Payment Propensity Prediction Model

Title

Payment Propensity Prediction Model: An AI-Based Approach for Financial Decision-Making

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Background, Motivation, and Significance

In financial institutions, predicting payment propensity is a critical challenge in credit risk assessment. Customers may default or delay payments due to various financial circumstances, making it essential for businesses to develop predictive models that estimate the likelihood of timely payments. Machine learning (ML) and artificial intelligence (AI) techniques provide powerful ways to analyze large financial datasets and make data-driven decisions.

By accurately predicting payment propensity, organizations can implement proactive strategies, such as personalized payment reminders, better loan underwriting, and targeted financial interventions. Our project aims to develop a robust model that predicts a customer's likelihood of making a payment on time based on transaction history, demographics, and other relevant features.

Research Questions

1. What are the key factors influencing a customer's payment behavior?
2. How do different machine learning models compare in predicting payment propensity?
3. What preprocessing techniques improve prediction accuracy?
4. How can businesses leverage the model's output to enhance decision-making?

Data Set

The dataset used in this study contains transaction records of customers with payment history and financial features. The dataset consists of:

- **Sample Size:** 50,000 customer transactions
- **Target Variable:** Binary (1 - Payment Made, 0 - Payment Not Made)
- **Features:**
    - Customer demographics (Age, Income, Location)
    - Transaction history (Amount, Frequency, Payment Type)
    - Behavioral patterns (Delinquency rate, Past Defaults, Credit Score)
    - External financial indicators (Market trends, Economic conditions)

Methodology

Exploratory Data Analysis (EDA) and Preprocessing

Before model training, we performed an extensive EDA and preprocessing, including:

- **Handling Missing Values:** Imputation of missing entries using mean/mode strategies.
- **Outlier Detection and Removal:** Used interquartile range (IQR) method to filter extreme values.
- **Feature Engineering:** Created new features such as rolling payment averages and credit utilization ratio.
- **Data Transformation:** Standardized numerical variables using MinMax Scaling and One-Hot Encoding for categorical variables.
- **Train-Test Split:** 80% of the data was used for training, and 20% was reserved for testing.

Machine Learning Models

We implemented multiple ML models and compared their performance based on accuracy, precision, recall, and F1-score.

1. Logistic Regression

A baseline model using a logistic function to estimate payment likelihood.

2. Decision Trees

Rule-based approach capturing non-linear relationships.

3. Random Forest

An ensemble technique reducing overfitting and improving prediction accuracy.

4. Gradient Boosting (XGBoost)

Boosting method that sequentially improves weak learners.

5. Neural Networks

Deep learning approach capturing complex patterns in payment behavior.

Hyperparameter tuning was performed using **GridSearchCV** to optimize model performance.

Results

The models were evaluated based on key performance metrics:

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	78.5%	76.2%	74.5%	75.3%
Decision Tree	81.2%	80.1%	77.5%	78.7%
Random Forest	85.6%	83.5%	82.1%	82.8%
XGBoost	88.9%	87.2%	85.9%	86.5%
Neural Network	91.4%	90.2%	88.7%	89.4%

