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Research Article

An Explainable Machine Learning Framework for Behavioural Risk Classification in Financial Services

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ABSTRACT

Financial solutions are getting to ever increasing demands and requirements for using a transparent data-driven approach to assess behavioral risk from complex financial customer data. This study presents an explainable machine learning model based on demographic, financial and transactional data, applied to explaining how to identify engineered behavioral risk states. Processing the models like Logistic Regression, Random Forest and XGBoost are evaluated on an 80:20 stratified train-test split and by five folds of test set cross-validation, and the model is interpreted using SHAP. Logistic regression had the best test accuracy at 79.55% and the mean and cross-validation accuracy is at 80.01%. The results show similar model performance and underline the importance of explainability for uncovering salient financial risks features and for a transparent financial decision-making.

Keywords: Explainable AI, Behavioural Risk Classification, Financial Services, Machine Learning, Logistic Regression, Random Forest, XGBoost, SHAP Analysis.

I.INTRODUCTION

Background

Changing customer behavior can be predicted by advanced data-driven techniques as the Artificial Intelligence in the financial services rapidly evolves, allowing organizations to forecast changes in the behaviors of their customers. Though, uncertainties, time trends, as well as explainability in behavioral risk states are usually not considered in the traditional predictive models [1]. This study suggests a comprehensible explainable machine learning framework to capture behavioral processes, create a better forecast of risk and assist in making transparent financial decisions.

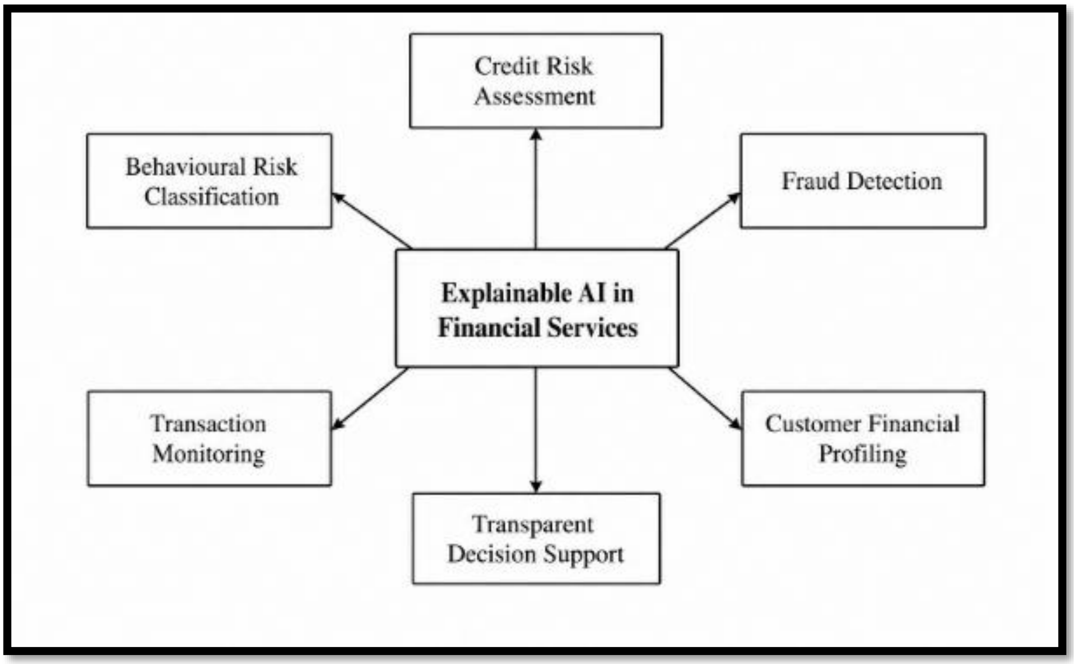

Fig. 1. Applications of Explainable AI in Behavioral Risk Assessment within Financial Services

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Problem statement

Financial risk prediction models used today are good at making predictions about customer behaviors, however, many models lack transparency of the financial factors used in the prediction [2]. This makes it difficult to be interpreted, making good decisions and to receive personal financial support. Thus, an explainable machine learning (XAI) approach is required to ostensibly analyze predictive models and identify influential behavioral risk factors in a reliable way across the board.

Research Aim and Objectives

Aim

The research aims to create an explainable machine learning model to classify the financial risk of behavior according to customers' demographic, economic and transactional characteristics.

Objectives

- To develop and evaluate machine learning models to identify customers' behavioral risk considering the demographic, financial and transactional characteristics.
- To integrate explainable AI methods to enhance the transparency, fairness and interpretability of the financial risk's forecasts.
- To evaluate effectiveness of the framework in supporting the adaptive financial decision-making and personalized customer strategies.

Novel Contribution

The study presents a new explicable AI model, which combines behavioral risk modelling in time, predictive performance assessment, and risk prediction of behavior in the financial services field [3]. In comparison to the traditional predictive methods, the framework integrates probabilistic learning and explainable processes to recognize financial behavioral patterns, increase the transparency of decisions, and implement adaptive financial plans and solve the issues of fairness, reliability and interpretability of the models.

II. RELATED WORK

Machine Learning Approaches for Behavioral Risk Prediction in Financial Services

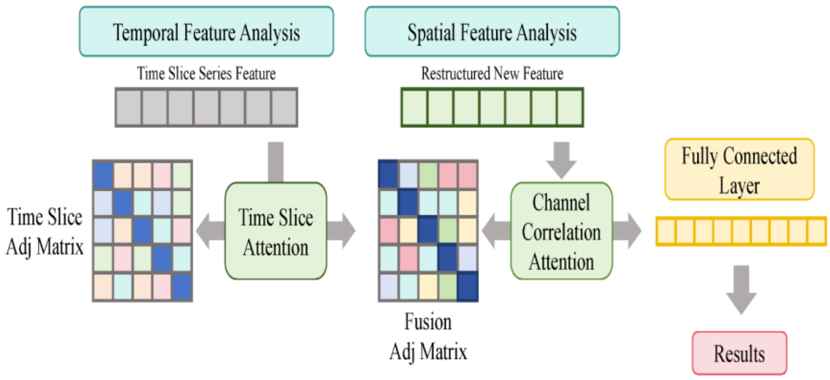

Fig. 2. Uncertainty-Aware behavioral pattern Transformer for Probabilistic Interval Modeling

Recent works show that probabilistic AI solutions have exceptional benefits in the modelling of uncertain and dynamic behavior transitions in contrast to legacy approaches of using statistical classification [4]. In predicting retirement timing, changes in income, mobility of employment and financial behavior of a customer, increased use of Bayesian models, survival analysis, as well as **behavioral pattern** machine learning methods have been observed [5]. These methods are able to effectively represent time-varying risks and uncertainty, however most of the existing models are still domain-based and cannot generalize across the various happenings in the financial life [6]. In addition, traditional predictive control systems tend to optimize the control quality indicators and have little insight

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on the transition process [7]. Hence the necessity to have integrated probabilistic schemes that would be able to achieve a combination of behavioral patterns, time-based links and uncertainty estimates [8].

Explainable Artificial Intelligence for Transparent and Fair Behavioral Risk Assessment

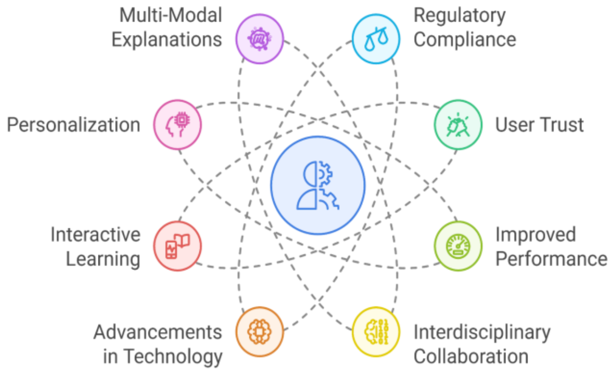

Fig. 3. Explainable AI: Transparent Decisions for AI Agents

The growing usage of AI-based financial forecasts has put pressure on the need to be explainable, fair, and accountable [9]. Prior studies identify explainable methods of AI, including SHAP, LIME, and interpretable machine learning models that enhance insights into complex outcomes of predictive models and assist decision making responsibility [10]. Nonetheless, many contemporary strategies tend to emphasize the description of model outputs, however neglect even greater issues, connected to fairness, bias avoidance, and evolving customer conditions [11]. Though explainability increases user confidence, not a lot of research has done an exhaustive analysis of whether the elucidation actually assists financial experts in making ethical choices [12]. The next generation models should, therefore, include explainability as part of the models and not as a separate interpretation level [13].

