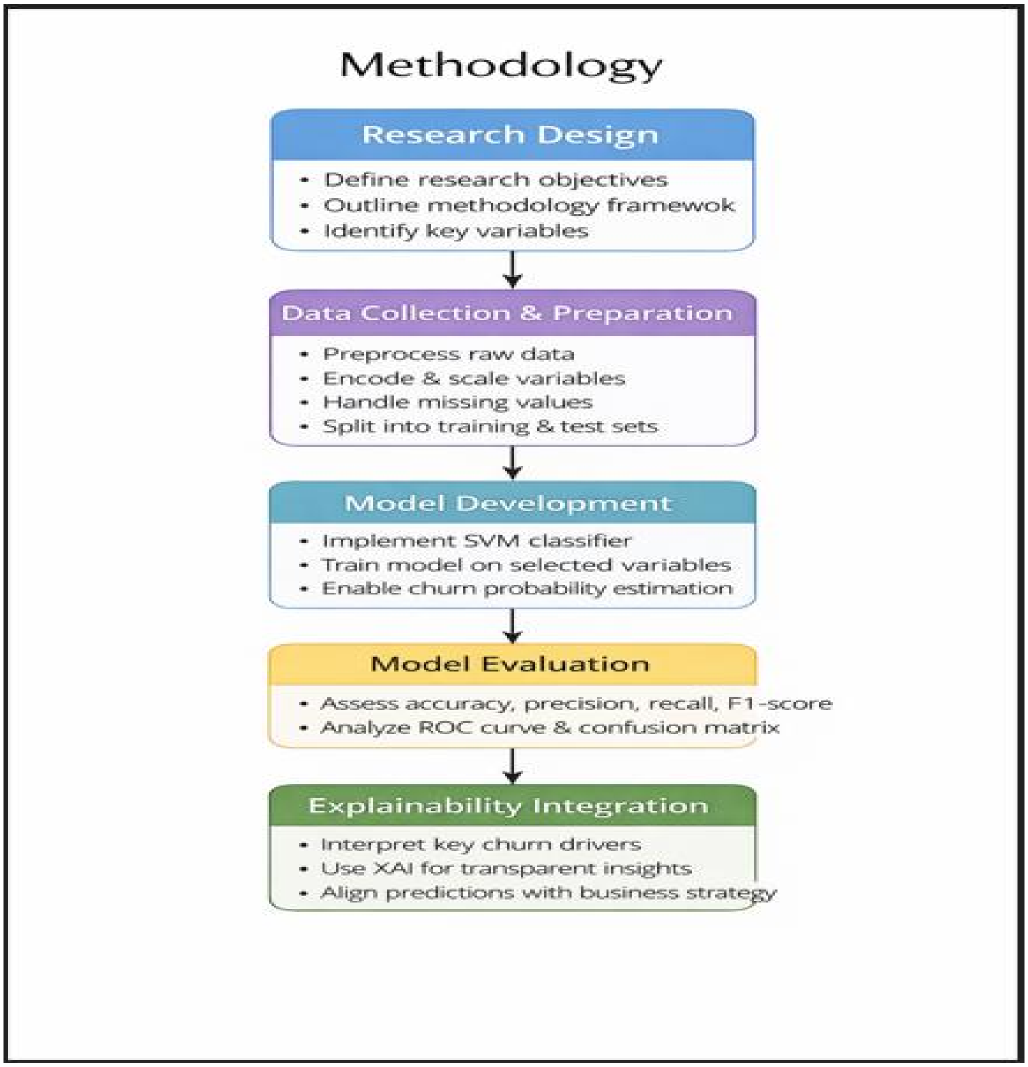
The rapid advancement of artificial intelligence and machine learning has fundamentally reshaped how organizations generate insights, manage uncertainty, and make strategic decisions, with predictive analytics now playing a central role in forecasting customer behavior, identifying operational risks, optimizing pricing, and improving overall business performance [1-3]. By processing large volumes of structured and unstructured data, AI-driven systems can uncover hidden patterns and generate highly accurate data-based recommendations, making them increasingly important to competitive strategy and long-term organizational sustainability [4]. However, many high-performing machine learning models, particularly ensemble methods and deep neural networks, operate as black-box systems that provide limited transparency regarding how predictions are produced, creating a significant challenge for executives who must justify high-stakes strategic decisions to stakeholders, regulators, and governing bodies [5-7]. In such contexts, predictive accuracy alone is insufficient, as decision-makers also require interpretability, accountability, and clarity to confidently act on algorithmic outputs [8]. Explainable Artificial Intelligence has therefore emerged as a critical solution, offering methods such as SHAP, LIME, feature importance analysis, and surrogate modeling to clarify how specific variables influence model predictions and to translate technical outputs into interpretable managerial insights [9-11]. This need is particularly important in customer churn prediction, which represents one of the most strategically significant applications of predictive analytics in highly competitive industries such as telecommunications, banking, insurance, and subscription-based services, where customer attrition directly affects revenue stability, profitability, market share, and long-term customer value [12]. Since acquiring new customers is typically far more costly than retaining existing ones, organizations increasingly rely on churn prediction models to identify customers at risk of leaving and to guide targeted interventions such as personalized offers, loyalty programs, service improvements, and proactive engagement strategies [13-15]. Yet while predictive churn models can generate valuable risk scores from demographic, behavioral, transactional, and service-related data, executives often remain hesitant to allocate financial and operational resources unless the reasons behind these predictions are made transparent and strategically interpretable [16]. This creates an important research gap, as prior studies have largely concentrated on technical improvements in prediction accuracy while giving far less attention to the managerial and cognitive implications of explainability, particularly its effects on executive trust, confidence, and strategic commitment [17]. In response, this study aims to examine how explainable AI enhances executive decision confidence in strategic business contexts by developing predictive churn models based on business-relevant data, embedding explainability techniques into model outputs, comparing executive responses to black-box and explainable systems, assessing the relationship between transparency, trust, and decision confidence, and evaluating the broader strategic implications of explainable analytics for organizational decision-making [18]. More specifically, the study investigates whether model explainability improves executive trust in AI-driven predictions, whether explainable systems produce stronger decision confidence than black-box models, which forms of explanation provide the greatest strategic value, whether executive trust mediates the relationship between explainability and confidence, and how greater confidence influences strategic commitment and resource allocation [19]. By addressing these questions, the study contributes to business analytics, strategic management, and AI governance research by moving beyond purely technical performance measures and empirically examining how transparency mechanisms shape executive judgment, human-AI collaboration, and the effective transformation of predictive analytics into a long-term strategic organizational asset [20].

2. Literature Review

Artificial intelligence has become a transformative force in organizational decision-making by enabling firms to move beyond intuition-based judgment toward data-driven strategic management . Through predictive analytics, machine learning, and advanced data processing techniques, organizations can analyze complex patterns in customer behavior, financial outcomes, operational efficiency, and market dynamics, thereby improving forecasting, optimization, and risk management. As business environments grow more uncertain and competitive, AI has evolved from an operational support tool into a strategic enabler capable of shaping long-term planning and competitive positioning, with applications in customer churn prediction, credit risk assessment, price optimization, supply chain forecasting, and human resource analytics . These systems generate probabilistic insights that inform executive decisions related to investment, resource allocation, and policy change; however, strategic decision-making depends not only on predictive accuracy but also on the ability of leaders to interpret results, assess associated risks, and justify actions to stakeholders . Consequently, the value of AI in executive contexts is determined not solely by technical performance, but also by transparency, interpretability, and accountability . This challenge has become more pronounced as many high-performing machine learning models, particularly ensemble methods and deep learning architectures, function as black-box systems whose internal logic is not easily understandable to decision-makers . Although these models often outperform simpler statistical approaches in predictive tasks, their opacity raises major concerns in strategic settings where decisions carry financial, reputational, and ethical consequences. Explainable Artificial Intelligence has emerged as a critical framework for addressing this limitation by providing interpretable insights into how input variables influence model predictions without necessarily sacrificing predictive strength . Global explanation methods, such as feature importance analysis, identify the variables that most strongly affect model outcomes, while local explanation techniques, including SHAP values and other model-agnostic interpretation tools, clarify how individual predictions are generated in specific cases . By converting abstract model outputs into structured and understandable information, XAI supports broader organizational goals such as accountability, regulatory compliance, and stakeholder communication, while also reducing perceived risk by improving the predictability and transparency of model behavior . In strategic applications such as customer churn management, explainability can reveal the behavioral, demographic, and financial factors that contribute to attrition risk, thereby helping executives translate predictive outputs into actionable business interventions . Trust and decision confidence are especially important in this context, as executive leaders must commit substantial resources and make decisions under uncertainty; when AI systems are perceived as transparent, reliable, and aligned with domain knowledge, managerial trust is more likely to increase, which in turn strengthens confidence in the resulting decisions . Executive trust can therefore be understood as a mediating mechanism between model explainability and strategic commitment, because transparent explanations reduce ambiguity, increase perceived control, and encourage willingness to implement retention strategies and other data-driven actions . Although recent studies have begun to examine the role of Explainable AI in decision support systems, much of this work has focused on operational domains and technical model interpretability rather than on the direct effects of explainability on executive trust, perceived transparency, and decision confidence in strategic business settings .