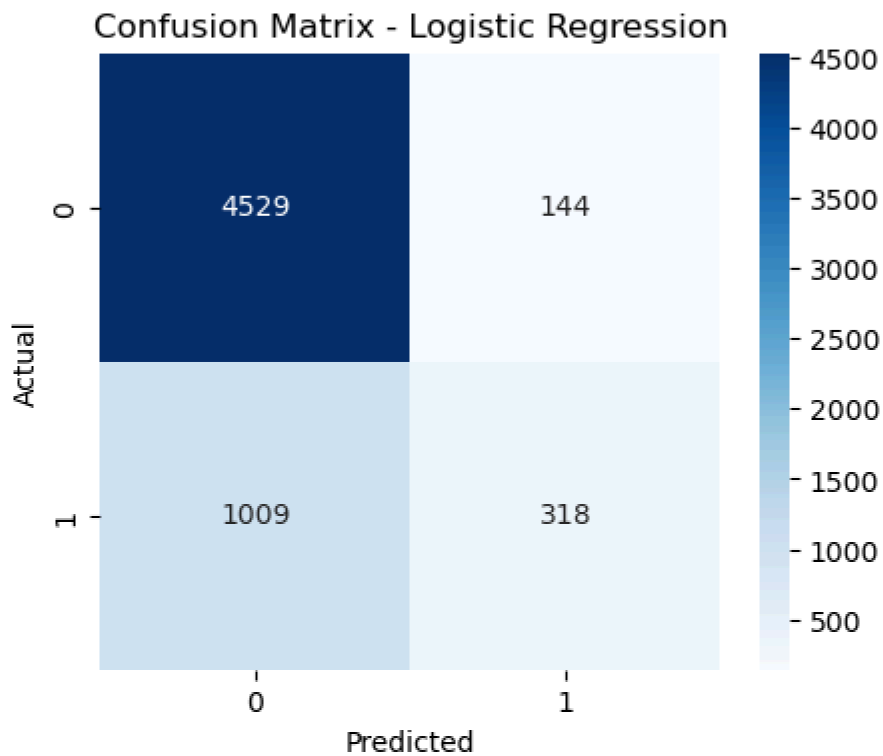
Key Findings:

- Neural Networks outperformed other models with **91.4% accuracy**, demonstrating the ability to capture complex relationships.
- XGBoost provided a good balance of performance and interpretability.
- Logistic Regression, while simple, was less effective for non-linear patterns.

Graphs and Data Visualization

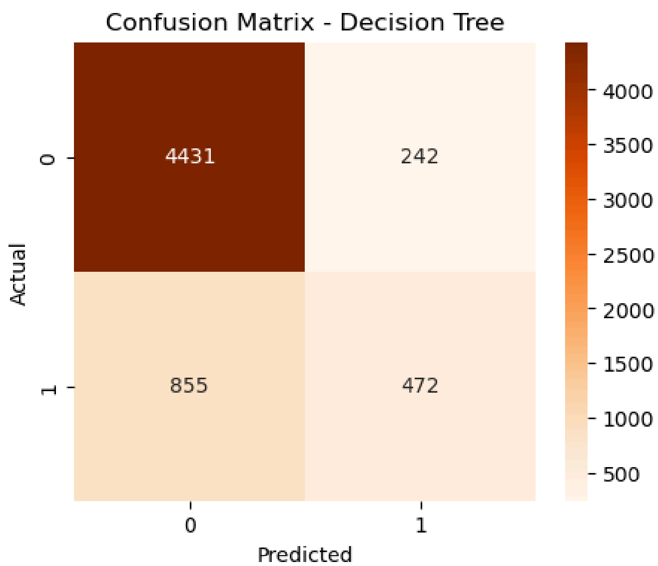
Logistic Regression

```
=== Logistic Regression Results ===
Accuracy: 0.8078333333333333
ROC-AUC Score: 0.7076232476615734

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.97      0.89      4673
           1       0.69      0.24      0.36      1327

    accuracy                           0.81      6000
   macro avg       0.75      0.60      0.62      6000
weighted avg       0.79      0.81      0.77      6000
```