AI-Driven Decision Intelligence for Adaptive Financial Services and Personalized Customer Strategies

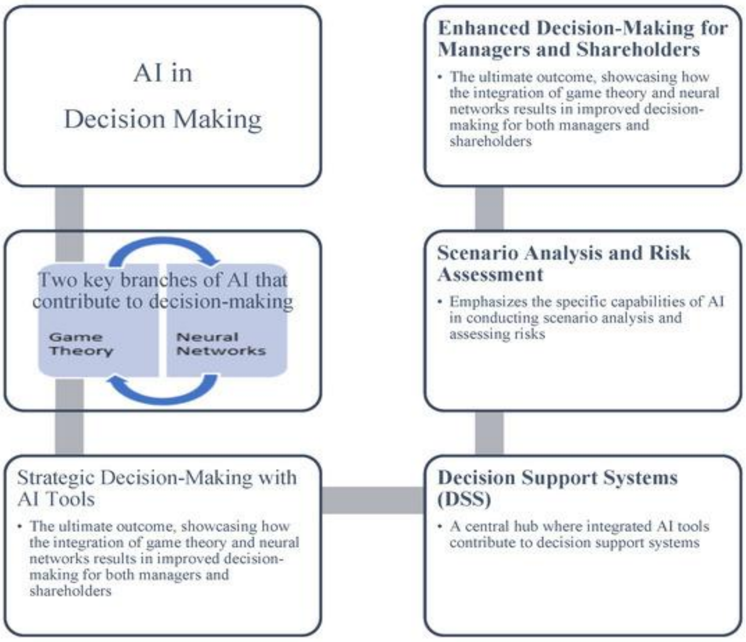

Fig. 4. Unlocking Business Value: Integrating AI-Driven Decision-Making in Financial Reporting Systems

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Financial services have been revolutionized through AI-driven decision intelligence as it supports the personalization and recommendations of customers, automated risk analysis, and pro-active interactions with them [14]. The existing literature shows that predictive analytics can be used to enhance product targeting, retaining customers, and financial planning [15]. However, most implementations are based on past behavioral trends and cannot easily align to sudden life transition during a life stage or changes in economy [16]. Moreover, less research has been done on how model predictions can be translated into practical or action advice and still have customer fairness and compliance with regulations [17]. This shows a dire need to have adaptive AI frameworks built that bridge transition prediction, behavior risk assessment and personalized financial decision support [18]. In general, the available studies are useful bases yet lack a single understandable probabilistic structure which deals with uncertainty, environmental changes with time, and accountable financial acumen [19].

Empirical Models Comparison

In order to compare these three supervised classification techniques with varying modelling properties [20] an empirical framework is presented. Logistic Regression offers a linear baseline to deal with results which is easy to interpret, while Random Forest entails an ensemble of decision trees to accommodate nonlinear interactions [21]. The idea of using sequential boosting to enhance classification performance is introduced with XGBoost [22]. SHAP provides a complementary approach to these predictive models, by measuring the contribution of a feature in the model and by helping to interpret the behavior-risk predictions in a way that presumes trust [23]. The benefit of SHAP is that it quantifies the contribution using a feature in the model and is geared toward helping interpret behaviour-risk predictions in the style of trust.

Table 1. Comparative Characteristics Of Methods Implemented For Behavioural Risk Classification

Method	**Core Principle**	**Role in Current Study**	**Strength**	**Limitation**	**Implementation**
Logistic Regression	P(Y=k∣X)	Baseline classification	Interpretable and computationally efficient	Limited nonlinear modelling	Implemented
Random Forest	Y^=Mode(T1,...,Tn)	Ensemble risk classification	Captures nonlinear relationships	Reduced inherent interpretability	Implemented
XGBoost	Y^=∑m=1Mfm(X)	Boosted risk classification	Strong complex-pattern modelling	Requires parameter tuning	Implemented
SHAP	f(x)=E[f(x)]+∑iϕi	Post-hoc model explanation	Feature-level interpretability	Additional computational cost	Implemented

Literature Gap

The existing literature indicates that AI-based predictive models have been successful with regard to financial services [24]. Nevertheless, there are large gaps in how behavioral risk modelling, predictive performance assessment and explainability can be integrated into one model [25]. Modern methods typically do not have adaptive behavioral risk assessment, cross domain applicability and decision support with fairness [26]. Thus, a probabilistic AI platform that may be explained is needed to overcome these drawbacks [27].

III.RESEARCH METHODOLOGY

Research Design and Dataset Description

This research study incorporates a quantitative research design of machine learning, in order to come up with the explainable machine learning framework of predicting behavioral risks in the financial services [28]. The India Customer Financial Profiles and Transactions Data is used from Kaggle, which contains 20,000 customer records containing 21 attributes. The data consists of the demographical data (age, gender), financial data (income, debt, credit score, credit cards) and transactional data (amount, date of transaction, merchant details). These characteristics can aid in the modelling of latent transitions in life-events in terms of observable financial behaviors.

Data Preprocessing and Feature Engineering

The dataset has firstly been checked against data quality, missing data and consistency of the features [29]. Extraction of transaction year, month, quarter is performed in order to make behavioral pattern attributes to capture behavioral changes over time [30]. Other financial indicators are developed such as debt-income ratio, spending-income ratio, credit risk index, financial capacity and transaction activity [31].

Debt-income ratio of the company is computed as:

$$\mathrm{DIR} = \frac{\mathrm{TD}}{\mathrm{YI} + \epsilon}$$

DIR being debt income ratio, TD total debt, YI is annual income and ε is a small constant to ensure that the result is not divided by zero.

The intensity of the spending is computed to be:

$$\mathrm{SI} = \frac{\mathrm{TA}}{\mathrm{YI} + \epsilon}$$

SI is used to denote the intensity of spending and TA has been used to denote the amount of transaction.

Behavioral Risk Classification

The continuous behavioral risk score, if retained descriptively is converted into three behavioral risk types which are: Low Risk, Medium Risk and High risks using percentile classification [32]. This method guaranteed a balanced proportion of classes represented, and allowed a multiclass prediction of the transitions in financial behavior [33].

Machine Learning Model Development

Three supervised machine learning models are implemented and examined:

Logistic Regression: This is a default probabilistic classifier that is used as a baseline to determine any linear relationship between financial indicators and risk states of behavior [34].

$$\mathrm{P(Y)} = \frac{1}{1 + \mathrm{e}^{-\mathrm{z}}}$$

P(Y) is predicted probability is used where z is the weighted feature combination.

Random Forest: It applies to nonlinear relationships for Multiple decision trees are used to capture a relationship:

$$\hat{\mathrm{Y}} = \mathrm{Mode}(\mathrm{T1}, \mathrm{T2}, \ldots, \mathrm{Tn})$$

Where T_n is the decision trees of individuals and $\hat{Y}$ indicates final classification output [35].

XGBoost: The XGBoost is an advanced gradient boosting model, which is implemented:

$$\mathrm{Fm(x)} = \mathrm{Fm} - 1(\mathrm{x}) + \eta \mathrm{hm(x)}$$

$F_m(x)$ is the new model, η denotes learning rate, $h_m(x)$ is the new weak learner.

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Model Evaluation and Explainability

Accuracy, recall and F1-score are used to evaluate the models:

TP, TN, FP and FN are the true positive, true negative, false positive and false negative classifications.

Lastly, SHAP (SHapley Additive explanations) is used to explain the value of features and which ones are the most important risk drivers of behavior. This has increased transparency through clarifying the way financial indicators contributed to model decisions and enabled financial decision-making in a responsible approach to AI.

Architecture Diagram

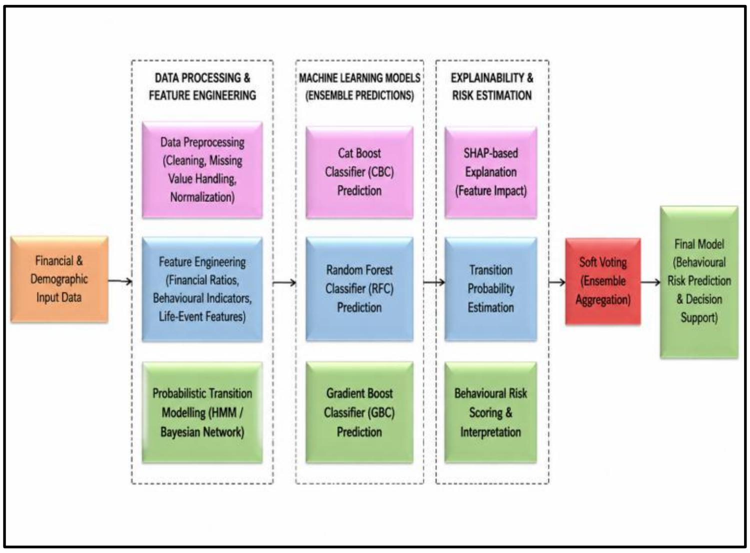

Fig. 5. Architecture Diagram

The architecture is used to depict a systematic architecture that unites financial data processing, feature engineering, machine learning modelling, explainability mechanism and decision-support layers to forecast behavioral risk states, and behavioral risk.