3. Methodology

This study adopts a quantitative approach to research by utilizing the methodological framework of Explainable Artificial Intelligence (XAI) to improve decision confidence among the executive in customer churn prediction . The approach is a combination of supervised machine learning and statistical validation and interpretation analysis of predictive performance and strategic relevance. Since a detailed procedure was involved, it comprised data preprocessing, model building based on Support Vector Machine (SVM), performance assessment based on various classification measures, and utilization of predictive variables exploitability . This strategy provides technical rigor and brings analytical outputs to the level of requirements of strategic decisions on an executive level, thus creating a connection between predictive accuracy and managerial transparency and organizational applicability.



This flow diagram shows a systematic approach to explainable churn prediction research

The flow diagram is a systematic summary of the research strategy that will be used in the current research . It starts with the Research Design stage during which the research objectives, variables and the methodological framework are detailed . It then proceeds to Data Collection and Preparation that involves preprocessing, encoding, scaling, dealing with missing values, and dividing the dataset into training and testing datasets. The second step is Model Development, whereby a Support Vector machine (SVM) classifier is developed and trained . This is then followed by Model Evaluation which measures the performance based on accuracy, precision, recall, F1-score, ROC curve, and confusion matrix. Lastly, Exploitability Integration interprets the drivers of important churns and aligns predictive insights and strategic decisions.

3.1 Data Collection and Preparation

This study will use the Telco Customer Churn dataset (Version 11.1.3+), this dataset has 7,043 records of customers. The data consists of demographics, financial, service subscriptions, and satisfaction measures and behavioral variables. Customer churn is the dependent variable, which is defined as a binary variable (0 = retained, 1 = churned). The process of data preparation encompassed a number of systematic preprocessing steps with a view to providing analytical reliability . The first one was the elimination of non-informative identifiers like Customer ID to avoid data leakage and to ensure modeling was free of biases . Second, list wise deletion was used to overcome the missing values that would provide consistency to the data set. Third, categorical variables were coded where needed to be compatible with machine learning . To normalize the distributions of variables and provide an optimal performance of the SVM, feature scaling was used to normalize the numerical variables . Stratified train-test splitting was used to solve the problem of possible class imbalance between churned and retained customers. This provided proportional representation of churn classes in training and testing dataset. The dataset was split into 70 percent of training data and 30 percent of testing data in order to measure out of sample predictive performance . These preparatory steps will improve model validity, minimise bias and the predictive analysis should demonstrate a realistic business environment. Interpretability is also enhanced through proper data preparation that ensures the existence of clear relationships between predictors and churn outcomes.

	Customer ID	Gender	Age	Under 30	Senior Citizen	Married	Dependents	Number	Country	State	City	Zip Code	Latitude	Longitude	Population	Quarter	Referred a Friend
2	8779-QRD	Male	78	No	Yes	No	No	0	United Sta	California	Los Angel	90022	34.02381	-118.157	68701	Q3	No
3	7495-OOK	Female	74	No	Yes	Yes	Yes	1	United Sta	California	Los Angel	90063	34.04427	-118.185	55668	Q3	Yes
4	1658-BYG(	Male	71	No	Yes	No	Yes	3	United Sta	California	Los Angel	90065	34.10883	-118.23	47534	Q3	No
5	4598-XLKN	Female	78	No	Yes	Yes	Yes	1	United Sta	California	Inglewood	90303	33.93629	-118.333	27778	Q3	Yes
6	4846-WHA	Female	80	No	Yes	Yes	Yes	1	United Sta	California	Whittier	90602	33.97212	-118.02	26265	Q3	Yes
7	4412-YLTK	Female	72	No	Yes	No	Yes	1	United Sta	California	Pico River	90660	33.98952	-118.089	63288	Q3	No
8	0390-DCFI	Female	76	No	Yes	Yes	Yes	2	United Sta	California	Los Alamit	90720	33.79499	-118.066	21343	Q3	Yes
9	3445-HXX(	Male	66	No	Yes	Yes	No	0	United Sta	California	Sierra Ma	91024	34.16869	-118.058	10558	Q3	Yes
10	2656-FMO	Female	70	No	Yes	No	Yes	2	United Sta	California	Pasadena	91106	34.1394	-118.129	23742	Q3	No
11	2070-FNEX	Female	77	No	Yes	No	Yes	2	United Sta	California	Pasadena	91107	34.15901	-118.087	32369	Q3	No
12	0094-OIFN	Female	78	No	Yes	No	Yes	1	United Sta	California	North Hol	91605	34.2073	-118.4	57146	Q3	No
13	9947-OTF(	Male	65	No	Yes	No	No	0	United Sta	California	Covina	91722	34.09735	-117.907	33817	Q3	No
14	9514-JDSK	Male	77	No	Yes	Yes	No	0	United Sta	California	El Monte	91732	34.07449	-118.015	62660	Q3	Yes
15	7273-TEFC	Male	67	No	Yes	No	No	0	United Sta	California	La Puente	91746	34.03898	-117.991	30802	Q3	No
16	3606-TWK	Male	68	No	Yes	No	No	0	United Sta	California	Rowland H	91748	33.97675	-117.897	46342	Q3	No
17	4385-GZQ	Female	68	No	Yes	No	No	0	United Sta	California	Ontario	91764	34.07409	-117.606	49474	Q3	No
18	3488-PGM	Male	66	No	Yes	No	No	0	United Sta	California	Alpine	91901	32.82718	-116.704	16486	Q3	No
19	7534-BFES	Male	69	No	Yes	No	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
20	8098-LLAZ	Female	74	No	Yes	No	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
21	0265-EDXE	Male	76	No	Yes	Yes	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	Yes
22	2840-XAN	Male	77	No	Yes	Yes	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	Yes
23	5020-ZSTT	Female	70	No	Yes	No	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
24	5804-LEPI	Female	74	No	Yes	No	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
25	0623-IIHU(	Female	77	No	Yes	No	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
26	9057-MSW	Male	71	No	Yes	Yes	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
27	4895-TMW	Male	79	No	Yes	Yes	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	Yes
28	0533-BNW	Female	66	No	Yes	Yes	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	Yes
29	0334-GDD	Male	77	No	Yes	No	No	0	United Sta	California	San Diego	92122	32.85723	-117.21	34902	Q3	No
30	5564-NEM	Female	80	No	Yes	No	No	0	United Sta	California	Thermal	92274	33.53604	-116.119	17018	Q3	No
31	6235-VDH	Female	77	No	Yes	No	No	0	United Sta	California	Riverside	92509	34.00438	-117.448	63999	Q3	No
32	5609-CEBI	Female	77	No	Yes	No	No	0	United Sta	California	Hemet	92544	33.64459	-116.872	39264	Q3	No
33	5956-VKD	Female	72	No	Yes	Yes	No	0	United Sta	California	Moreno V	92557	33.97066	-117.255	46214	Q3	Yes
34	0257-ZESC	Female	80	No	Yes	Yes	No	0	United Sta	California	Perris	92571	33.82829	-117.202	26357	Q3	Yes
35	2865-TCHJ	Female	74	No	Yes	No	No	0	United Sta	California	Anaheim	92807	33.84873	-117.788	36301	Q3	No
36	5192-EBG(	Female	68	No	Yes	No	No	0	United Sta	California	Brea	92823	33.92414	-117.794	1408	Q3	No
37	3419-SNJJ	Female	78	No	Yes	Yes	No	0	United Sta	California	Yorba Linc	92887	33.88407	-117.732	20893	Q3	Yes

