ANALYSIS OF BUSINESS PERFORMANCE MANAGEMENT OF SOFT DRINK ENTERPRISES

Through Coca - Cola

Presented by
GROUP 01

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Introduction to Coca-Cola's Competitive Landscape

Consumer Priorities:
- Increasing focus on healthy and sustainable products

Competitive Dynamics:
- Coca-Cola (CCE):
  - Innovative promotions.
  - Portfolio of over 4,300 products.
- PepsiCo:
  - Generates billions annually with 22 major brands.

Research Objectives:
Evaluate business performance through financial indicators (focus on stock metrics)
Assess human resource factors influencing performance.

Methodology:
Qualitative Analysis: Identifies strategies impacting performance.
Quantitative Analysis: Utilizes algorithms (e.g., linear regression, KNN, logistic regression).

Coca-Cola's Business Performance Management

- **Market Leadership**
  - CCE leads the carbonated soft drink market with over 400 brands in 200 countries
- **Financial Performance**
  - 24% profit margin
  - 0.48 debt/equity ratio indicates financial stability.
- **Strategic Approaches**
  - "Glocal" Model: Tailors strategies to local markets.
  - Balanced Scorecard (BSC): Enhances efficiency and cost optimization.
- **Human Resource Strategies**
  - Group interviews and internal selection.
  - 70:20:10 training model boosts employee motivation and morale.
- **Global Success Factors**
  - $61 billion brand value and advanced supply chains.
  - Focus on healthier products and digital transformation.
  - Use of Decision Support Systems (DSS) for strategic decision-making.

Linear Regression Model for Coca-Cola Stock Prices

I. INTRODUCTION

Objective:

Implement a Linear Regression model to predict future closing prices of Coca-Cola stock.

Dataset Features:

Input Variable: Opening price

Target Variable: Closing price

1. Data Pre-Processing

Step 1: Check data types for cleaning.

```
df.info()
```

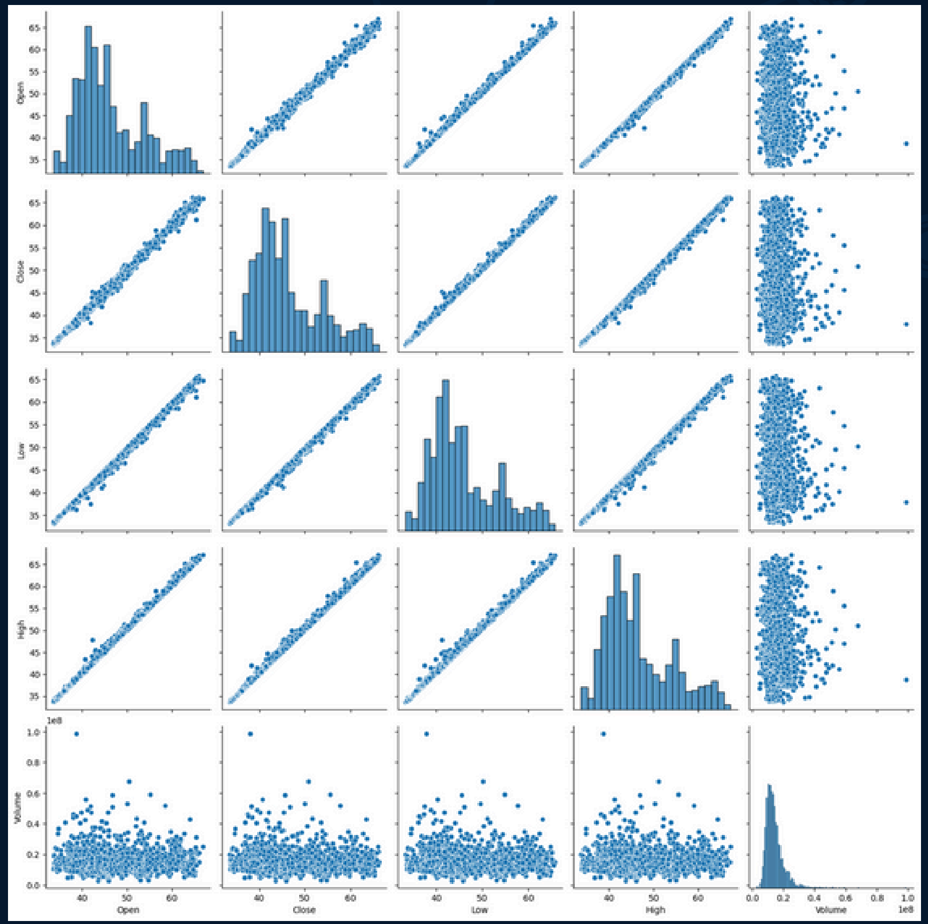
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2768 entries, 0 to 2767
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Date          2768 non-null   object
 1   Open          2768 non-null   float64
 2   High          2768 non-null   float64
 3   Low           2768 non-null   float64
 4   Close         2768 non-null   float64
 5   Volume        2768 non-null   int64
 6   Dividends     2768 non-null   float64
 7   Stock Splits  2768 non-null   int64
dtypes: float64(5), int64(2), object(1)
memory usage: 173.1+ KB
```

	Open	High	Low	Close	Volume	Dividends	Stock Splits
count	2768.000000	2768.000000	2768.000000	2768.000000	2.768000e+03	2768.000000	2768.000000
mean	46.240986	46.550983	45.925972	46.244491	1.439106e+07	0.005549	0.000723
std	7.337608	7.415198	7.255777	7.340632	6.255951e+06	0.044749	0.038014
min	33.650000	33.720000	33.280000	33.490000	2.996300e+06	0.000000	0.000000
25%	40.857500	41.110000	40.630000	40.880000	1.050740e+07	0.000000	0.000000
50%	44.495000	44.775000	44.150000	44.510000	1.307250e+07	0.000000	0.000000
75%	50.990000	51.365000	50.472500	50.872500	1.650562e+07	0.000000	0.000000
max	67.000000	67.200000	65.720000	66.210000	9.896750e+07	0.440000	2.000000

Step 2: Confirm no null or missing values.

Step 3: Remove unnecessary columns:

- Dividends and Stock Splits (constant values).



Summary: Data is clean; Date column is not required for modeling.