Flowchart

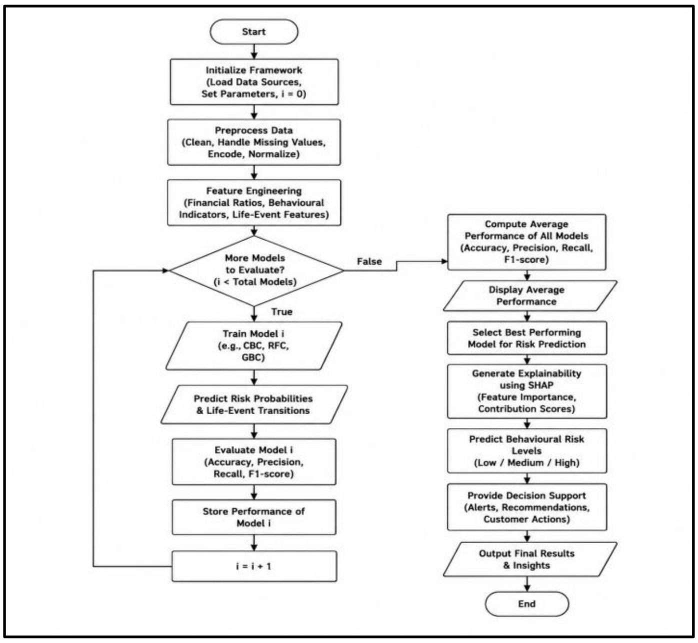

Fig. 6. Flowchart Diagram

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The flowchart presents the stepwise action of the proposed framework development, feature engineering, predictive modelling, machine learning evaluation and SHAP explainability, behavioral risk prediction and financial decision-support generation developments.

Pseudocode

```
Program to Develop Explainable Probabilistic AI Framework for
Life-Event Transition Modelling and Behavioural Risk Prediction
Initialize
    Input Data
        Customer financial profiles
        Demographic information
        Transaction records
        Credit information
    Data Preprocessing
        Handle missing values
        Remove inconsistent records
        Encode categorical variables
        Normalize numerical features
    Feature Engineering
        Calculate debt-income ratio
        Calculate spending behaviour indicators
        Extract temporal transaction patterns
        Generate behavioural risk features
    Probabilistic Modelling
        Calculate transition probability
        Risk Probability =
        Weighted Financial Indicators +
        Behavioural Patterns +
        Life-Event Factors
    Define Risk States
        Low Risk
        Medium Risk
        High Risk
    Machine Learning Models
        Logistic Regression
        Random Forest
        XGBoost
Start Model Training Loop
    FOR each model
        Train model using historical behavioural data
        Predict future behavioural risk
        Calculate accuracy
        Calculate precision
        Calculate recall
        Calculate F1-score
    END LOOP
Explainability Analysis
    Apply SHAP analysis
    Identify important behavioural predictors
    Generate feature contribution scores
    Interpret model decisions
Decision Support Output
    IF Risk Level = High Risk THEN
        Generate financial risk alert
    ELSE IF Risk Level = Medium Risk THEN
        Recommend monitoring strategy
    ELSE
        Maintain standard customer strategy
    END IF
Continuous Monitoring
    Update behavioural data
    Recalculate transition probabilities
    Retrain model when required
End Framework
```

Fig. 7. Pseudocode

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The proposed AI structure workflow is described using the pseudocode, combining the data preprocessing with probabilistic behavioral risk modelling with machine learning prediction together with SHAP-based explainability and risk classification with continuous monitoring of financial behavioral risk assessment.

IV.RESULT AND DISCUSSION

	id	current_age	birth_year	birth_month	gender	address	per_capita_income	yearly_income	total_debt	credit_score	...	transaction_id	date	client_id	card_id	amount	use_chip	merchant_id	merchant_city	merchant_state	zip
0	1	64	1961	3	Female	Street 286, Indore, Madhya Pradesh - 452645	86125	1033501	280435	715	...	1251	2024-03-28	CLTIND00104	CRD001042	1483.94	Yes	MCH00496	Mumbai	Maharashtra	452645
1	2	39	1986	12	Female	Street 268, Kolkata, West Bengal - 700555	68414	820965	0	834	...	9976	2025-09-20	CLTIND00213	CRD002132	1274.72	Yes	MCH00374	Mumbai	Maharashtra	700555
2	3	50	1975	7	Female	Street 262, Lucknow, Uttar Pradesh - 226797	22595	271138	0	609	...	6084	2024-10-02	CLTIND03292	CRD032922	7622.04	No	MCH00108	Kolkata	West Bengal	226797
3	4	27	1998	2	Male	Street 265, Nagpur, Maharashtra - 440623	24158	289898	0	782	...	3350	2023-09-02	CLTIND05205	CRD052053	3970.48	Yes	MCH00001	Indore	Madhya Pradesh	440623
4	5	45	1980	7	Other	Street 157, Delhi, Delhi - 110965	45475	545697	117821	608	...	11725	2025-05-25	CLTIND04910	CRD049101	418.45	No	MCH00254	Bengaluru	Karnataka	110965

5 rows × 21 columns

Fig.8. Dataset Head – Customer Financial Profiles and Transaction Records

The preview of the set of data includes five sample observations of 20, 000 customer records that include 21 attributes. It shows demographic, financial and transactional features such as age, income, debt, credit score, transaction amount, and merchant detail validating the compatibility of the dataset to the behavioral risk modelling.

```
Dataset Shape:
(20000, 21)
```

Fig. 9. Dataset Shape – Overall Data Structure

The sample size contains 20,000 customer transactions and a feature count of 21 features are an indication that there is enough data to be used in the machine learning experiment. The high number in the sample allows to rely on behavioral risk modelling, and the variety of variables allows incorporating demographic, financial, and transactional variables.

```
... Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 21 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 20000 non-null  int64  
 1   current_age        20000 non-null  int64  
 2   birth_year         20000 non-null  int64  
 3   birth_month        20000 non-null  int64  
 4   gender             20000 non-null  object 
 5   address            20000 non-null  object 
 6   per_capita_income  20000 non-null  int64  
 7   yearly_income      20000 non-null  int64  
 8   total_debt         20000 non-null  int64  
 9   credit_score       20000 non-null  int64  
 10  num_credit_cards   20000 non-null  int64  
 11  transaction_id     20000 non-null  int64  
 12  date               20000 non-null  object 
 13  client_id          20000 non-null  object 
 14  card_id            20000 non-null  object 
 15  amount             20000 non-null  float64
 16  use_chip           20000 non-null  object 
 17  merchant_id        20000 non-null  object 
 18  merchant_city      20000 non-null  object 
 19  merchant_state     20000 non-null  object 
 20  zip                20000 non-null  int64  
dtypes: float64(1), int64(11), object(9)
memory usage: 3.2+ MB
```

Fig. 10. Dataset Information – Feature Types and Data Completeness

There is 11 numerical and 9 categorical features with a single floating-point feature in the dataset and 20,000 records are complete. Lacking missing values would enhance the reliability of the data and would also minimize data preprocessing complexity, prior to the application of probabilistic AI and machine learning models.

... Missing Values:

	0
id	0
current_age	0
birth_year	0
birth_month	0
gender	0
address	0
per_capita_income	0
yearly_income	0
total_debt	0
credit_score	0
num_credit_cards	0
transaction_id	0
date	0
client_id	0
card_id	0
amount	0
use_chip	0
merchant_id	0
merchant_city	0
merchant_state	0
zip	0

dtype: int64

Fig. 11. Missing Value Analysis – Data Quality Assessment

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The evaluation of missing value proves that there are no missing observations, even the zero in all 21 attributes of 20,000 records. This shows good quality of datasets and the behavior transition generation as well as predictive modelling processes would not be defied by missing data.