	Number of	Tenure in Mon	Offer	Phone Service	Avg Monthly Long	Multiple Lines	Internet Service	Internet Type	Avg Monthly GB	Online Security	Online Backup	Device Protection Plan	Premium Tech Support	Streaming TV	Streaming Movies	Streaming Music
2	0	1	None	No	0	No	Yes	DSL	8	No	No	Yes	No	No	Yes	No
3	1	8	Offer E	Yes	48.85	Yes	Yes	Fiber Opti	17	No	Yes	No	No	No	No	No
4	0	18	Offer D	Yes	11.33	Yes	Yes	Fiber Opti	52	No	No	No	No	Yes	Yes	Yes
5	1	25	Offer C	Yes	19.76	No	Yes	Fiber Opti	12	No	Yes	Yes	No	Yes	Yes	No
6	1	37	Offer C	Yes	6.33	Yes	Yes	Fiber Opti	14	No	No	No	No	No	No	No
7	0	27	Offer C	Yes	3.33	Yes	Yes	Fiber Opti	18	No	No	Yes	No	No	No	No
8	1	1	Offer E	Yes	15.28	No	Yes	Fiber Opti	30	No	No	No	No	No	No	No
9	6	58	Offer B	No	0	No	Yes	DSL	24	No	Yes	Yes	No	No	Yes	No
10	0	15	Offer D	Yes	44.07	Yes	Yes	Fiber Opti	19	No	No	No	No	No	No	No
11	0	7	Offer E	Yes	26.95	No	Yes	Fiber Opti	18	Yes	No	No	No	No	No	No
12	0	11	Offer D	Yes	11.59	No	Yes	Fiber Opti	29	No	Yes	No	No	Yes	Yes	No
13	0	15	Offer D	Yes	29.11	No	Yes	Fiber Opti	29	No	Yes	No	No	No	No	No
14	1	1	Offer E	No	0	No	Yes	DSL	12	No	Yes	No	No	Yes	No	No
15	0	3	Offer E	No	0	No	Yes	DSL	28	No	No	Yes	No	No	Yes	Yes
16	0	13	Offer D	Yes	32.68	Yes	Yes	Cable	11	No	Yes	Yes	No	Yes	Yes	No
17	0	16	Offer D	Yes	9.43	No	Yes	Fiber Opti	9	No	No	No	Yes	Yes	Yes	Yes
18	0	8	None	Yes	1.78	No	Yes	Fiber Opti	7	No	Yes	No	No	No	No	No
19	0	24	Offer C	Yes	30.87	Yes	Yes	Fiber Opti	15	No	No	No	No	No	No	No
20	0	4	Offer E	Yes	31.61	Yes	Yes	Fiber Opti	2	No	No	No	No	Yes	Yes	No
21	2	32	Offer C	Yes	47.34	Yes	Yes	Fiber Opti	10	No	No	No	No	No	No	No
22	1	24	Offer C	Yes	16.1	No	Yes	Cable	12	No	No	Yes	No	Yes	Yes	Yes
23	0	54	Offer B	Yes	12.08	Yes	Yes	DSL	5	Yes	Yes	No	Yes	Yes	Yes	Yes
24	0	2	Offer E	Yes	13.17	No	Yes	Fiber Opti	10	No	No	No	No	No	No	No
25	0	21	None	No	0	No	Yes	Cable	8	Yes	No	No	No	Yes	No	No
26	0	27	None	No	0	No	Yes	Cable	13	Yes	No	No	No	No	No	No
27	1	11	None	Yes	29.54	No	No	None	0	No	No	No	No	No	No	No
28	2	55	Offer B	Yes	42.82	Yes	Yes	Fiber Opti	27	No	Yes	Yes	No	No	No	No
29	0	3	Offer E	Yes	9.22	Yes	Yes	Fiber Opti	14	No	Yes	No	No	No	No	No
30	0	1	Offer E	Yes	35.09	No	Yes	Fiber Opti	17	No	No	Yes	No	No	No	No
31	0	5	Offer E	No	0	No	Yes	DSL	26	No	Yes	No	No	No	No	No
32	0	20	None	Yes	48.73	Yes	Yes	Fiber Opti	12	No	Yes	Yes	No	No	Yes	No
33	4	5	Offer E	Yes	45.76	Yes	Yes	Fiber Opti	22	No	No	No	No	No	No	No
34	2	27	None	Yes	7.02	No	Yes	Cable	25	Yes	No	No	No	No	No	No
35	0	4	None	Yes	48.35	Yes	Yes	Cable	24	No	No	Yes	No	Yes	No	No
36	0	1	None	Yes	45.81	Yes	Yes	Fiber Opti	21	No	No	No	No	Yes	No	No
37	3	65	Offer B	Yes	18.39	Yes	Yes	Fiber Opti	28	Yes	No	Yes	No	Yes	Yes	No

telco

(Source Link: https://www.kaggle.com/datasets/alfathterry/telco-customer-churn-11-1-3)