```
irrelevant_columns = ['Dividends', 'Stock Splits']
df = df.drop(columns=irrelevant_columns)
```

Data Analysis

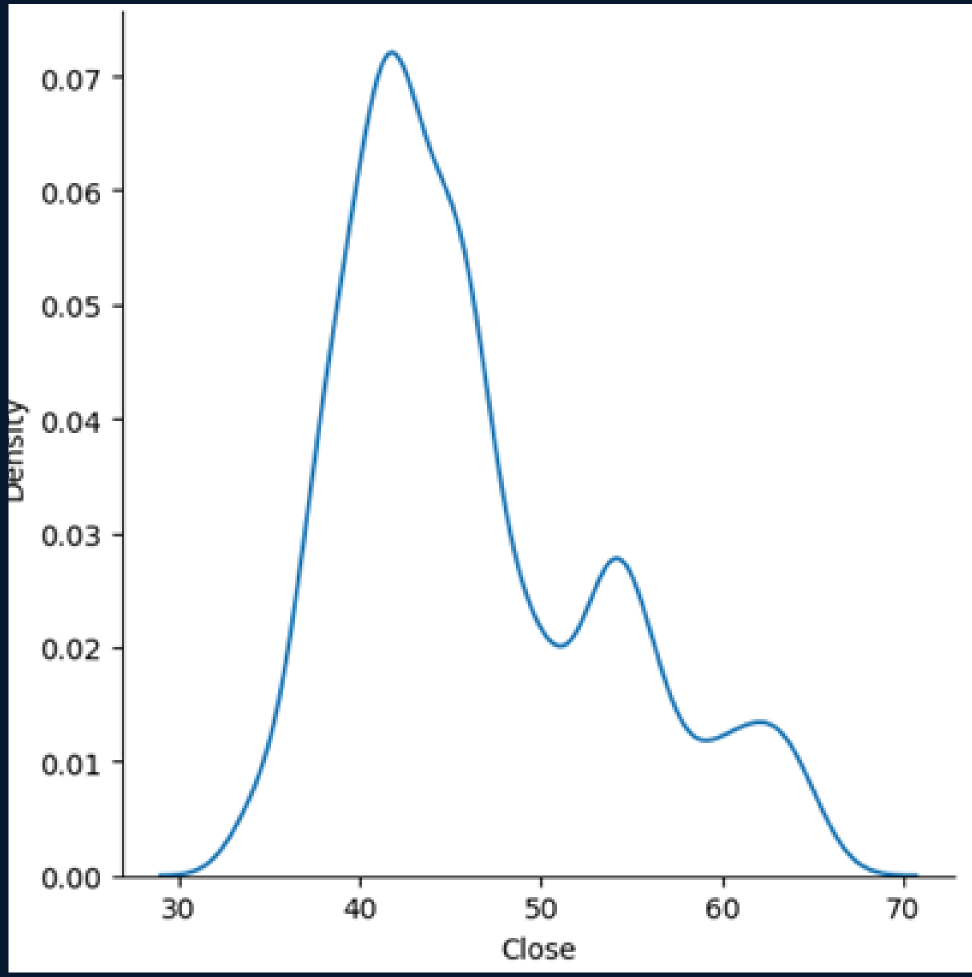
Correlation: Strong correlation (0.998) between Opening and Closing prices.

```
Correlation = df['Open'].corr(df['Close'])
print(f'The correlation coefficient between "Open" and "Close" is: {Correlation}')
```