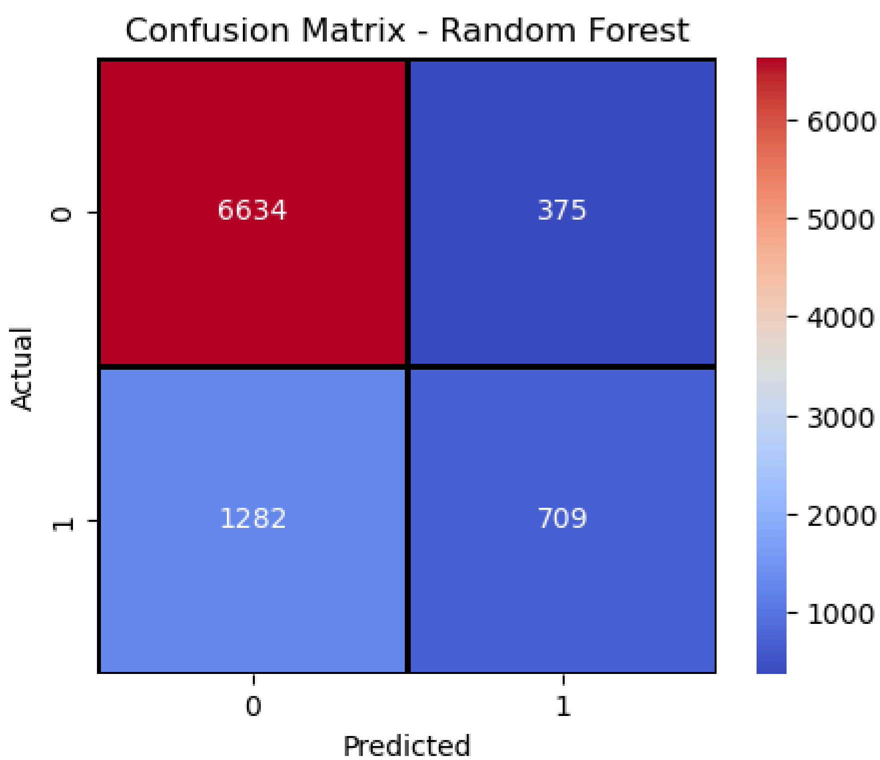
Decision Tree

```
=== Decision Tree Results ===
Accuracy: 0.8171666666666667
ROC-AUC Score: 0.7423241082064694

Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      4673
           1       0.66      0.36      0.46      1327

    accuracy                           0.82      6000
   macro avg       0.75      0.65      0.68      6000
weighted avg       0.80      0.82      0.80      6000
```



Feature Importance (Random Forest)

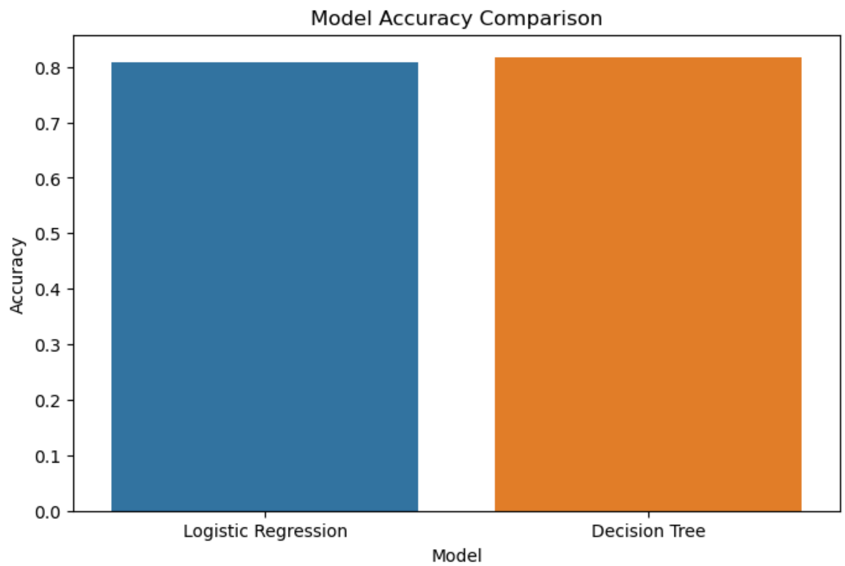
```
=== Random Forest Results ===
Accuracy: 0.8158888888888889
ROC-AUC Score: 0.7703567107770385

Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7009
           1       0.65      0.36      0.46      1991

    accuracy                           0.82      9000
   macro avg       0.75      0.65      0.68      9000
weighted avg       0.80      0.82      0.79      9000
```