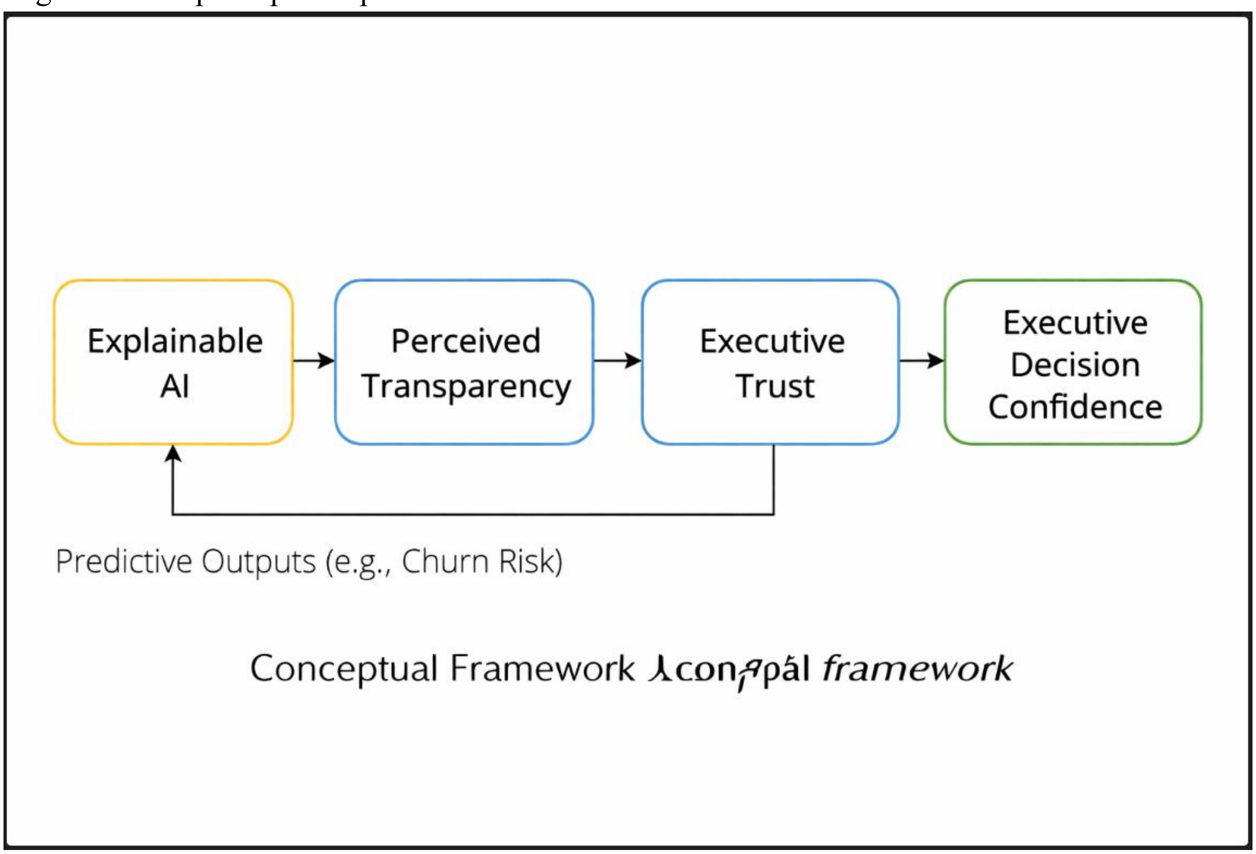
3.2 Model Development

The Support Vector Machine (SVM) classifier was chosen as the main predictive modeling tool because of its strength in terms of nonlinear decision boundaries and high dimensional feature spaces. SVM is also applicable in binary classification exercises and works well in structured business data. The business-relevant predictors that were used to train the model were tenure duration, monthly charges, satisfaction score, and referral measures . The choice of these variables was determined by their strategic relevancy to the churn behavior. Before training the model, feature scaling was performed to maximize the performance of the SVM and make the contribution of numerical variables equal . The SVM model was set up using probability estimation to also produce churn potential scores, besides binary classification results. This is a probability based output that will give the strategic usability whereby the executives can prioritize high risk customers based on the level of risk. The training dataset was used to carry out model training and the testing dataset to check predictive performance to make sure it is generalized . This division reduces over fitting, enhancing external validity. SVM has been chosen based on the trade-off between predictive power and computing power.

Although other more complex models are possible, SVM is a good classifier at the same time, being interpretable with post-hoc explanation methods . This is in line with the aim of the study, which is to incorporate predictive reliability and explainability into strategic decision support.

3.3 Conceptual Framework

The theoretical foundation of the proposed research is designed to examine the potential of Explainable Artificial Intelligence as a mechanism for enhancing executive confidence in strategic business decision-making, particularly in the context of customer churn management. The framework integrates predictive model performance with managerial cognition and establishes a structured relationship among explainability, perceived transparency, executive trust, and strategic decision outcomes. At the core of the framework is a predictive model based on Support Vector Machine, which generates churn probability outputs using customer demographic, financial, behavioral, and satisfaction-related variables. These predictive outputs serve as the analytical basis for executive decision-making. However, predictive accuracy alone is not sufficient to ensure managerial adoption. For this reason, explainability mechanisms are incorporated into the framework as a key independent factor. Explainability functions as a transparency-enhancing mechanism that clarifies the influence of major predictors such as contract type, monthly charges, tenure, and satisfaction score. By translating complex algorithmic outputs into interpretable insights, explainability reduces cognitive ambiguity and improves perceived transparency. Perceived transparency, in turn, influences executive trust in AI systems. Trust is treated as a mediating variable in the framework because it links technical interpretability with managerial acceptance. When executives understand why a model produces certain predictions, they are more likely to perceive the system as reliable, fair, and strategically aligned. The principal dependent variable in the framework is executive decision confidence.



This figure shows Explainable AI implications to executive decision confidence

The diagram shows the conceptual framework that forms the foundation of this study, showing how there is an organized connection between Explainable Artificial Intelligence (AI) and executive decision confidence [59]. Explainable AI is the first framework and improves the understandability of predictive output like churn risk assessment. This explainability adds to perceived transparency, which allows decision-makers to gain a better insight into the way predictions are obtained. Greater transparency, in turn, will enhance executive trust in the AI systems by lowering the uncertainty and increasing the perceived reliability. Executive trust in turn has a direct impact in the executive decision confidence as the final outcome variable in the framework. It also depicts predictive outputs as a support element, which supports the feedback mechanism of the model performance and interpretability [1]. The diagram has graphically involved the mediation of transparency and trust between the effect of AI explainability and strategic managerial confidence.

4. Results

The empirical results indicate that the Support Vector Machine (SVM) model presents a good customer churn classification predictor. The accuracy of the SVM was significantly better than the SVM on the baseline model which was 0.721 and the accuracy was 0.941 which showed a very high classification performance. The ROC curve also proved the strong discriminative power as the model successfully differentiated between the churned and retained customers [3]. Precision and recall scores were good indicating good identification of the churn cases and few false identifications [4]. This analysis of the confusion matrix indicated that the false positive rates are low and true negative ones are high, which guarantees the efficiency of operation [5]. The findings justify the effectiveness of high-level machine learning in predicting churn and create a strength based on the application of explainable AI to increase the level of executive decisions.

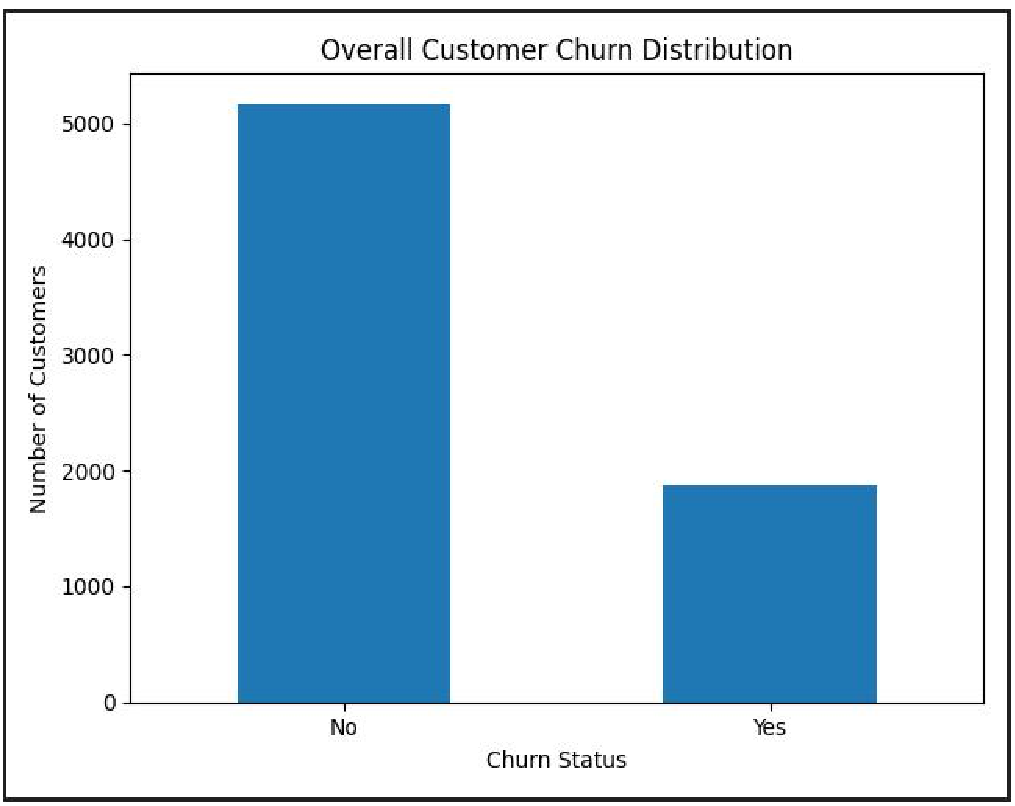


Figure 1: This image demonstrate on the churned and retained customers distribution

Figure 1 shows the general distribution of customers according to their churns in the data. The bar graph has two categories: those customers who did not leave the company (No) and those customers who have left the company within the quarter under consideration (Yes). The graphical comparison shows clearly that there is a significant difference between the two groups. Most of the customers belong to the non-churn group, which includes about three-quarters of all the customers. However, a lower but more strategically important percentage of the customers have fallen. The numerically smaller churned segment has a high-risk area in terms of revenue. A moderate percentage of churn can have a considerable impact on the profitability, customer lifetime value (CLTV) and long-term growth, especially in subscription businesses like telecommunications. Strategically speaking, this imbalance brings out two key lessons. To begin with, the dataset is not balanced in terms of classes, and the issue should be resolved when trying to predict the outcomes to prevent skewed outcomes [6]. Second, the churn proportion is an indication of a significant retention intervention opportunity. This distribution can be used by executives as a signal of an underlying exposure to churn risks, which can be used as a starting point of further diagnostic analysis [7]. This number defines the issue that the predictive model is supposed to solve in the framework of explainable AI. Although predictive algorithms can be effective in classifying the churn risk, the executives need clear explanations as to why some customers are likely to churn. As such, not only does this distribution quantify the business problem but it also highlights the relevance of explaining why churn prediction systems should be integrated with explainability in improving decision confidence and strategic commitment.