```
The correlation coefficient between "Open" and "Close" is: 0.998191824395903
```

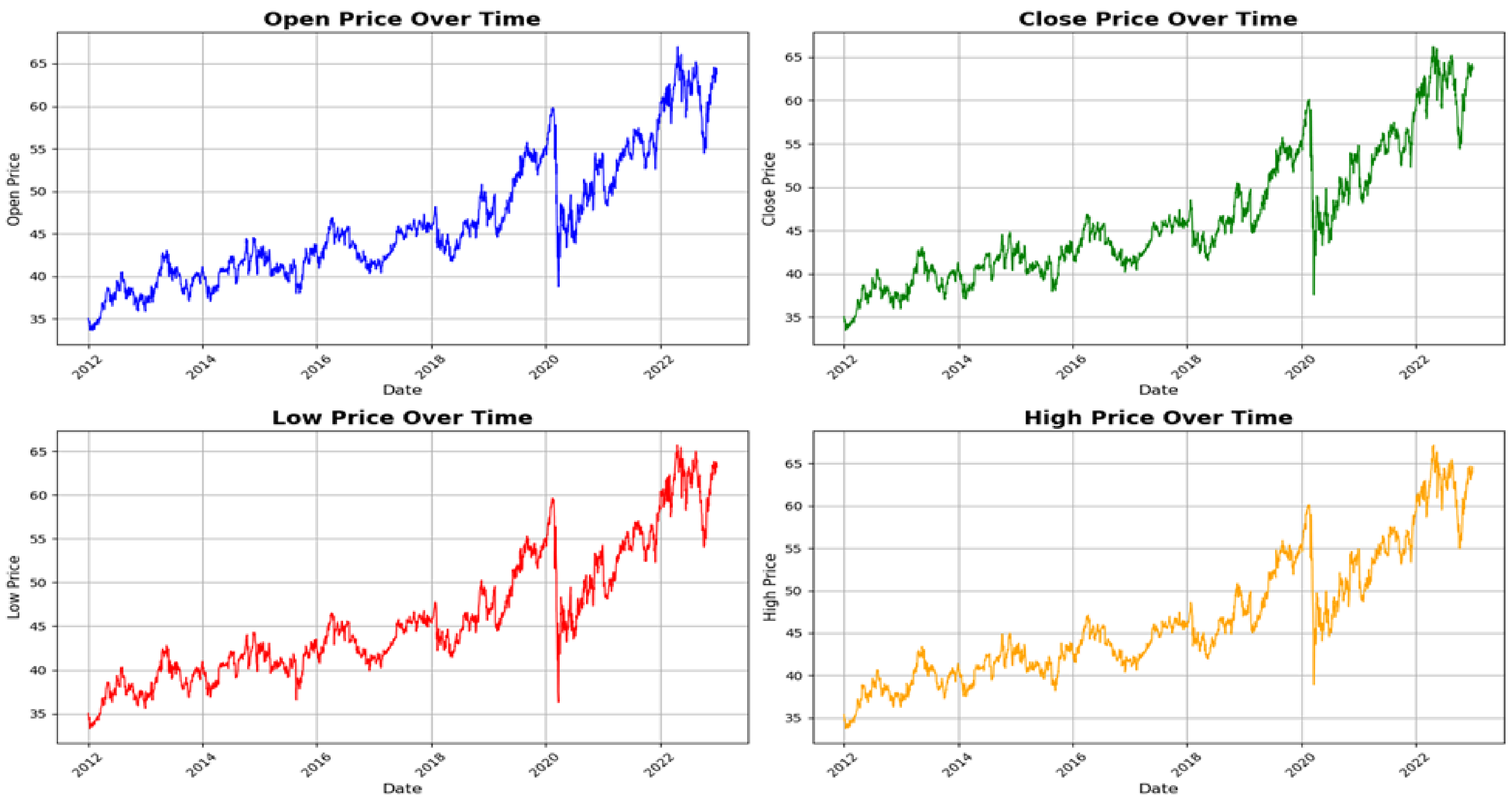
Visualizations

- **KDE Chart**: Distribution of Closing prices.



Visualizations

- **OHLC Chart**: Stock price fluctuations over time.



2. Building the model

Visualizing Relationships

- Chart A & B:Visual representation of two key variables:
  - Target Variable: Close
  - Input Variable: Open

Linear Regression Model

- Utilized Linear Regression to understand the relationship between variables.
- **Coefficients:**
  - Slope (a): 0.99860318
  - Intercept (b): 0.06809476
- The regression line is illustrated in the charts, indicating a strong correlation.