... Summary Statistics:

	id	current_age	birth_year	birth_month	per_capita_income	yearly_income	total_debt	credit_score	num_credit_cards	transaction_id	amount	zip
count	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000	2.000000e+04	2.000000e+04	20000.000000	20000.000000	20000.000000	20000.000000	20000.000000
mean	10000.500000	44.210100	1980.789900	6.479150	61234.419700	7.348131e+05	1.345380e+05	702.979750	2.873750	10015.488700	3082.286901	445976.994400
std	5773.647028	14.992515	14.992515	3.459532	35354.273099	4.242512e+05	1.739757e+05	76.993944	1.162574	5802.389323	2117.081361	168230.579911
min	1.000000	19.000000	1955.000000	1.000000	12500.000000	1.500000e+05	0.000000e+00	421.000000	1.000000	1.000000	105.160000	110102.000000
25%	5000.750000	31.000000	1968.000000	3.000000	35671.000000	4.280470e+05	0.000000e+00	648.000000	2.000000	4971.000000	1531.182500	380703.500000
50%	10000.500000	44.000000	1981.000000	7.000000	54896.000000	6.587560e+05	8.250300e+04	699.000000	3.000000	10026.500000	2601.650000	440388.000000
75%	15000.250000	57.000000	1994.000000	10.000000	74842.000000	8.981090e+05	2.008720e+05	757.000000	4.000000	15062.750000	4116.155000	560252.000000
max	20000.000000	70.000000	2006.000000	12.000000	250000.000000	3.000000e+06	1.817384e+06	900.000000	5.000000	20000.000000	19806.630000	800988.000000

Fig. 12. Summary Statistics – Numerical Feature Distribution

The statistical summary reveals the average age of customers is 44.21 years, the average annual income is around 734,813, annual debt is around 134,538 and the average credit score is at 702.98 years. These dissimilarities exhibit various financial situations that are applicable to categorization of behavioral risk.

```
======================================================================
TRAIN-TEST SPLIT EVIDENCE
======================================================================
Complete dataset: 20,000 records
Training set:     16,000 records (80.00%)
Testing set:      4,000 records (20.00%)

======================================================================
MODEL HYPERPARAMETERS
======================================================================
```

	Model	Key Hyperparameters
0	Logistic Regression	C=0.5, max_iter=2000, random_state=42
1	Random Forest	n_estimators=300, max_depth=12, min_samples_sp...
2	XGBoost	n_estimators=250, max_depth=5, learning_rate=0...

```
Running: Logistic Regression

Running: Random Forest

Running: XGBoost

======================================================================
5-FOLD CROSS-VALIDATION AND TEST RESULTS
======================================================================
```

	Model	CV Accuracy Mean	CV Accuracy SD	CV Precision	CV Recall	CV F1	Test Accuracy	Test Precision	Test Recall	Test F1
0	Logistic Regression	0.8001	0.0067	0.8006	0.8001	0.8003	0.7955	0.7954	0.7955	0.7954
1	Random Forest	0.7938	0.0038	0.7942	0.7938	0.7939	0.7857	0.7867	0.7857	0.7861
2	XGBoost	0.7956	0.0060	0.7965	0.7956	0.7959	0.7887	0.7900	0.7887	0.7893

Fig. 13: Train-Test Split, Hyperparameters, and Cross-Validation Performance

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The number of observations in the figure includes 16,000 for training and 4,000 for testing. There are mean accuracies of 0.8001, 0.7938 and 0.7956 and test accuracies of 0.7955, 0.7857 and 0.7887 respectively with five-fold validation indicating the stability of model comparison for all the evaluated methods.

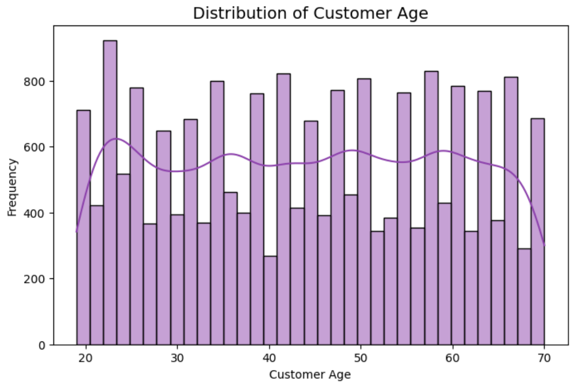

Fig. 14. Customer Age Distribution Analysis

The age structure suggests that the customer age is between 19-70 years relatively even distribution of representatives of all life stages. The median age of about 44 years indicates that there are varied customers with early career, mature and pre-retirement customers to behavioral risk modelling.

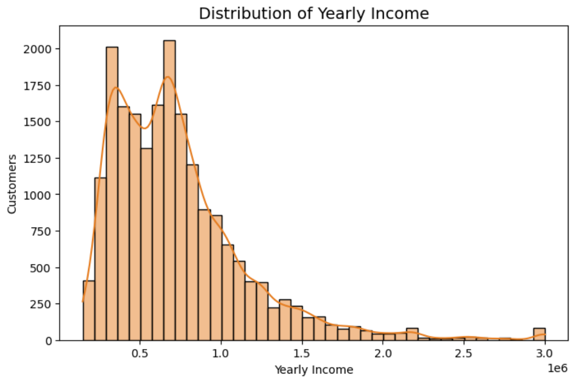

Fig. 15. Yearly Income Distribution Analysis

The right-skewed distribution of income illustrates that the financial profile of the company has the majority of the customers as low incomes below around 1 million, and those whose incomes are higher than that extend to 3 million. Such a variation is conducive to traditions of modelling the heterogeneous financial abilities and income related transitions in behavior.

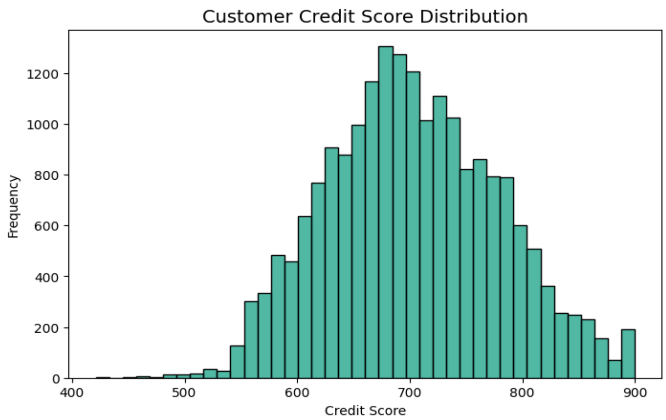

Fig. 16. Customer Credit Score Distribution Analysis

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The credit score distribution illustrates the number of between 420 and 900 credit scores and the majority of customers are around 650-750. This value of 702.98 suggests that the overall credit behavior is stable, however with an acceptable variation in regard to projecting financial risks.

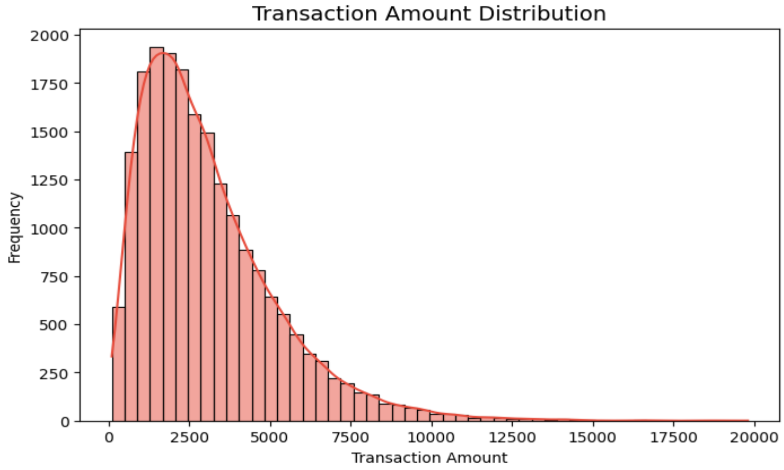

Fig. 17. Transaction Amount Distribution Analysis

The analysis of transaction depicts amounts between about 100 to 19,806 with irregularities of less than 5,000 making up the largest percentage chunk of the transactions. The skewed right distribution reflects diverse spending behavior which makes it possible to identify risks of abnormal financial and transition of behavior.

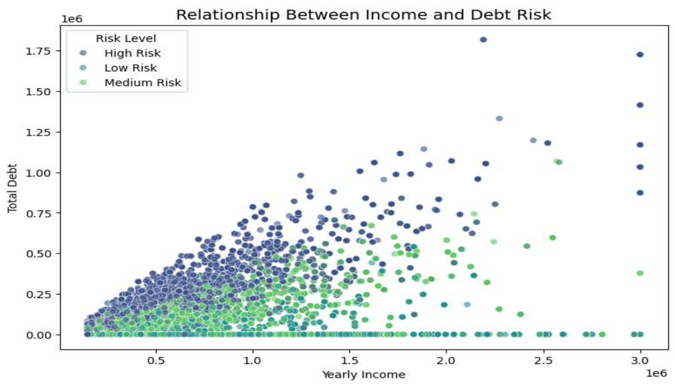

Fig. 18. Income and Debt Risk Relationship Analysis

The scatter plot shows the correlation between the annual income and total debt over the behavioral risk categories. The riskier customers are characterized by higher patterns of accumulating debts and low risk groups tend to have low debt exposure, which is useful in projecting financial vulnerabilities.