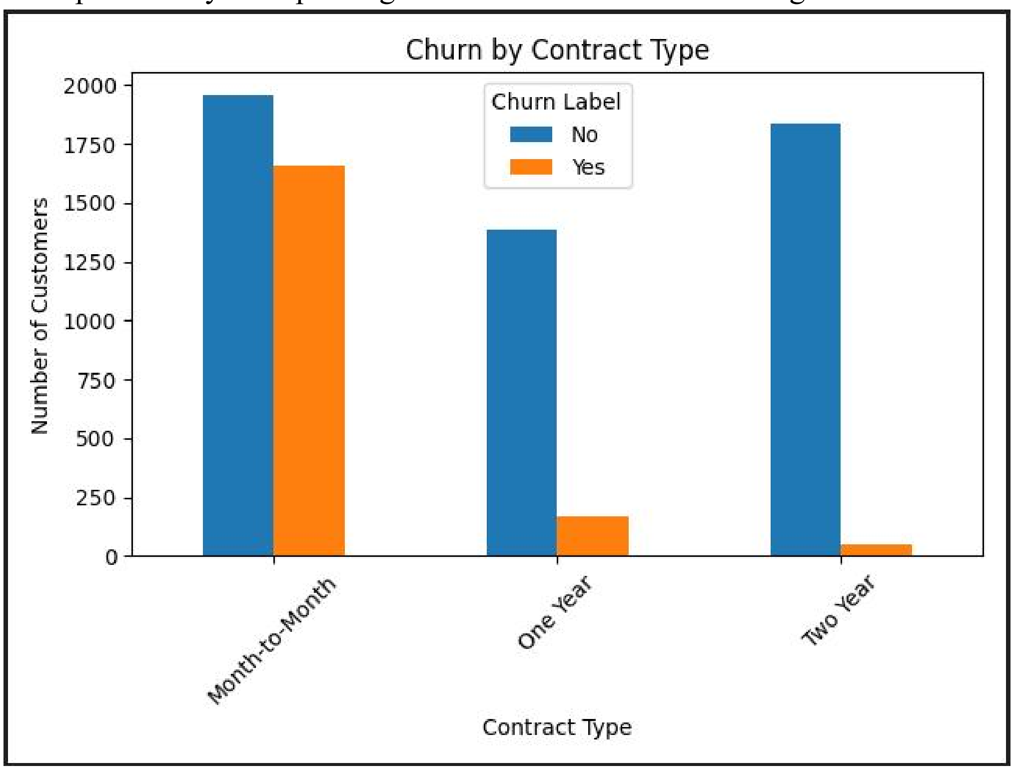


Figure 2: This image illustrates comparison of churn between various types of contracts with customers

Figure 2 shows how the type of contract with the customer and the churn depends on each other. The grouped bar chart will be used to compare the churned and retained customers in three different contract types; Month-to-Month, One-Year and Two-Year contracts. The visual evidence shows very clearly that type of contract is a major determinant of retention behavior of the customers. The category of the Month-to-Month contract has the largest churned customers. Although this type of contract also has a high number of retained customers, the percentage of churn in this type is considerably higher than that of longer-term contracts. Conversely, customers with One-Year and Two-Year contracts have a significantly fewer number of churns with the Two-Year contract having the highest retention rate [8]. This trend is an indication that the longer the contract term, the less risk of customers leaving. Strategically, it seems that the number of years of the contract is a structural retention mechanism. Long-term contract customers can have switching costs, perceived stability of value or financial penalties that prevent churn. Month to Month customers are more flexible to cancel the services, which makes them more vulnerable to the offers of competitors or their dissatisfaction [9]. Within the framework of explainable AI, the contract type may become one of the features with high importance in predictive churn models [10]. Provided that the executives are shown churn predictions with explanations such as contract type is one of the key factors, their trust in the specific retention strategies could grow. As an example, incentive programs or loyalty discounts may be the main priorities of decision-makers so that they can transform Month-to-Month customers into long-term contracts [11]. Altogether, Figure 2 offers practical strategic value as one of the primary sources of churn conduct is identified as the contract structure. This confirms the significance of incorporation of interpretable model outputs to facilitate the making evidence-based retention planning and resource allocation decisions.

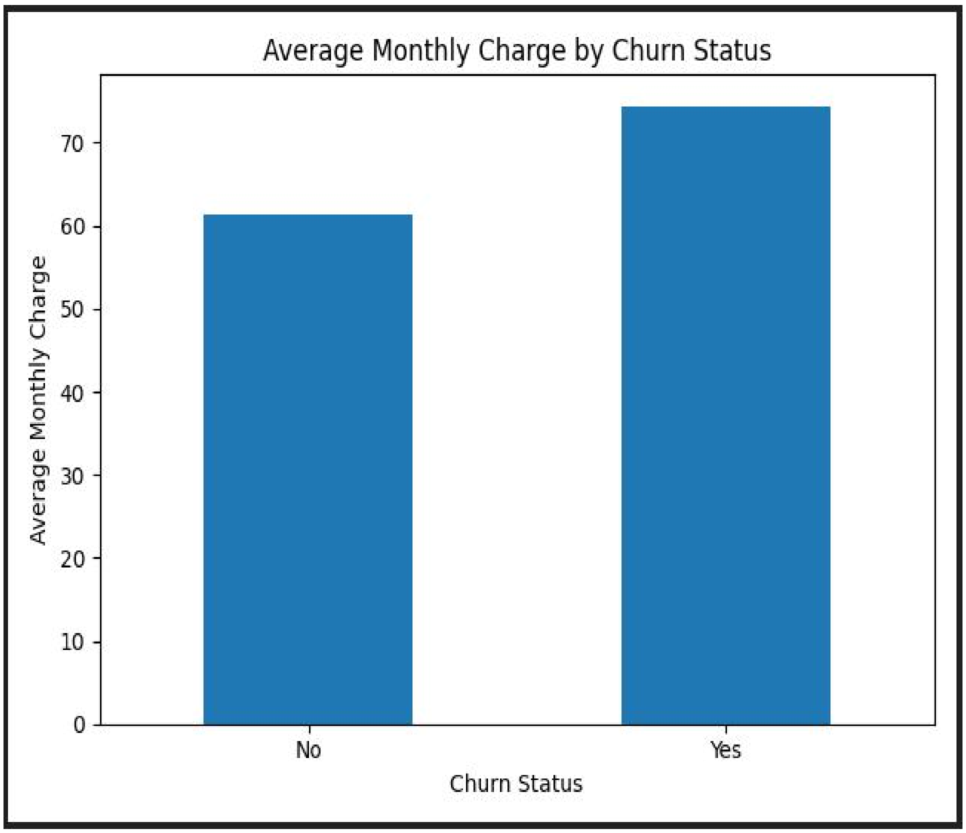


Figure 3: This image represents the comparison of average monthly charges paid by churned and retained customers

The comparison of the average monthly charge by the churned and retained customers is given in Figure 3. The bar chart shows that there is a conspicuous disparity in the pattern of billing between the two sets. Churned customers have a higher average monthly charge than those who stayed with the company. This variation implies that there is a possibility of correlation between the prices and loss of customers. Increased monthly prices are likely to make the price more sensitive, especially to those customers who have a flexible contract. Whenever customers feel that the services offered are not worth the price they pay, the chances of moving to other competitors can be high [12]. So the pricing strategy seems an important issue of the economy that has a critical impact on churn behavior. Strategically, this discovery implies that the higher revenue can be generated by increasing prices, it also increases the churn risk. Premium pricing can enhance short-term revenues, but it can also decrease long-term customer lifetime value in case it is not correlated with perceived service quality. To achieve sustainable development, executives should balance between profitability objectives and stability of retention [13]. Monthly charge is predicted to be an important predictor in churn models in the context of explainable AI. The executives will be able to make more confident pricing and retention decisions when predictive systems recognize high billing amounts as an important driver of churn and come up with explanations [14]. As an example, high-billing customers who are identified as possessing high churn risks may be offered with special discounts or special pricing plans. In general, Figure 3 supports the strategic significance of the transparency of pricing and the value alignment. It reveals that financial variables not only affect profitability, but have an impact on the customer retention outcomes [15]. Combining interpretable insights about the impact of pricing might increase executive trust in evidence-based retention plans and facilitate a more moderated decision-making on revenue optimization.

