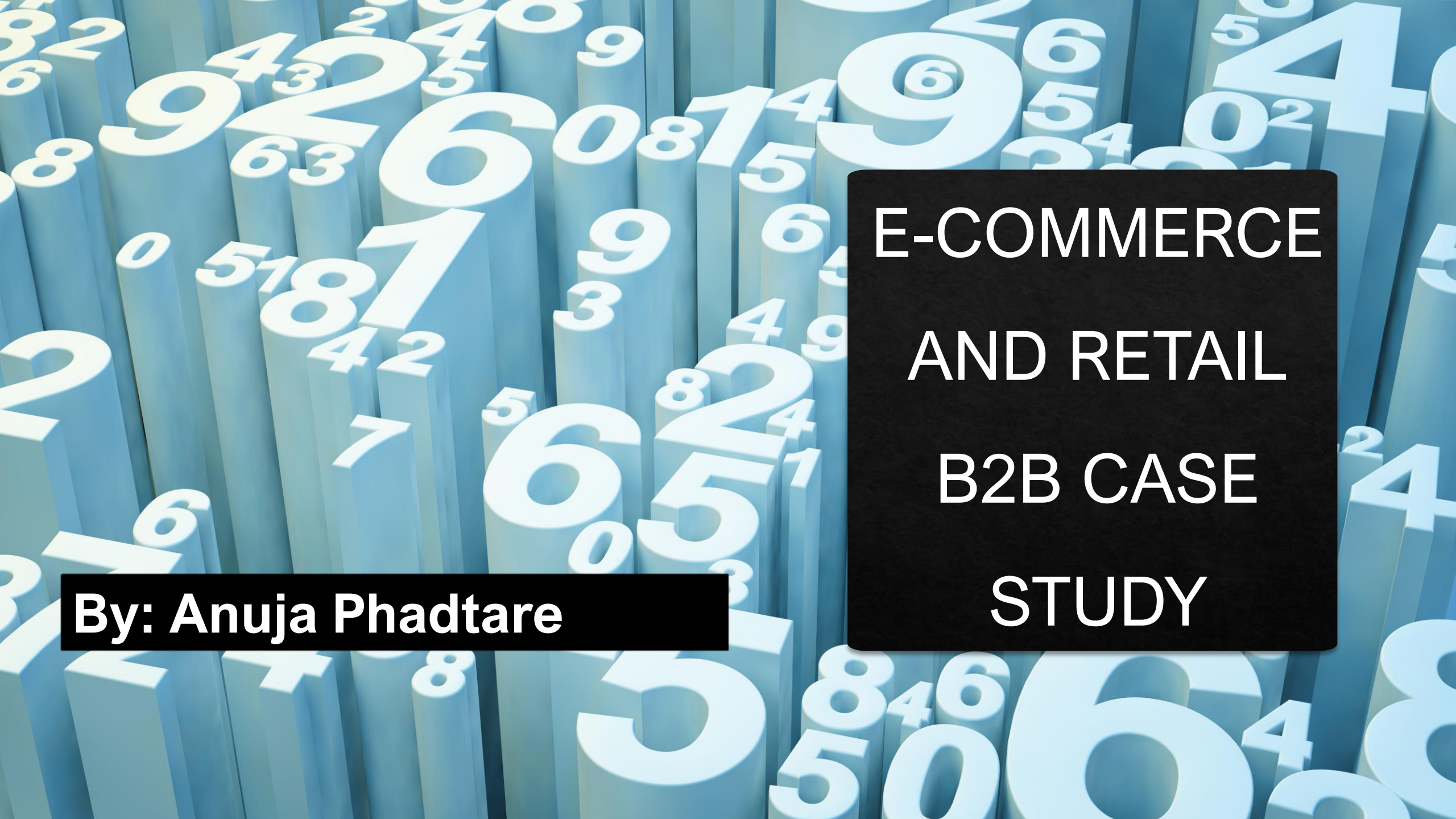


E-COMMERCE AND RETAIL B2B CASE STUDY

By: Anuja Phadtare

Problem Statement

- Schuster is a multinational retail company dealing in sports goods and accessories. Schuster conducts significant business with hundreds of its vendors, with whom it has credit arrangements. Unfortunately, not all vendors respect credit terms and some of them tend to make payments late. Schuster levies heavy late payment fees, although this procedure is not beneficial to either party in a long-term business relationship. The company has some employees who keep chasing vendors to get the payment on time; this procedure nevertheless also results in non-value-added activities, loss of time and financial impact. Schuster would thus try to understand its customers' payment behavior and predict the likelihood of late payments against open invoices.

Objective

Schuster would like to better understand the customers' payment behavior based on their past payment patterns (customer segmentation).

Using historical information, it wants to be able to predict the likelihood of delayed payment against open invoices from its customers.