Model Training and Testing

- **Divided the test data into:**
  - X_train: Input features for training
  - y_train: Target variable for training
  - X_test: Input features for testing
  - y_test: Target variable for testing
- **Conducted training to produce predictions:**
  - y_train_pred: Predictions on training data
  - y_test_pred: Predictions on test data

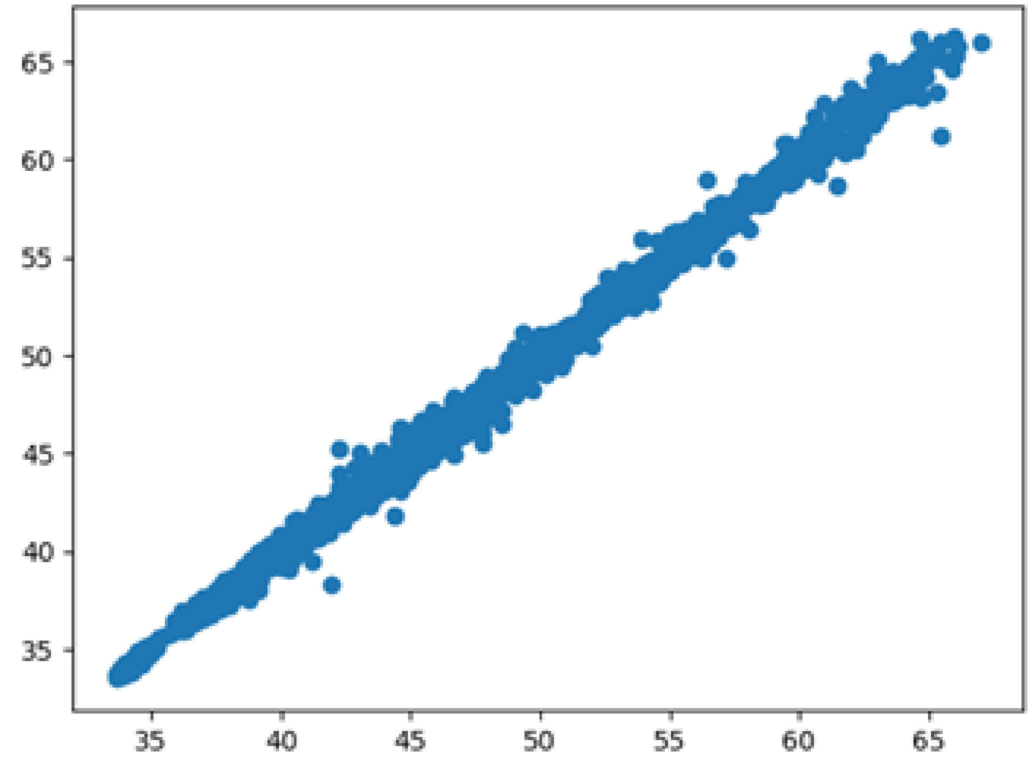


Chart A

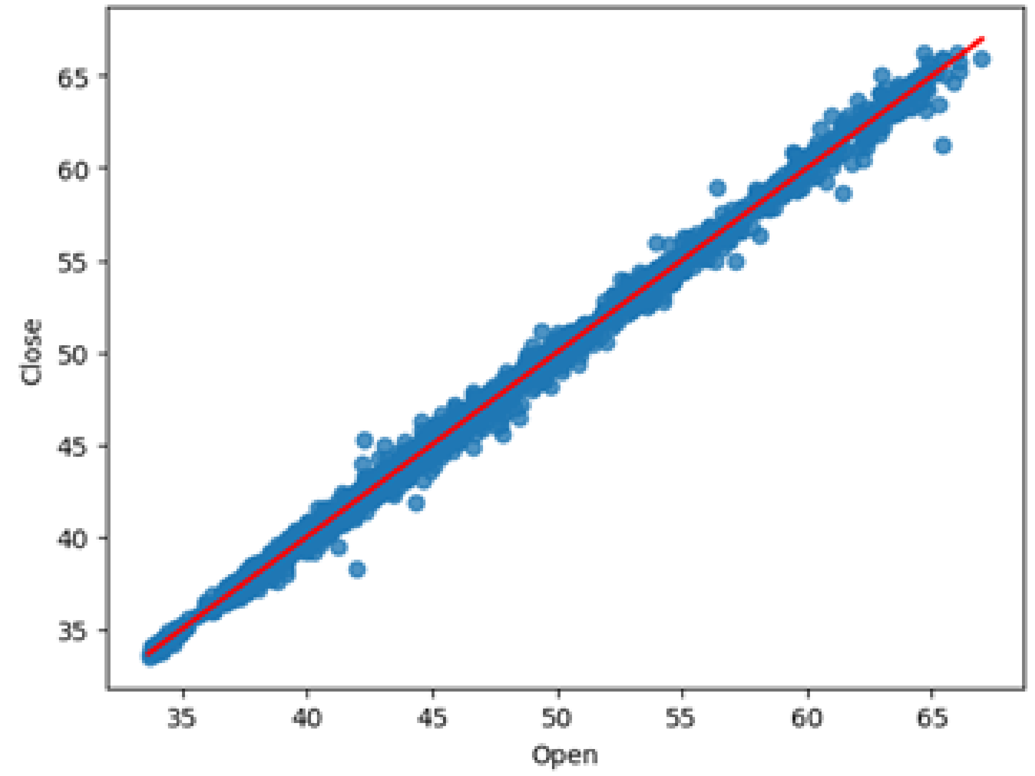


Chart B

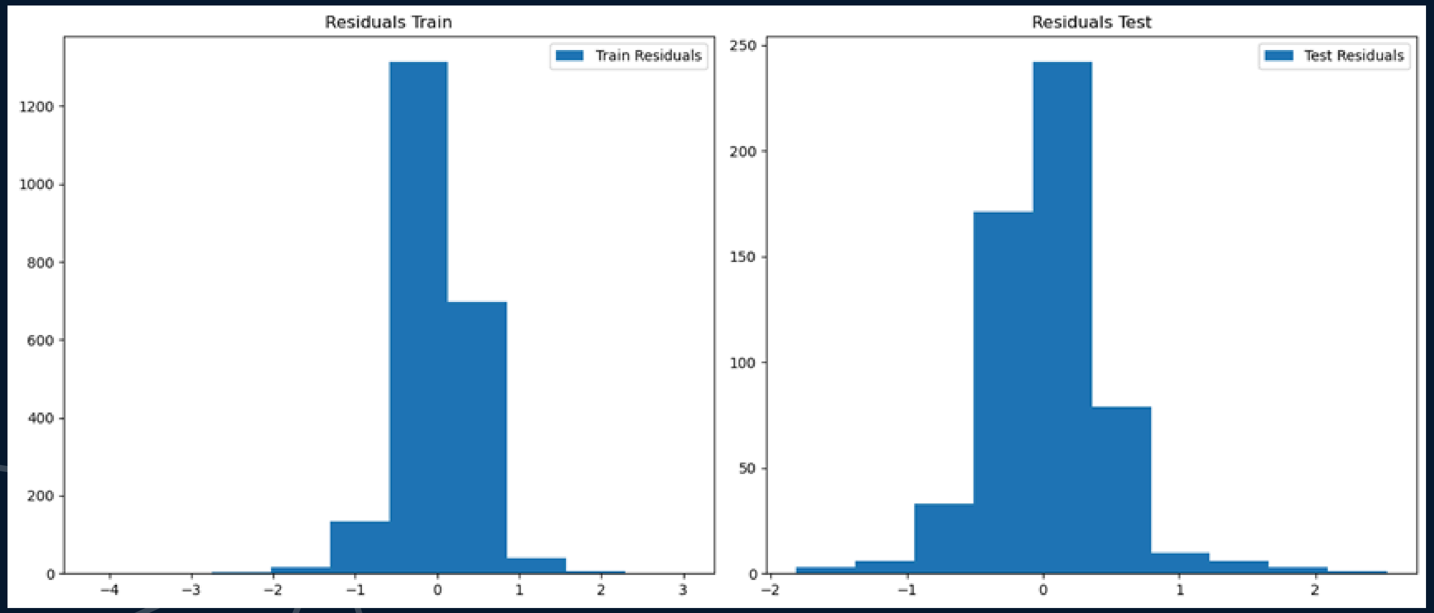
3. Make Prediction

R^2 Values:

- R^2_train: 0.9963
- R^2_test: 0.9967

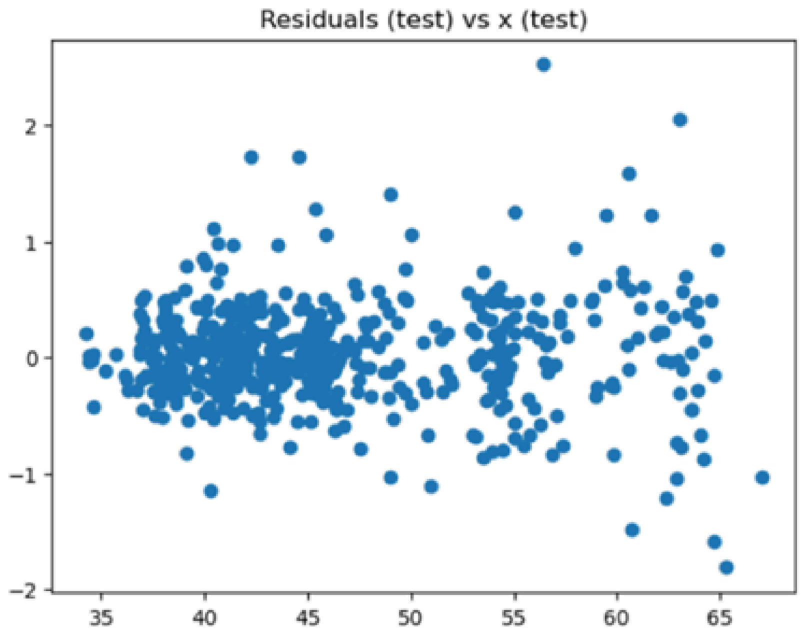
Mean Squared Error (MSE):

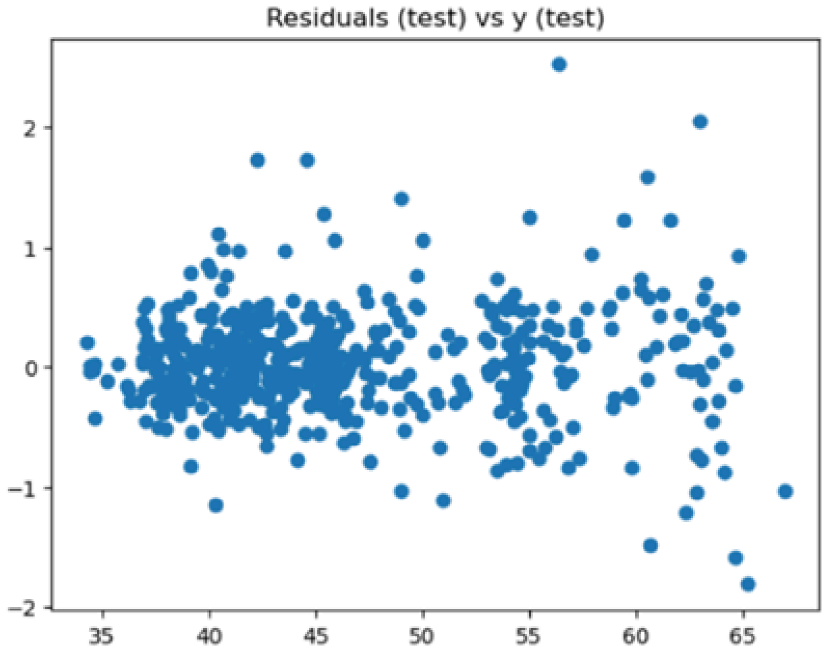