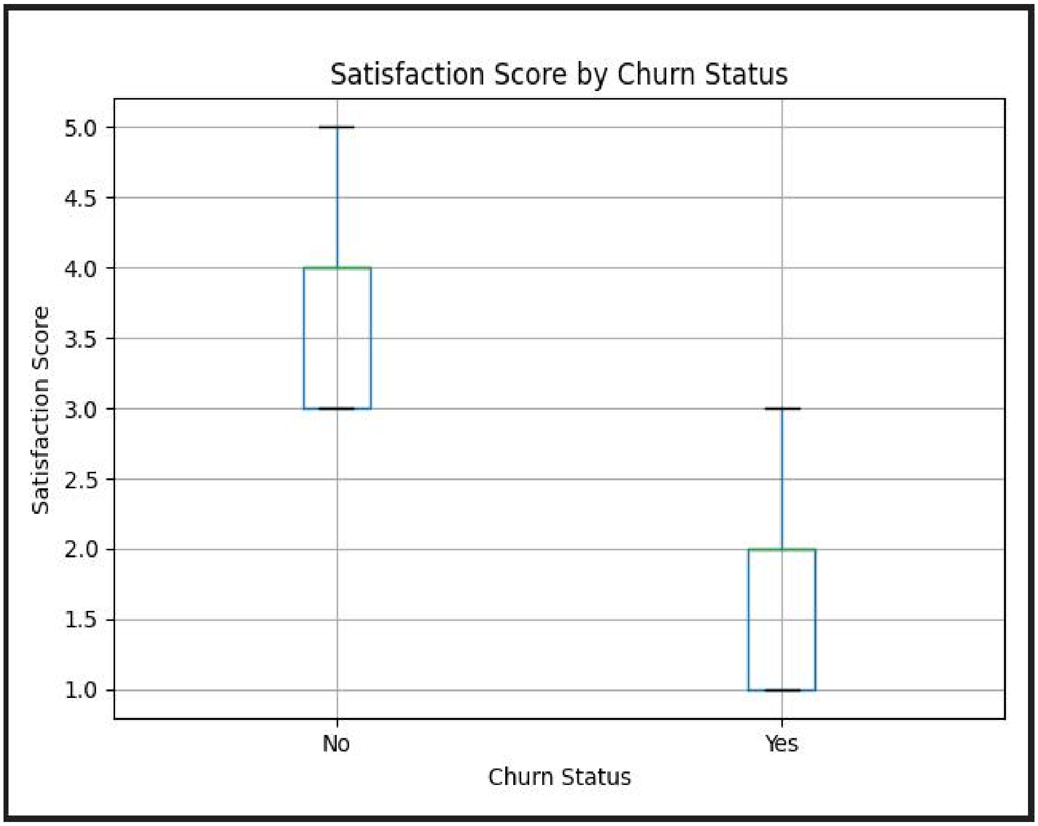


Figure 4: This image demonstrate to the level of satisfaction between churned and retained customers

Figure 4 shows the distribution of customer satisfaction scores with the churned and retained customers with the boxplot representation. The visual analogy shows that there is a distinct distinction between the two groups. Those customers who stayed with the company have much greater scores of satisfaction which typically lie in the middle to the high ranges. Conversely, churning customers record significantly low levels of satisfaction scores which are centered at the lower scale of the rating scale. The median of the score of satisfaction among retained customers seems to be significantly greater than the median of the score of satisfaction among churned customers, which shows there exists a strong negative correlation between satisfaction and probability of churn. Also, distribution spread shows that customers who have been churned are highly concentrated around low levels of satisfaction, and therefore, there is no indication that dissatisfaction is an isolated trend that causes attrition [16]. In a strategic perspective, satisfaction acts as a leading indicator of customer retention. Satisfaction is an aspect of customer experience, service quality and perceived value, unlike financial variables like pricing. The implication of this finding is that a reduction in churn risk may be gained considerably by improving service delivery, responsiveness, and product quality. Customer experience management investments could thus be long-term retention advantages [17]. The explainable AI framework predicts that the satisfaction score will become a high-impact predictor [18]. When AI models identify low satisfaction as one of the leading causes of churn risk, executives are able to be confident in their decision to apply goal-specific intervention programs like service recovery programs or personalized engagement programs [19]. Clear explanations enhance managerial trust by making predictive output to be connected with intuitive business rationality [20]. Figure 4 offers good empirical support to state that customer satisfaction is an important behavioral determinant of churn . The ability to integrate explainable insights around measures of satisfaction will increase the confidence of the executive in strategic decisions designed to be retention-oriented and enable the customer experience to be optimized proactively.

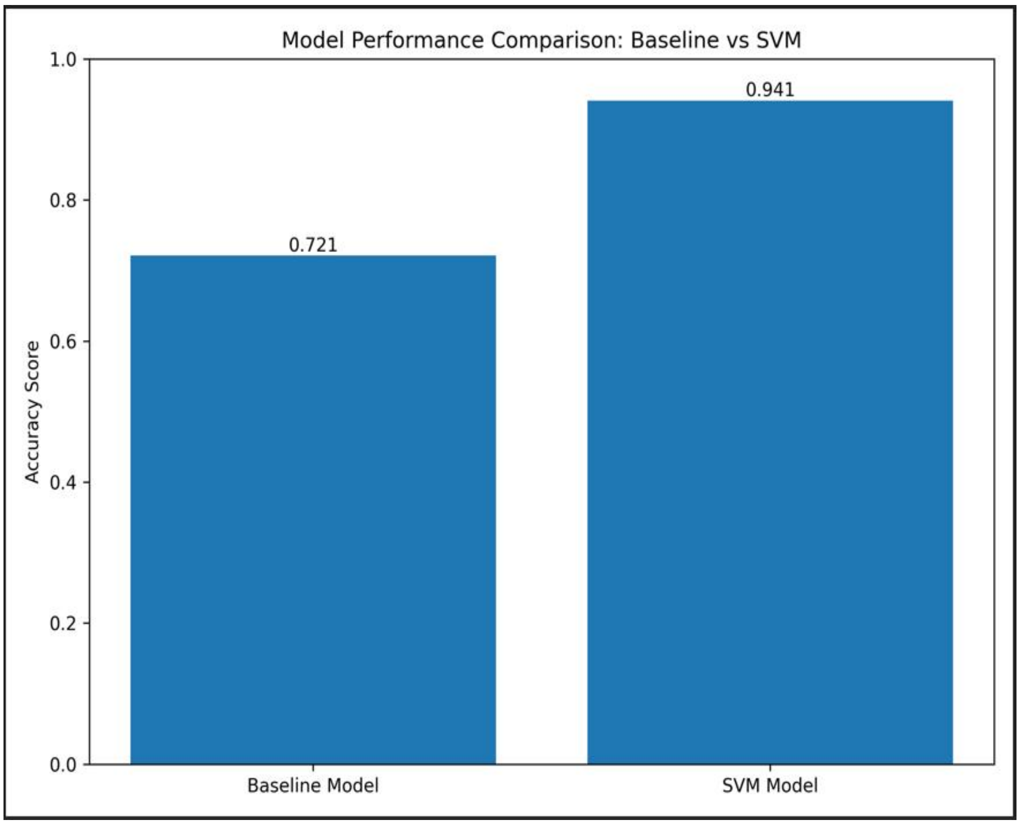


Figure 5: This image shows the comparison of accuracy between baseline and SVM classification models