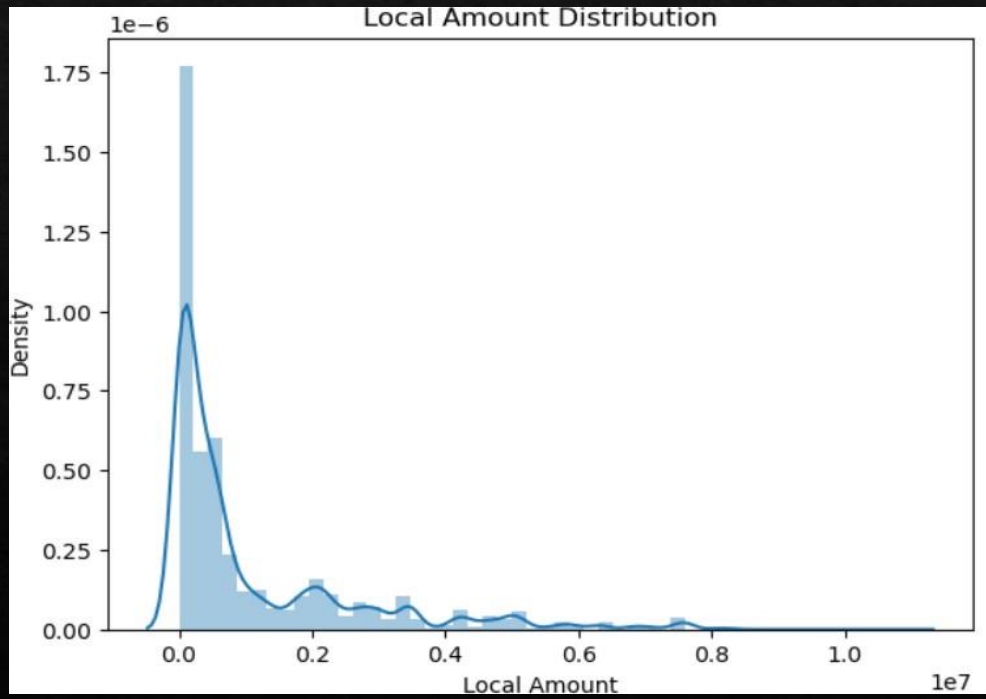
It wants to use this information so that collectors can prioritize their work in following up with customers beforehand to get the payments on time.

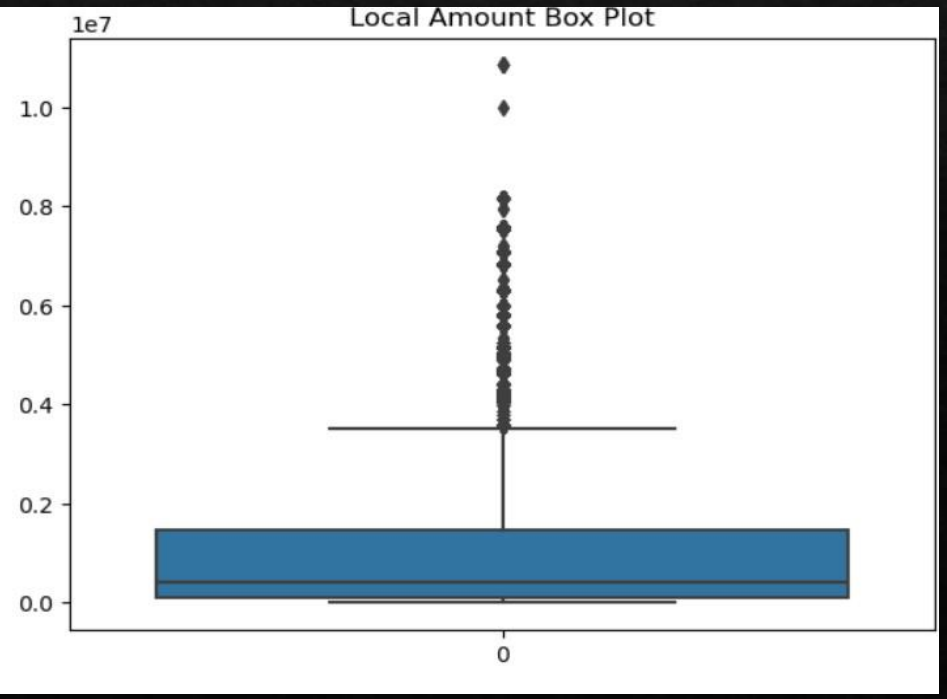
Solution Methodology

1. Reading and Understanding the data
2. Data Cleaning
   - Delete null values
   - Dropping columns which contains only one value
   - Dropping duplicated columns
   - Dropping columns which are not important for the analysis
3. Exploratory Data Analysis
   - Data imbalance check
   - Creating derived metrics (Ex: overdue_days, credit_period)
4. Clustering
5. Data Preparation
   - Outlier treatment
   - Creating dummy variables Feature scaling
   - Train Test split
6. Model Building
7. Model Evaluation
8. Conclusion