- MSE_train: 0.1949
- MSE_test: 0.1939



Residuals:

- Range of (-2, 2), indicating good model fit





Model Evaluation

Durbin-Watson Statistic: 1.91 (indicates no significant autocorrelation).

Significance:

- Open variable P-value < 0.01 shows statistical relevance.

Conclusion

The model effectively predicts Coca-Cola's closing prices, capturing 99.6% of market fluctuations with minimal error.

OLS Regression Results

Dep. Variable:	Close	**R-squared:**	0.996
Model:	OLS	**Adj. R-squared:**	0.996
Method:	Least Squares	**F-statistic:**	5.974e+05
Date:	Wed, 18 Dec 2024	**Prob (F-statistic):**	0.00
Time:	18:21:14	**Log-Likelihood:**	-1331.1
No. Observations:	2214	**AIC:**	2666.
Df Residuals:	2212	**BIC:**	2678.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.0548	0.060	0.906	0.365	-0.064	0.173
Open	0.9987	0.001	772.938	0.000	0.996	1.001

Omnibus:	616.469	**Durbin-Watson:**	1.918
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	9101.514
Skew:	-0.900	**Prob(JB):**	0.00
Kurtosis:	12.768	**Cond. No.**	302.

Human Resource Dataset Analysis

I. INTRODUCTION

Objective:

Implement the classification algorithm: Logistic Regression.

Dataset Description:

Due to confidentiality in enterprises like Coca-Cola, a publicly accessible HR dataset is used to derive insights relevant to business performance.

1. Data Preprocessing

Step 1: Check data types for cleaning.