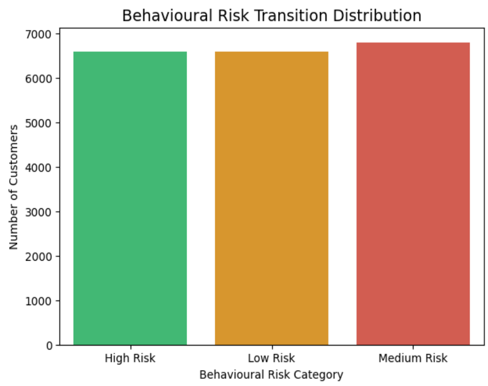

Fig. 19. Behavioral Risk Transition Distribution

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The classes of behavioral risks that are created show equal levels of representation whereby there are about 6,600 high, 6,600 low and 6,800 moderate risk customers. This equal distribution enhances fairness of models since the algorithms are able to learn all categories of transitions.

TABLE 2. Key Behavioural Risk Predictors

Rank	Feature	Impact
1	Debt-Income Ratio	High
2	Total Debt	High
3	Credit Score	Medium
4	Current Age	Medium
5	Credit Risk	Medium
6	Financial Capacity	Low

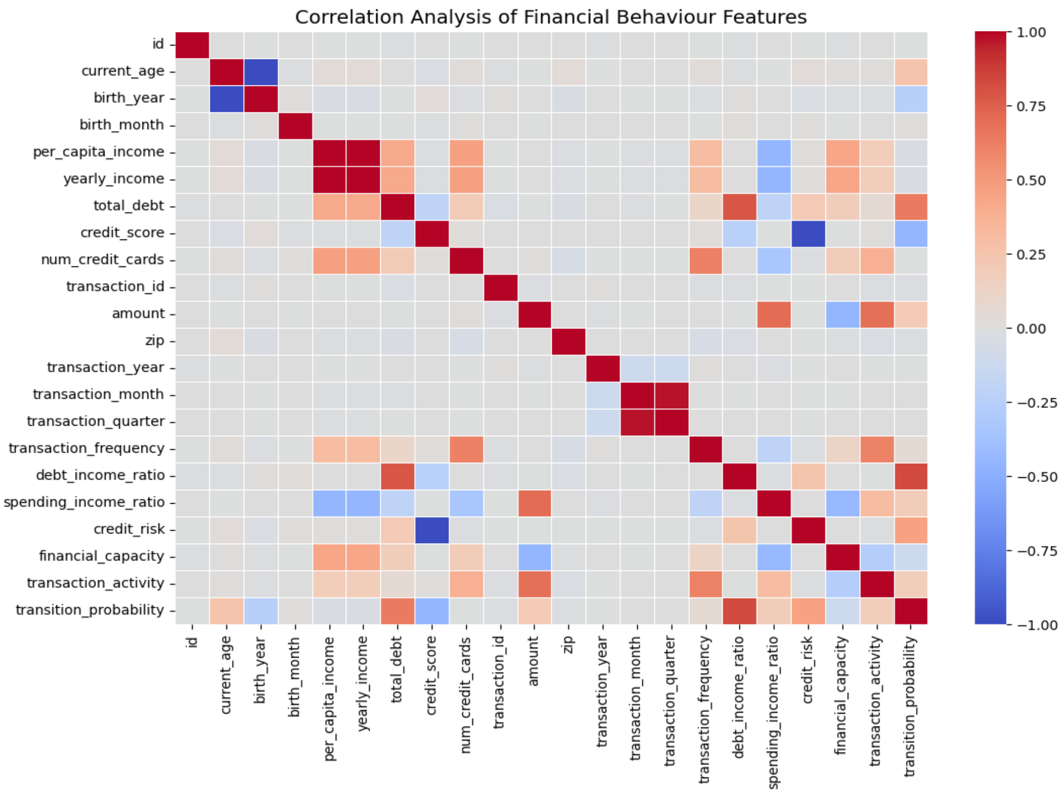

Fig. 20. Financial Behavior Feature Correlation Analysis

The correlation table underlines the relations between the financial indicators. Decent positive relationships are found between the income-related variables on one hand and debt on the other hand, and credit score exhibits negative relationships with risk indicators. The analysis confirms the choice of features in terms of prediction of behavioral transition and explainable modelling of AI.

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```
risk_level
Medium Risk    6800
High Risk      6600
Low Risk       6600
Name: count, dtype: int64
Remaining Missing Values: 0
```

Fig. 21. behavioral Risk Class Distribution

The behavioral transition target has a balanced classification pattern as there are 6, 800 Medium Risk, 6,600 High Risk, and 6,600 Low Risk customers. This even allocation competes away model bias to dominating sets of classes and facilitates effective multiclass prediction of the transitions of financial behavior.

```
LOGISTIC REGRESSION
              precision    recall  f1-score   support

   High Risk       0.86      0.85      0.86      1320
    Low Risk       0.83      0.84      0.83      1320
 Medium Risk       0.70      0.70      0.70      1360

    accuracy                           0.80      4000
   macro avg       0.80      0.80      0.80      4000
weighted avg       0.80      0.80      0.80      4000
```

Fig. 22. Logistic Regression Classification Performance

The accuracy of the Logistic Regression model is 79.55% and weighted accuracy as well as weighted precision and F1-score seem to be around 0.80. High Risk classification had the best recall (0.85), and Medium Risk had inferior performance (0.70) showing that it was not easy to consider transitional financial states.

```
RANDOM FOREST
              precision    recall  f1-score   support

   High Risk       0.84      0.85      0.85      1320
    Low Risk       0.84      0.81      0.82      1320
 Medium Risk       0.68      0.69      0.69      1360