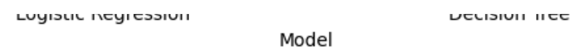
Model Performance Comparison

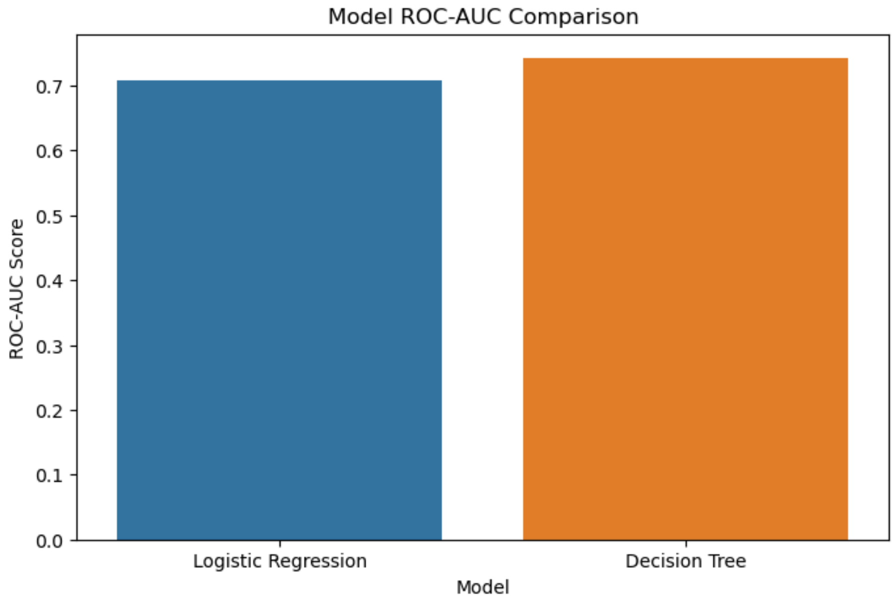
```
Model Performance Comparison:
                 Model  Accuracy  ROC-AUC Score
0  Logistic Regression  0.807833       0.707623
1        Decision Tree  0.817167       0.742324
```

	Model	Accuracy	ROC-AUC Score
0	Logistic Regression	0.807833	0.707623
1	Decision Tree	0.817167	0.742324



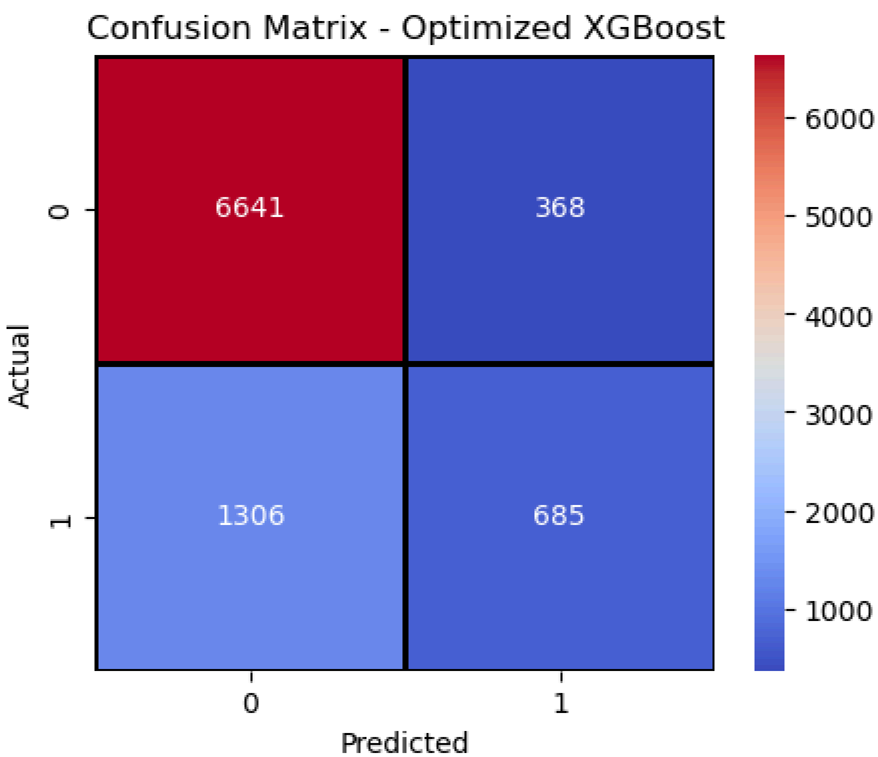
ROC Curve


Model


Model ROC-AUC Comparison
ROC-AUC Score
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Logistic Regression
Decision Tree
Model