Step 2: Select "Attrition" as the target variable (predicting employee departures).

Step 3: Address binary classification issues.

Step 4: Encode Attrition to binary.

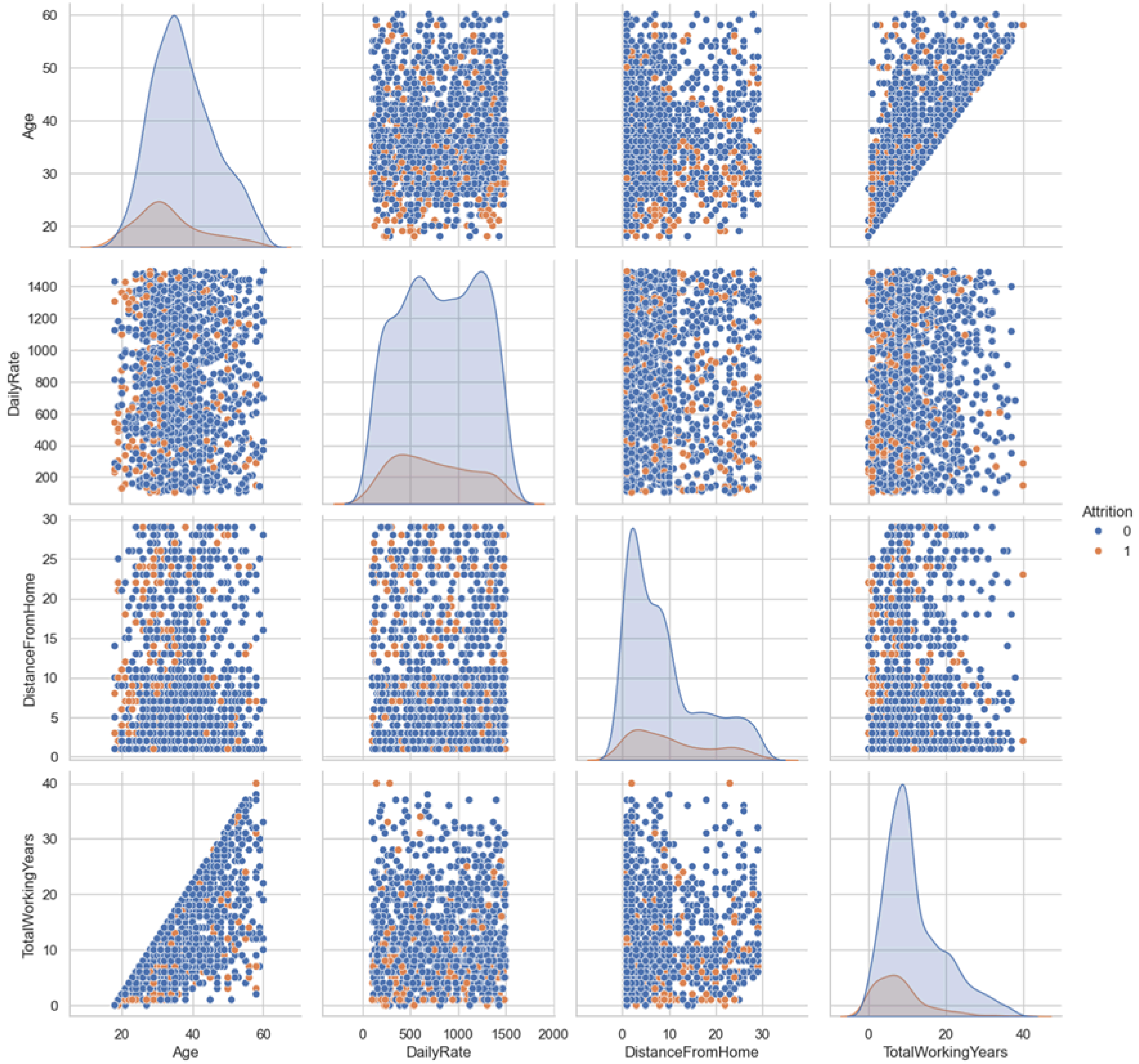
Step 5: Separate dataset into X (features) and y (target).

Step 6: Drop irrelevant or constant columns.

Step 7: Identify numerical and categorical features.

Step 8: Standardize numerical data and apply One-Hot Encoding for categorical variables.

Step 9: Visualize relationships using a pairplot.

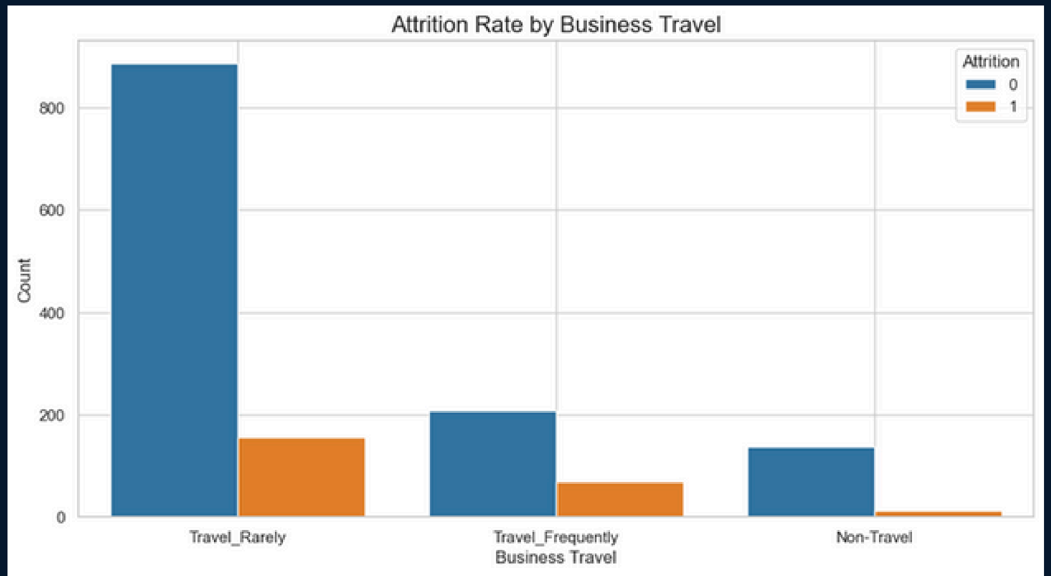


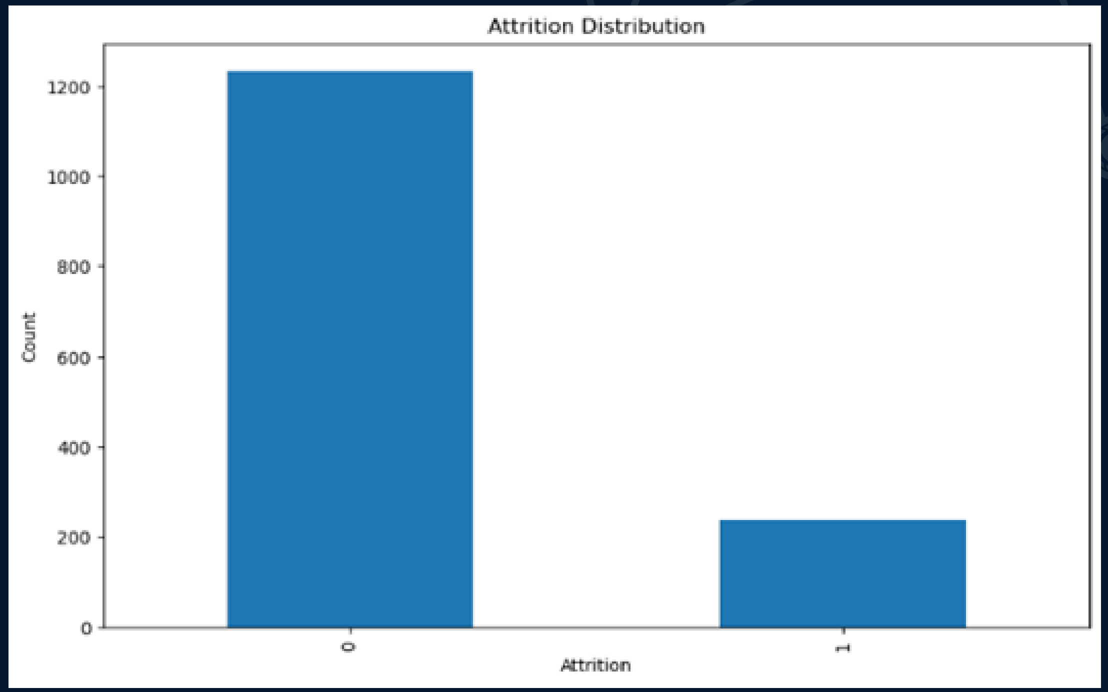
2. Building the Model

Step 1: Preprocess data and prepare to build the model.