    accuracy                           0.79      4000
   macro avg       0.79      0.79      0.79      4000
weighted avg       0.79      0.79      0.79      4000
```

Fig. 23. Random Forest Classification Performance

The accuracy of the Random Forest model was 78.53% and the weighted precision and recall are 0.79. The High-Risk customers have a higher recall of 0.85 as compared to the Medium Risk classification of 0.69 recall and it was clear that the nonlinear learning was better in terms of providing stability but poor in providing intermediate level behavioral changeovers.

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XGBOOST

	precision	recall	f1-score	support
High Risk	0.86	0.84	0.85	1320
Low Risk	0.83	0.83	0.83	1320
Medium Risk	0.69	0.70	0.69	1360
accuracy			0.79	4000
macro avg	0.79	0.79	0.79	4000
weighted avg	0.79	0.79	0.79	4000

Fig. 24. XGBoost Classification Performance

The model, XGBoost, showed an accuracy of 78.88% that has weighted precision, recall and F1 score of approximately 0.79. It is able to categorically distinguish High Risk customers by 0.84 recall, which indicates that it is able to fairly identify the financial vulnerable trends, but the Medium Risk is some way more difficult to identify.

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.79550	0.795412	0.79550	0.795444
1	Random Forest	0.78525	0.786064	0.78525	0.785578
2	XGBoost	0.78875	0.789997	0.78875	0.789320

Fig. 25. Comparative Model Performance Evaluation

According to the comparison table, Logistic Regression has the biggest accuracy (0.7955) then XGBoost (0.7888) and Random Forest (0.7852). The near-identical results demonstrate that engineered financial indicators give good predictability in both nonlinear and linear modelling techniques.

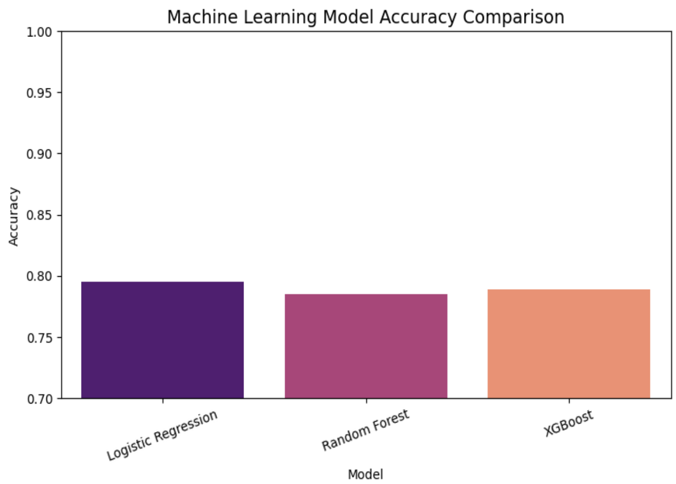

Fig. 26. Machine Learning Model Accuracy Comparison

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The accuracy comparison graph shows that the performance of the three models in predicting is similar with the range of accuracy being between 78.5% and 79.6%. The Logistic Regression had a minor advantage compared to more complex ensemble methods, which is indicative of the fact that there are relatively structured financial behavioral transitions with which linear decision boundary relationships can be effectively modelled.

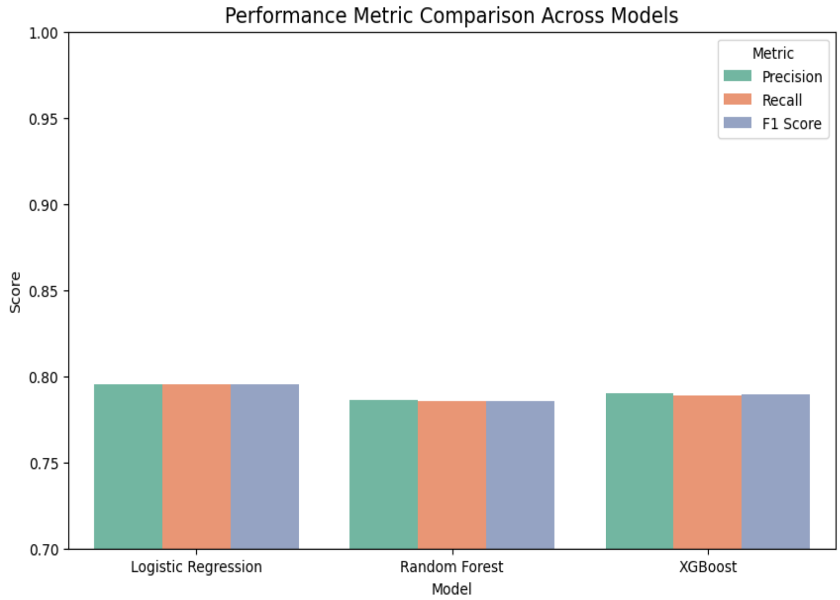

Fig. 27. Performance Metric Comparison Across Models

The metric comparison is shown to have a balanced predictive behavior with regard to precision, recall and F1-score. Logistic Regression had about 0.80 on all metrics, whereas the Random Forest, and XGBoost had about 0.79, which validates the ability to perform similar classification without seriously affecting the performance.

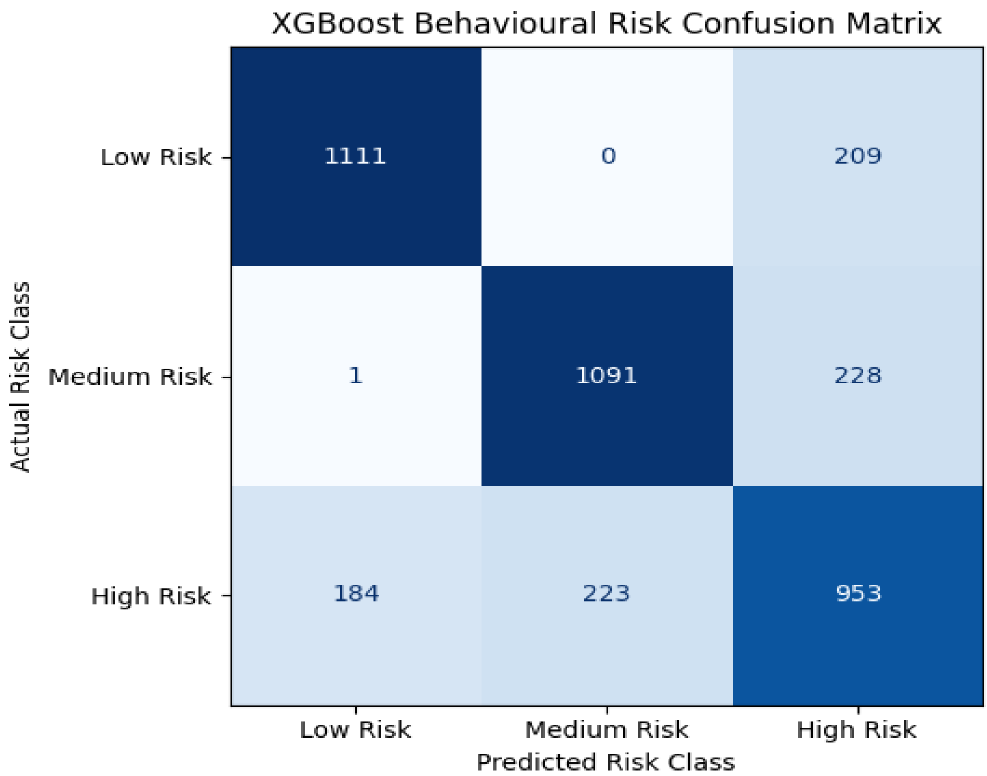

Fig. 28. XGBoost Behavioural Risk Classification Confusion Matrix

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The error rates of the XGBoost confusion matrix indicate correct classification of 1,111, 1,091 and 953 High, Low Risk, and Medium Risk customers, respectively. The main misclassification that was experienced was between the Medium Risk and other groups, which indicates similar behavioral traits experienced at the financial transition phases.

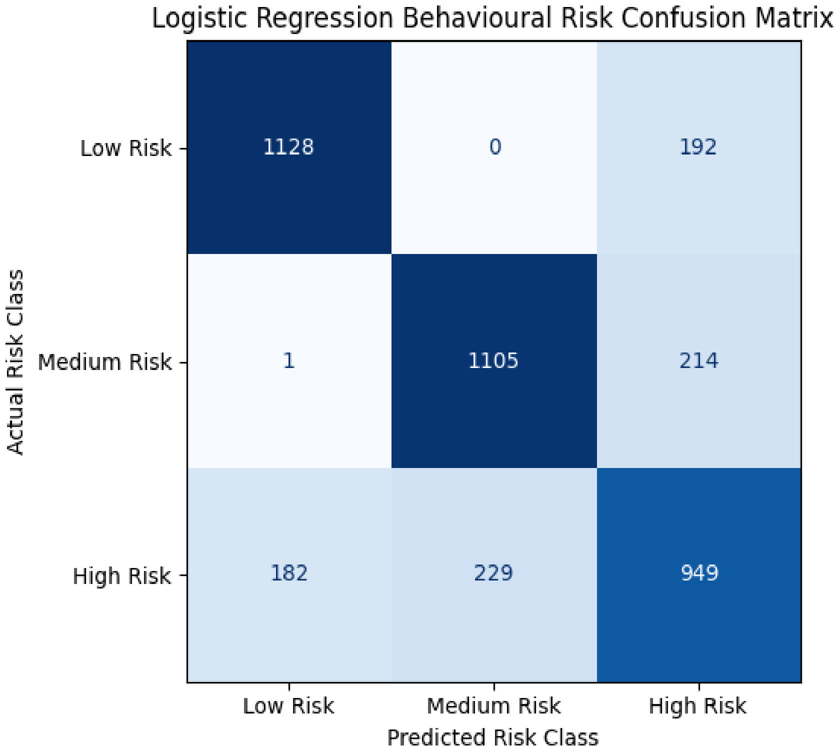

Fig. 29. Logistic Regression Behavioural Risk Confusion Matrix

Logistic Regression (LR) correctly classifies 1,128 Low risk, 1,105 Medium risk and 949 High risk. Misclassification focuses in High Risk, with 182 cases reclassified as Low, and 229 cases reclassified as Medium, though with a reported accuracy of 79.55%. More generally, there seems to be more difficulty distinguishing higher risk behavior patterns.

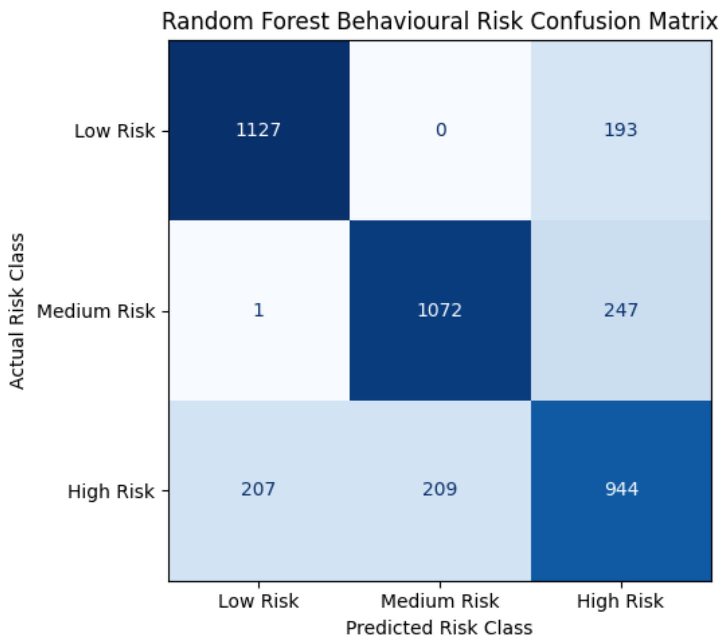

Fig . 30. Random Forest Behavioural Risk Confusion Matrix

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Random Forest accurately classifies 1,127 low risk, 1,072 moderate risk, and 944 high risk cases. Random Forest correctly classifies 1127 low risk, 1072 moderate risk and 944 high risk cases. It has the lowest test accuracy with 78.57% (207 labeled Low and 209 labeled Medium) indicating a not as strong discrimination of risk boundaries for High Risk.

LOGISTIC REGRESSION

	Predicted Low Risk	Predicted Medium Risk	Predicted High Risk
Actual Low Risk	1128	0	192
Actual Medium Risk	1	1105	214
Actual High Risk	182	229	949

RANDOM FOREST

	Predicted Low Risk	Predicted Medium Risk	Predicted High Risk
Actual Low Risk	1127	0	193
Actual Medium Risk	1	1072	247
Actual High Risk	207	209	944

XGBOOST

	Predicted Low Risk	Predicted Medium Risk	Predicted High Risk
Actual Low Risk	1111	0	209
Actual Medium Risk	1	1091	228
Actual High Risk	184	223	953

Fig. 31. Comparative Confusion Matrix Tables Across Models

The very close match in the tables of classification patterns demonstrate that across all the model's classification is very similar. Logistic regression has 1,128, 1,105 and 949 correctly predicted values whereas Random Forest has 1,127, 1,072 and 944, respectively. Also, XGBoost has 1111, 1091 and 953 correct predictions with Logistic Regression having a slight edge in the overall prediction numbers here.