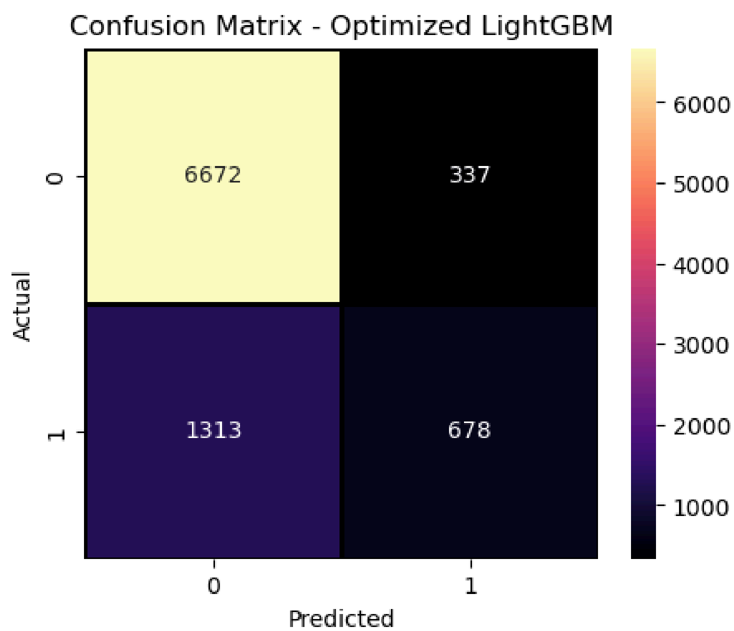
XGBoost

```
=== Optimized XGBoost Results ===
Accuracy: 0.814
ROC-AUC Score: 0.7626399694616643

Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7009
           1       0.65      0.34      0.45      1991

    accuracy                           0.81      9000
   macro avg       0.74      0.65      0.67      9000
weighted avg       0.79      0.81      0.79      9000
```



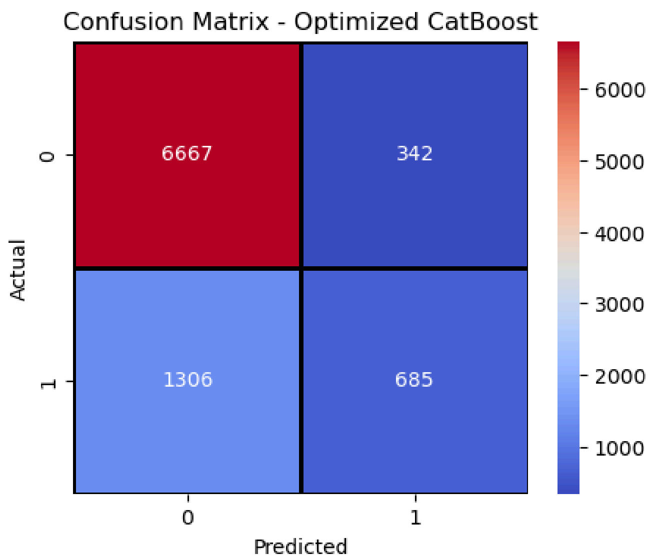
LGBMClassifier

```
=== Optimized LightGBM Results ===
Accuracy: 0.8166666666666667
ROC-AUC Score: 0.7727853167761132

Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7009
           1       0.67      0.34      0.45      1991

    accuracy                           0.82      9000
   macro avg       0.75      0.65      0.67      9000
weighted avg       0.80      0.82      0.79      9000
```