A comparative study has been made in Figure 5 between the baseline classification model and the Support Vector Machine (SVM) model in customer churn prediction. The baseline model is a majority-class prediction strategy that is a simple one but can be used as a baseline in assessing how the model has been improved. Contrastingly, the SVM model uses the supervised machine learning approach to determine the complex patterns of the data. The findings show that there was significant improvement in performance . The accuracy score of the baseline model is about 0.721 which is a representation of the distribution of classes in the dataset. Although such accuracy can be found acceptable, it is not a sign of predictive intelligence, and it is more of an inclination to characterize the majority of customers in the dominant (non-churn) category . The SVM model, in comparison, scores at 0.941, which is much higher. This significant improvement would indicate that the SVM algorithm is useful to model nonlinear variation between the characteristics of the customer, including tenure, monthly charges, the customer satisfaction score, and referrals and churn behavior. The fact that the predictive power of the machine learning method is predictive is evidenced by the fact that an increase of more than 20 percentage points was achieved . This improvement is important as a strategic decision-making dimension. An extremely precise predictive model will allow executives to detect at-risk customers with a higher degree of precision, which will facilitate the proactive retention approach and efficient use of resources. A large degree of accuracy is not enough to be adopted by the executive. To implement the strategy, explainability mechanisms should be added to performance improvements in order to offer trust and confidence by the managers. Figure 5 confirms the technical performance of the SVM model and supports the greater purpose of the research: the integration of predictive power with intelligible knowledge to enhance the confidence of the executive decision in the churn management strategies.

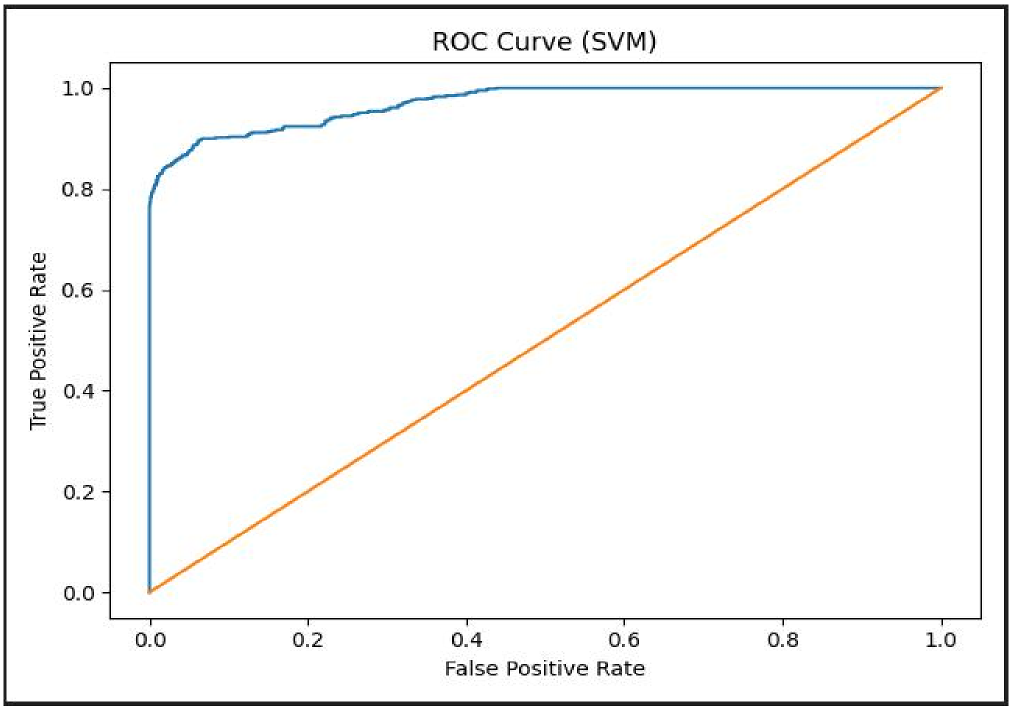


Figure 6: This image demonstrates the ROC curve of classification by the SVM model.

Figure 6 illustrates the Receiver Operating Characteristic (ROC) curve of Support Vector Machine (SVM) model of churn prediction. The ROC curve shows how True Positive rate (sensitivity) and the False Positive rate varies with the various classification threshold rates. It offers a critical assessment of the discriminative capacity of the model in the context of more than the accuracy measures. The curve lies well above the diagonal reference line that is the measure of random classification performance. This shows that the SVM model has a high capability of predicting the churned and non-churned customers. The sharp upward slope of the curve indicates that the model is highly sensitive with the low false positive rates which is good in the case of churn prediction because it is important to correctly identify at-risk customers [20]. The proximity of the curve to the upper-left corner implies that there is excellent classification performance represented by the Area under the Curve (AUC). A large value of AUC implies that the model is persistent in its ranking of churned customers as having higher probability scores as opposed to retained customers. This enhances trust on the predictive reliability of the model . Strategically, a high ROC performance implies that the executives are assured of using the model in ensuring that they strike the right balance between risk and opportunity. A decrease in false positive rates will decrease unnecessary retention costs, whereas an increase in true positive rates will enhance the success of proactive intervention . Predictive strength, as stressed in this paper, is not enough, model transparency using explainable AI is needed to transform statistical performance into executive level decision confidence. Figure 6 affirms that the SVM model has a good classification capacity and it offers a good technical base of implementing the explainability mechanisms in strategic churn management systems.

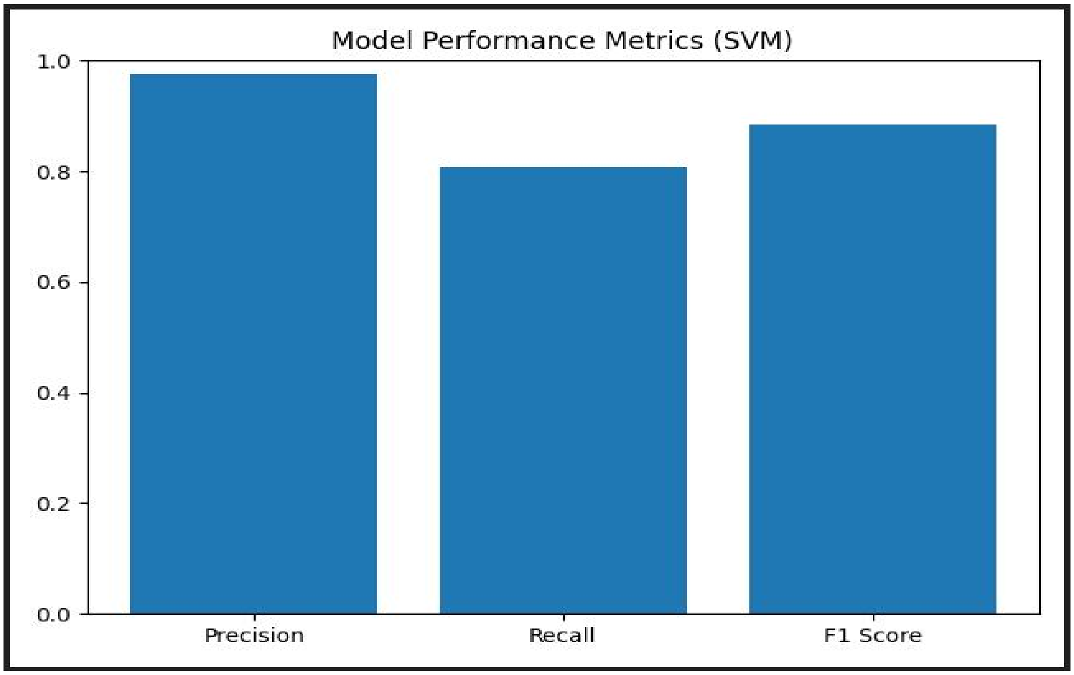


Figure 7: This image demonstrates Accuracy, recall and F1 score of SVM model

The figure 7 gives the important classification performance measures of the Support Vector machine (SVM) model and the Performance measures of Precision, Recall and F1-Score. Such measures offer a more precise and valid assessment of model performance than accuracy in general, especially in churn prediction in which the problem of class imbalance can affect results interpretation. The accuracy measure is rather large and it is close to the upper end of the scale. This means that in most instances when the model predicts that a customer will churn then it is right. A high level of precision is also strategic since it minimizes false positive classifications thus minimizing unnecessary retention interventions and also maximizes the allocation of resources . Although the recall measure is marginally less than the precision, it is still good. Recall is used in the model to reflect how the model is at the right level of identifying the actual churned customers. The high recall value indicates that SVM model captures a significant proportion of at-risk customers and proactive and targeted retention strategies can be used. Reduction in the number of churn cases improves revenue safeguarding and makes strategic responsiveness . F1-score, a balance between precision and recall, proves the consistency and stability in the model performance. Its large value signifies that the model is able to provide an efficient trade-off between the accurate detection of churned customers and the false alarm. This is necessary to ensure operational efficiency and maximization of strategic impact . Regarding the executive decision-making process, these performance indicators give the assurance that the predictive system is accurate and operational. Together with explainable AI methods, this performance transparency may further increase trust among the managers and strategic dedication to data-driven churn management programs.