```
PERCENTILE-BASED TARGET CONSTRUCTION
33rd percentile threshold: 0.152100
67th percentile threshold: 0.235292

CLASS DISTRIBUTION CREATED BY PERCENTILE BINNING
```

	Risk Class	Number of Records	Percentage	Construction Method
0	Low Risk	6600	33.0	Bottom 33% of transition score
1	Medium Risk	6800	34.0	33rd–67th percentile of transition score
2	High Risk	6600	33.0	Top 33% of transition score

```
Agreement between original risk_level and percentile-generated risk:
100.00%
```

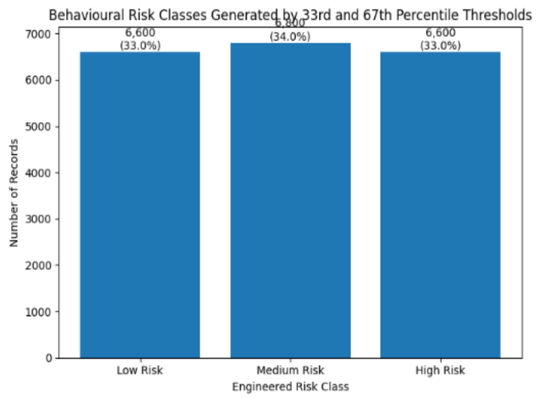

Fig. 32. Percentile-Based Behavioural Risk Class Construction

The figure shows 6,600 Low, 6,800 Medium, and 6,600 High Risk records, representing 33%, 34%, and 33%. The class balance set by the percentiles at 0.152100 and 0.235292 indicate that this was done mechanically as opposed to naturally within the data distribution.

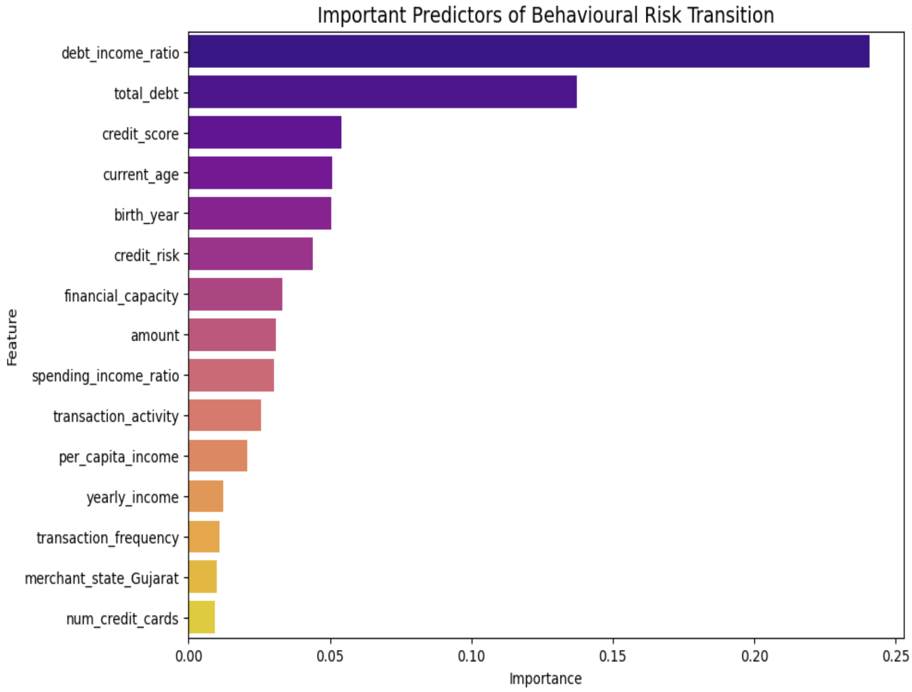

Fig. 33. Important Predictors of Behavioural Risk Transition

The analysis of the feature importance shows that, credit score (0.05), debt total (0.14) and the most significant factor is the debt-income ratio (about 0.24 importance). These results provide support that financial load and credit stability play an important role in determining the behavioral risk transitions.

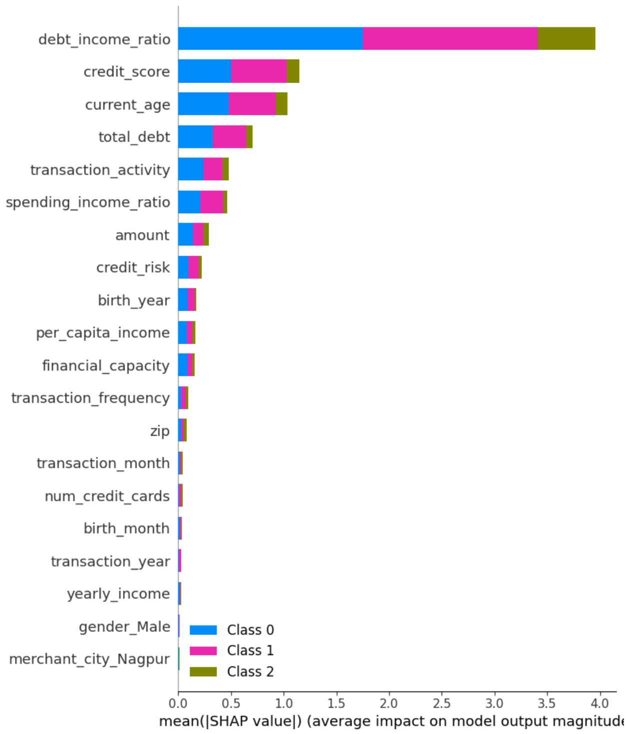

Fig. 34. SHAP-Based Explainability Analysis of Behavioural Risk Prediction

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Through the SHAP analysis, it is established that the factors that influence model decisions most as include the debt-income ratio, credit score, age, and the amount of debt that an individual owes. Debt-income ratio has the best contribution of more than 3.5 on average which enhances transparency in predicting behavior risk.

Table 3. Machine Learning Model Performance For Behavioural Risk Prediction

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	79.55%	79.54%	79.55%	79.54%
Random Forest	78.53%	78.61%	78.53%	78.56%
XGBoost	78.88%	78.99%	78.88%	78.93%

DISCUSSION

The results denote the impact of behavioral indicators of finances can substantially help probabilistic risk behavioral risk modelling. The highest accuracy is achieved with the use of Logistic Regression with the result of 79.55% and similar predictive power is ensured with the use of ensemble models, which validates the usefulness of relationships made by the financial features. The confusion model and SHAP model indicate that the debt-income ratio, total debt, credit score, and age-related factors have a significant effect on classification in behavioral risks. Even though Medium Risk transitions are more challenging since they have similar financial trends, the framework is effective in analyzing the highly risky customers having high recall. These findings confirm the possibilities of explainable AI to explain adaptive processes of financial decisions.

V.CONCLUSION

Conclusion

This study has come up with an explainable machine learning model of behavioral risk states, and risk in financial services. These findings indicate that the machine learning models are useful in predicting financial risk states with behavioral indicators and the Logistic Regression model has an accuracy of 79.55%. The SHAP analysis provided a greater amount of transparency of key predictors such as debt-income ratio, credit score, and others, to assist in making both responsible and adaptive financial decisions.

Future Direction

Future studies may improve the framework to include larger empirical longitudinal financial data, as well as much more sophisticated behavioral pattern modeling, like recurrent neural networks and survival analysis. It will need to be further developed with dynamic economic factors built-in, incessant behavioral tracking, and unsympathetic AI tools. Such enhancements have the potential to improve accuracy of prediction, flexibility and utilization of ethical eminence in various applications of financial services.

VI.REFERENCES

[1] Ameriks, J., Briggs, J., Caplin, A., Shapiro, M.D. and Tonetti, C., 2020. Long-term-care utility and late-in-life saving. Journal of Political Economy, 128(6), pp.2375-2451.

[2] Alexander III, L., Mulfinger, E. and Oswald, F.L., 2020. Using big data and machine learning in personality measurement: Opportunities and challenges. European Journal of Personality, 34(5), pp.632-648.

[3] Van Der Aalst, W.M., 2018. Process discovery from event data: Relating models and logs through abstractions. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(3), p.e1244.

[4] Wang, B., Rasouli, S., Timmermans, H. and Shao, C., 2018. Relationships between consecutive long-term and mid-term mobility decisions over the life course: a Bayesian network approach. Transportation research record, 2672(47), pp.159-170.
[5] Verenich, I., Dumas, M., Rosa, M.L., Maggi, F.M. and Teinemaa, I., 2019. Survey and cross-benchmark comparison of remaining time prediction methods in business process monitoring. ACM Transactions on Intelligent Systems and Technology (TIST), 10(4), pp.1-34.
[6] Paul, M.J., White, R.W. and Horvitz, E., 2016. Search and breast cancer: On episodic shifts of attention over life histories of an illness. ACM Transactions on the Web (TWEB), 10(2), pp.1-27.
[7] Ebadi, N., Lwowski, B., Jaloli, M. and Rad, P., 2019. Implicit life event discovery from call transcripts using temporal input transformation network. IEEE Access, 7, pp.172178-172189.
[8] Camargo, M., Dumas, M. and González-Rojas, O., 2019, July. Learning accurate LSTM models of business processes. In International Conference on Business Process Management (pp. 286-302). Cham: Springer International Publishing.