```
attrition_counts = df['Attrition'].value_counts()
print(attrition_counts)
```

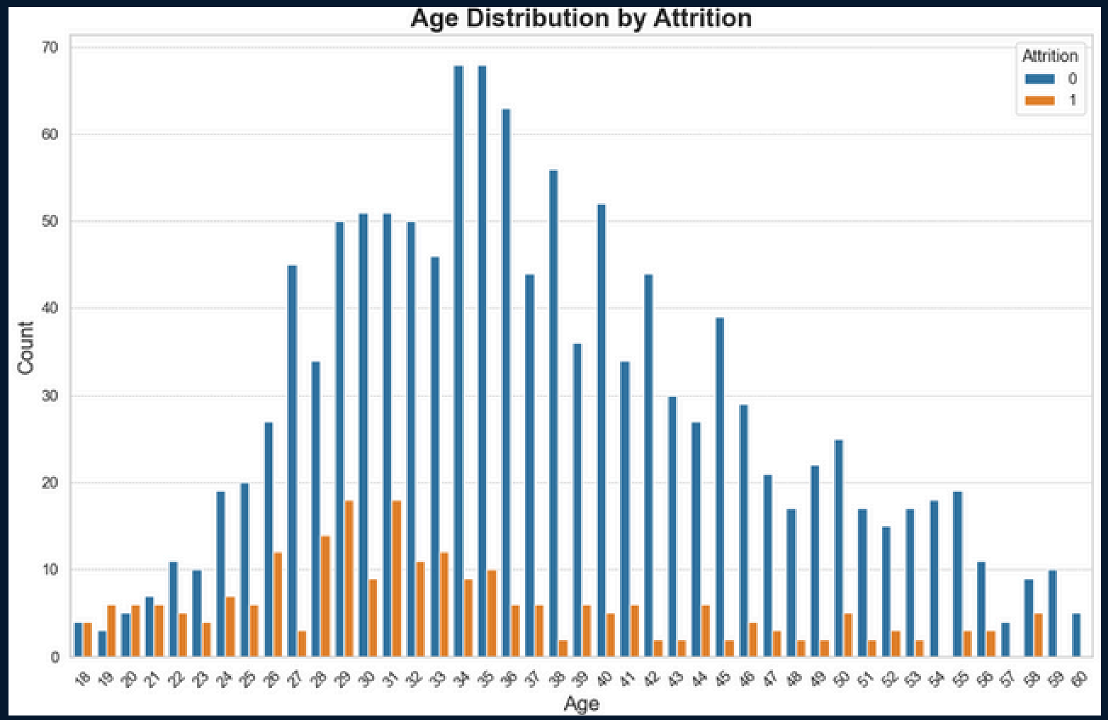
```
Attrition
0    1233
1     237
Name: count, dtype: int64
```





Step 2: Check class distribution in "Attrition":

- Imbalance detected; fewer employees left than stayed.
- Techniques to address imbalance:
  - Use stratify=y during train-test split to preserve class proportions.
  - Set class_weight='balanced' to adjust the importance of each class.



Step 3: Train-test split and build the logistic regression model.

3. Make Prediction

Step 1: Build the model and make predictions.

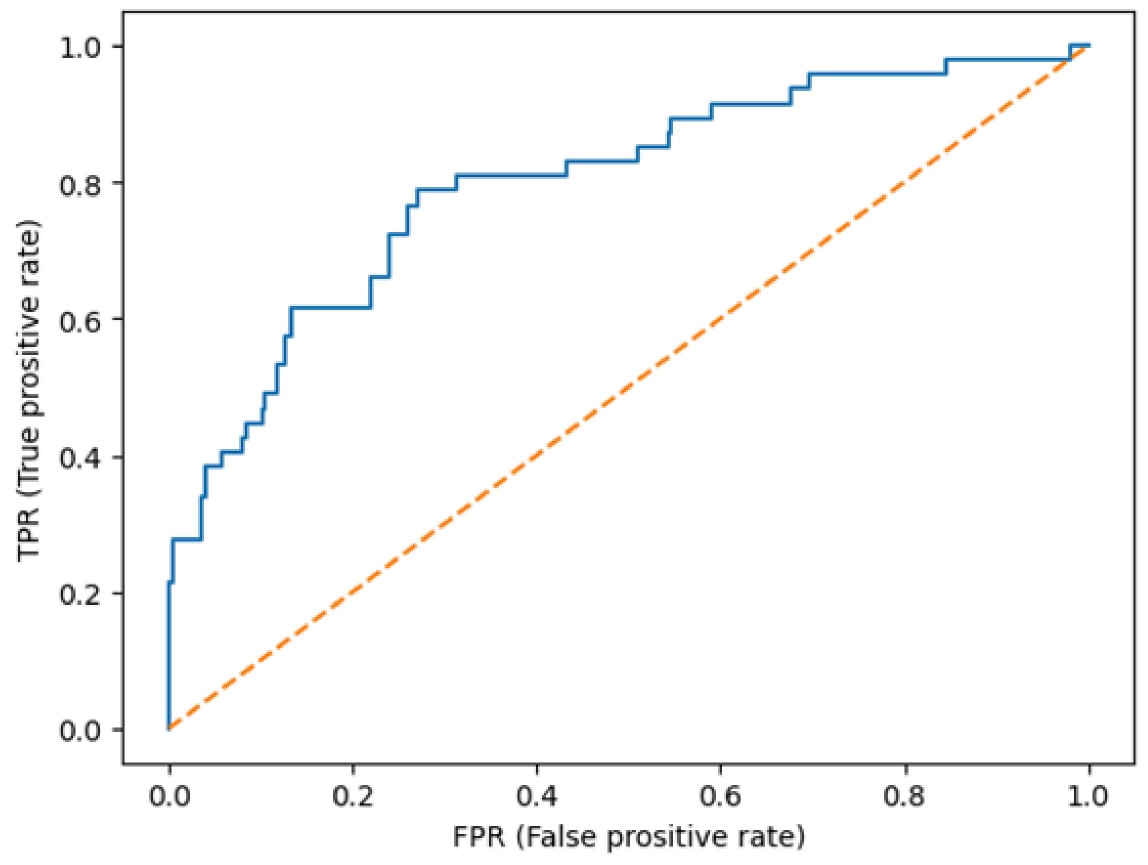
Step 2: Evaluate model accuracy:
Accuracy: 75.17%

- Confusion Matrix:
  - True Negatives (TN): 190
  - True Positives (TP): 31
  - False Positives (FP): 57
  - False Negatives (FN): 16

Classification Report:

	precision	recall	f1-score	support
0	0.92	0.77	0.84	247
1	0.35	0.66	0.46	47
accuracy			0.75	294
macro avg	0.64	0.71	0.65	294
weighted avg	0.83	0.75	0.78	294

- **AUC Value:** 0.7987 indicates good performance in distinguishing classes.
- **Insights for HR:** Utilize ROC curve analysis to enhance engagement strategies and reduce turnover.



SUMMARY OF KEY FINDINGS

HR Analysis:

- **Model Performance:** Logistic Regression achieved an accuracy of 75.17% and an AUC of 0.7987.
- **Significant Predictors:** Key factors influencing employee attrition include age and travel frequency.
- **Strategic Insights:** Highlights the importance of employee engagement and tailored retention strategies for sustaining business performance.

Stock Analysis:

- **Correlation:** Strong correlation of 0.9987 between opening and closing stock prices.
- **R-squared Value:** R-squared of 0.996, indicating that 99.6% of price fluctuations can be explained.
- **Financial Metrics:** Stock-related metrics effectively reflect Coca-Cola's market performance and inform strategic planning.

Overall Conclusion:

- **Data-Driven Strategies:** Emphasizes the role of financial ratios and human factors in guiding HR management and financial decision-making.
- **Sustained Competitiveness:** Underlines the necessity of leveraging data insights for continued success and competitiveness in the market.

THANKS FOR LISTENING