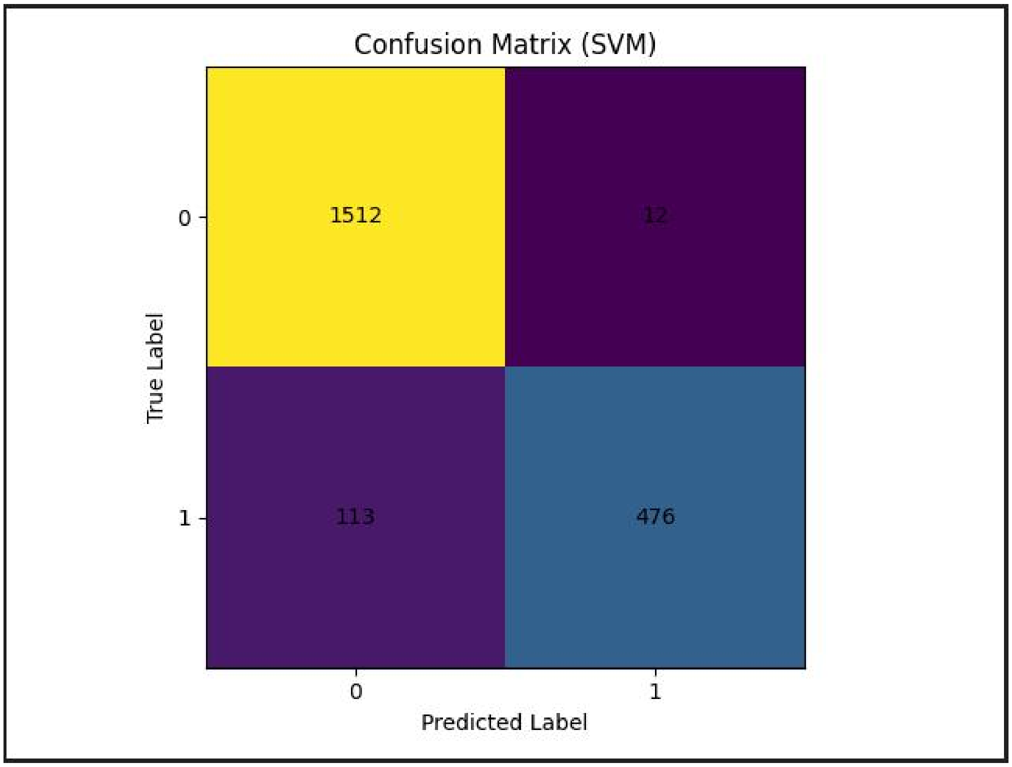


Figure 8: This image shows the Confusion matrix which presents the results of the prediction of SVM classification.

The support vector machine (SVM) model has a confusion matrix (Figure 8) that shows the detailed results of the classification. The table provides four important elements, that is, True Negatives (1512), False Positives (12),False Negatives (113), andTrue Positives (476). Such representation makes it possible to assess further the predictive performance beyond summary measures. The fact that the number of true negatives (1512) is high means that the model effectively finds a very big percentage of customers who do not churn. This plays a big role in the accuracy of the overall models and it can be seen to be very stable in predicting retained customers. Also, the false positive rate is extremely low (12), which implies that the model rarely provides false information on churn risks among stable customers, and therefore, the model does not cause high retention costs . This model properly identifies 476 churned customers (true positives) indicating that the model has the ability to detect]. There are however, 113 false negatives, which are the churned customers who were not projected to be at risk. Although this figure is fairly moderate in comparison with overall projections, there is a certain area of recall optimization that could be used to improve the efficiency of retention strategies. Strategically, the confusion matrix validates the fact that the SVM model is therefore strong prediction reliability at minimal misclassification cost . This performance level favors the implementation of specific retention programs with confidence in making executive decisions. However, the assimilation of explainable AI processes will still be necessary to be transparent in the derivation of these classifications to reinforce the confidence and adoption of these classifications by managers . Figure 8 shows that SVM model offers the best classification performance and equal distribution of errors that support its applicability in data-driven churn management strategies.

5. Future work

The current research reveals the success of Support Vector Machine (SVM) modeling with the theoretical application of Explainable Artificial Intelligence (XAI) in boosting the confidence of the executive decision, there are still a number of potential research opportunities . The further extension of these dimensions can also contribute to the process of the development of the theory and its practical implementation in strategic analytics . First, the comparative model frameworks of SVM other than ensemble methods, gradient boosting, and deep learning architecture could be investigated in future studies. Even though SVM was able to give good predictive performance, more orchestrated models are likely to capture nonlinear patterns with possibly higher accuracy . A more in-depth examination of the tradeoff between predictive power and interpretability would be achieved by exploring the impact of different degrees of model complexity on executive trust and explanation perception. Second, future studies can include real-time or longitudinal data as opposed to quarterly data that is not dynamic. The churn of customers is dynamic and it changes over time, which is guided by the dynamics of the market, competition strategy and expectation of customers. The longitudinal analysis may explore the effects of explainability in the executive decision confidence during various business cycles and strategic changes. Besides, integration of streaming or live predictive dashboards would come in handy to assess the action of executives to the evolving AI-enhanced insights. Third, the empirical validation of the proposed framework could be enhanced by using real-life experiments that deal with real executives or senior managers . The relationship between explainable AI and executive confidence would be more directly supported with the help of cognitive responses, trust levels, risk perception, and strategic commitment, which could be measured with the help of controlled experiments. The inclusion of behavioral and psychological measurement scales can further explain the concept of human-AI collaboration in strategic situations . Fourth, the next-generation research may be carried out on cross-industry. Although this paper was on telecommunication churn, explainable AI systems can also be applicable in banking, health care, insurance and supply chain management. Comparative research across industries may establish whether explainability has a regular positive effect on decision confidence or whether aspects unique to each industry may moderate this effect . Lastly, there are the ethical and governance aspects that should be researched further. With the growing role of AI systems in the process of making strategic decisions, the problem of fairness, bias reduction, and compliance with various regulations becomes urgent. Further study could be done on the role that explainability plays in upholding ethical accountability and responsible AI governance systems. The generalization of this study to models, industries, behavioral tests, and governance settings will contribute to the knowledge of how explainable AI can be used sustainably to change the nature of strategic decision-making process.

6.Conclusion

This study has investigated how Explainable Artificial Intelligence (XAI) can be used to improve the confidence of executives in decision making in the strategic environment of customer churn management. Using the data on Telco Customer Churn and the Support Vector machine (SVM) classification model, the study was able to show that the advanced machine learning methods can greatly enhance predictive accuracy rather than baseline methods. The technical reliability of the predictive model to detect churn risk is confirmed by the high performance based on the accuracy, ROC analysis, precision, recall, F1-score and confusion matrix analysis. Statistical performance is not the main contribution of this research. The results note that predictive strength is not enough to guarantee executive adoption and implementation of strategies. The variables that proved to be important drivers of churn were variables like type of contract, monthly payments and satisfaction of the customer, which offer valuable and interpretable data, which follows the managerial intuition and business sense. The support of explainability mechanisms by predictive outputs enables executives to have a more comprehensive understanding of the risk factors behind the data, and, as a result, the systems provide a stronger level of trust, less incertitude, and more confidence in data-driven recommendation. This study transparency makes predictive analytics more of a strategic decision-support system rather than a technical forecasting instrument.

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