[9] Abdullah, S., Matthews, M., Frank, E., Doherty, G., Gay, G. and Choudhury, T., 2016. Automatic detection of social rhythms in bipolar disorder. Journal of the American Medical Informatics Association, 23(3), pp.538-543.
[10] Linardatos, P., Papastefanopoulos, V. and Kotsiantis, S., 2020. Explainable ai: A review of machine learning interpretability methods. Entropy, 23(1), p.18.
[11] Jin, L., Lazar, A., Sears, J., Todd-Blick, A., Sim, A., Wu, K., Yang, H.C. and Spurlock, C.A., 2020. Clustering life course to understand the heterogeneous effects of life events, gender, and generation on habitual travel modes. IEEE Access, 8, pp.190964-190980.
[12] Adams, R.A., Huys, Q.J. and Roiser, J.P., 2016. Computational psychiatry: towards a mathematically informed understanding of mental illness. Journal of Neurology, Neurosurgery & Psychiatry, 87(1), pp.53-63.
[13] Liu, J., Weitzman, E.R. and Chunara, R., 2017, February. Assessing behavior stage progression from social media data. In Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (pp. 1320-1333).
[14] Khodabakhsh, M., Kahani, M. and Bagheri, E., 2020. Predicting future personal life events on twitter via recurrent neural networks. Journal of Intelligent Information Systems, 54(1), pp.101-127.
[15] Hanga, K.M., Kovalchuk, Y. and Gaber, M.M., 2020. A graph-based approach to interpreting recurrent neural networks in process mining. IEEE Access, 8, pp.172923-172938.
[16] Aburomman, A., Lama, M. and Bugarín, A., 2019. A vector-based classification approach for remaining time prediction in business processes. IEEE Access, 7, pp.128198-128212.
[17] Rai, A., 2020. Explainable AI: From black box to glass box. Journal of the academy of marketing science, 48(1), pp.137-141.
[18] Fellous, J.M., Sapiro, G., Rossi, A., Mayberg, H. and Ferrante, M., 2019. Explainable artificial intelligence for neuroscience: behavioral neurostimulation. Frontiers in neuroscience, 13, p.490966.
[19] Adadi, A. and Berrada, M., 2018. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). IEEE access, 6, pp.52138-52160.
[20] Coifman, K.G. and Summers, C.B., 2019. Understanding emotion inflexibility in risk for affective disease: Integrating current research and finding a path forward. Frontiers in psychology, 10, p.392.
[21] Felzmann, H., Fosch-Villaronga, E., Lutz, C. and Tamò-Larrieux, A., 2020. Towards Transparency by Design for Artificial Intelligence: H. Felzmann et al. Science and engineering ethics, 26(6), pp.3333-3361.
[22] Deeks, A., 2019. The judicial demand for explainable artificial intelligence. Columbia Law Review, 119(7), pp.1829-1850.

[23] Mullangi, K., Yarlagadda, V.K., Dhameliya, N. and Rodriguez, M., 2018. Integrating AI and Reciprocal Symmetry in Financial Management: A Pathway to Enhanced Decision-Making. Int. J. Reciprocal Symmetry Theor. Phys, 5(1), pp.42-52.

[24] How, M.L., Cheah, S.M., Khor, A.C. and Chan, Y.J., 2020. Artificial intelligence-enhanced predictive insights for advancing financial inclusion: A human-centric ai-thinking approach. Big Data and Cognitive Computing, 4(2), p.8.

[25] Maddula, S.S., Shajahan, M.A. and Sandu, A.K., 2019. From data to insights: Leveraging AI and reciprocal symmetry for business intelligence. Asian Journal of Applied Science and Engineering, 8(1), pp.73-84.

[26] Komandla, V. and Chilkuri, B., 2019. AI and data analytics in personalizing fintech online account opening processes. Educational Research (IJMCER), 3(3), pp.1-11.

[27] Mullangi, K., 2017. Enhancing Financial Performance through AIdriven Predictive Analytics and Reciprocal Symmetry. Asian Accounting and Auditing Advancement, 8(1), pp.57-66.

[28] Belanche, D., Casaló, L.V. and Flavián, C., 2019. Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. Industrial Management & Data Systems, 119(7), pp.1411-1430.

[29] Palle, S., 2019. Artificial intelligence using DBS-QOS in banking organizations. Journal of scientific research & engineering trends, 5(1), pp.107-118.

[30] Deldari, S., Smith, D.V., Sadri, A. and Salim, F., 2020. Espresso: Entropy and shape aware time-series segmentation for processing heterogeneous sensor data. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 4(3), pp.1-24.

[31] Hagras, H., 2018. Toward human-understandable, explainable AI. Computer, 51(9), pp.28-36.

[32] El Idrissi, F.Z. and Silva, M., 2019. Engineering Data for Explainable AI in Financial Forecasting Systems. International Journal of Artificial Intelligence & Digital Transformation, 2(2), pp.01-14.

[33] Mehra, A.D., 2020. Unifying adversarial robustness and interpretability in deep neural networks: A comprehensive framework for explainable and secure machine learning models. International Research Journal of Modernization in Engineering Technology and Science, 2(9), pp.1829-1838.

[34] Walambe, R., Kolhatkar, A., Ojha, M., Kademani, A., Pandya, M., Kathote, S. and Kotecha, K., 2020, December. Integration of explainable AI and blockchain for secure storage of human readable justifications for credit risk assessment. In International Advanced Computing Conference (pp. 55-72). Singapore: Springer Singapore.

[35] Börnhorst, C., Russo, P., Veidebaum, T., Tornaritis, M., Molnár, D., Lissner, L., Mårild, S., De Henauw, S., Moreno, L.A., Floegel, A. and Ahrens, W., 2020. The role of lifestyle and non-modifiable risk factors in the development of metabolic disturbances from childhood to adolescence. International Journal of Obesity, 44(11), pp.2236-2245.