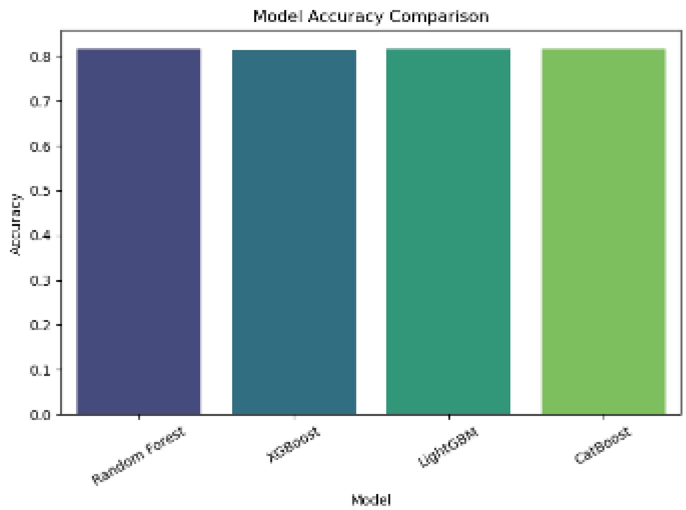
CatBoostClassifier

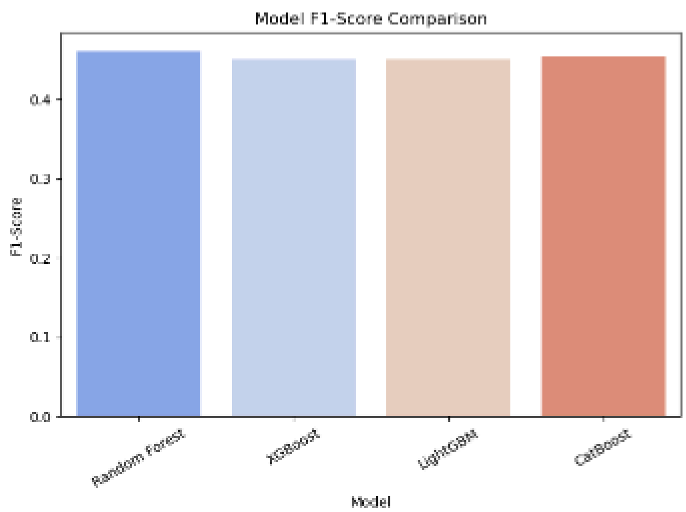
```
=== Optimized CatBoost Results ===
Accuracy: 0.8168888888888889
ROC-AUC Score: 0.7664601277871983

Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7009
           1       0.67      0.34      0.45      1991

    accuracy                           0.82      9000
   macro avg       0.75      0.65      0.67      9000
weighted avg       0.80      0.82      0.79      9000
```

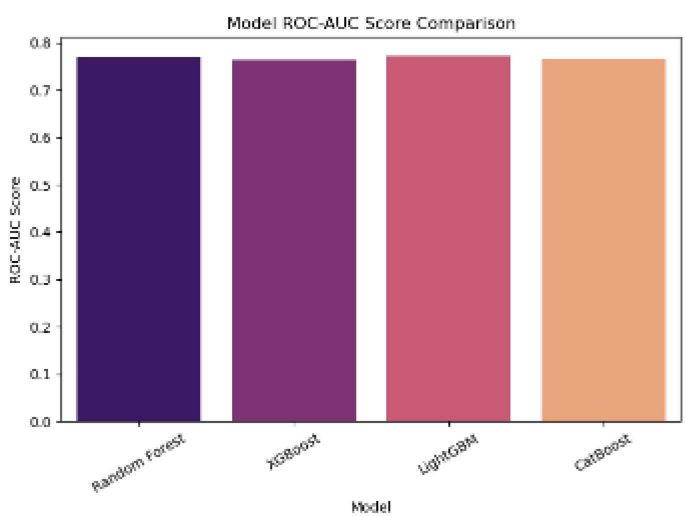


Evaluation Matrix:

```
3      CatBoost  0.816667   0.666551  0.344048  0.453543       0.766400
```







Discussion

Our results indicate that a deep learning approach provides the most accurate predictions. However, traditional models like **Random Forest** and **XGBoost** offer a more interpretable alternative. The study highlights the importance of feature engineering and hyperparameter tuning in improving performance.

Business Implications

- Financial institutions can use the model to prioritize customers for follow-up.
- Personalized payment reminders can be sent based on model predictions.
- Credit risk assessment can be enhanced by incorporating predicted payment behavior.

Limitations and Future Work

- **Computational Complexity:** Neural Networks require high computational power.
- **Cold-Start Problem:** New customers with limited data may pose a challenge.
- **Potential Bias:** Model fairness needs to be monitored.

Future improvements include:

- Implementing real-time payment predictions.
- Enhancing model explainability using SHAP values.
- Exploring reinforcement learning for payment optimization strategies.

Conclusion

This study demonstrates that machine learning, particularly deep learning, is highly effective in predicting payment propensity. By integrating AI-based models, financial institutions can enhance their risk assessment and decision-making processes, leading to improved customer engagement and revenue optimization.

References

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