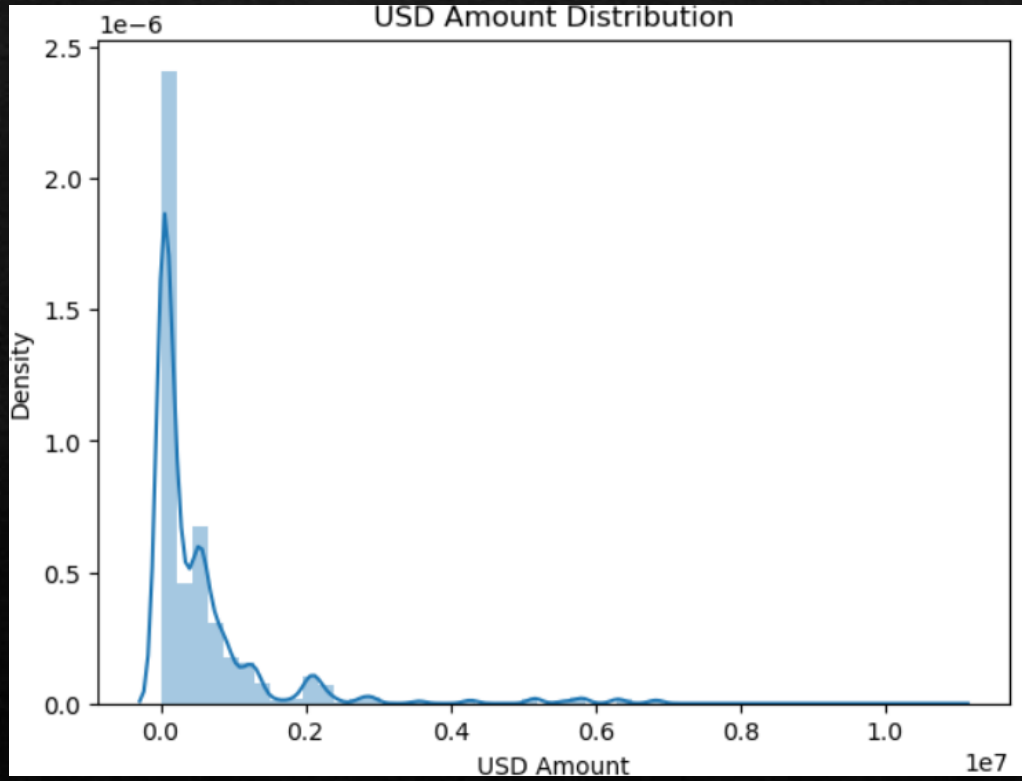
EXPLORATORY DATA ANALYSIS (EDA)

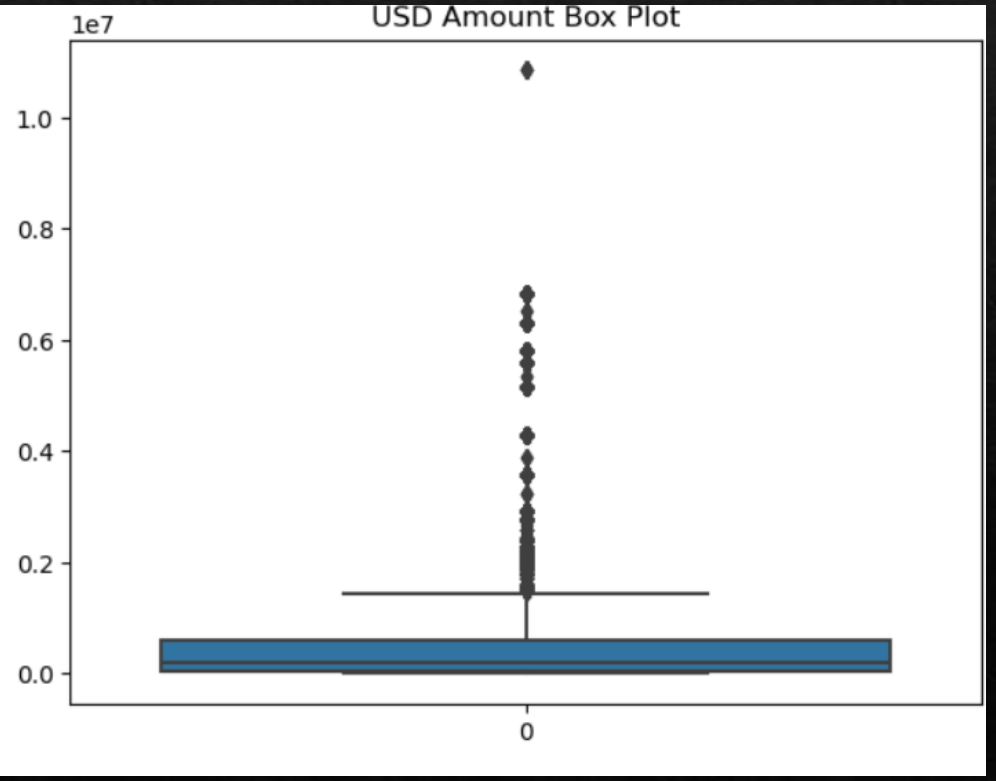
- **Uni-Variate Analysis**
  - **Customer Number :** No Changes required
  - **RECEIPT_DOC_NO :** No Changes required
  - **Local Amount :** Could be dropped as the local currencies are different & amounts will be not matching



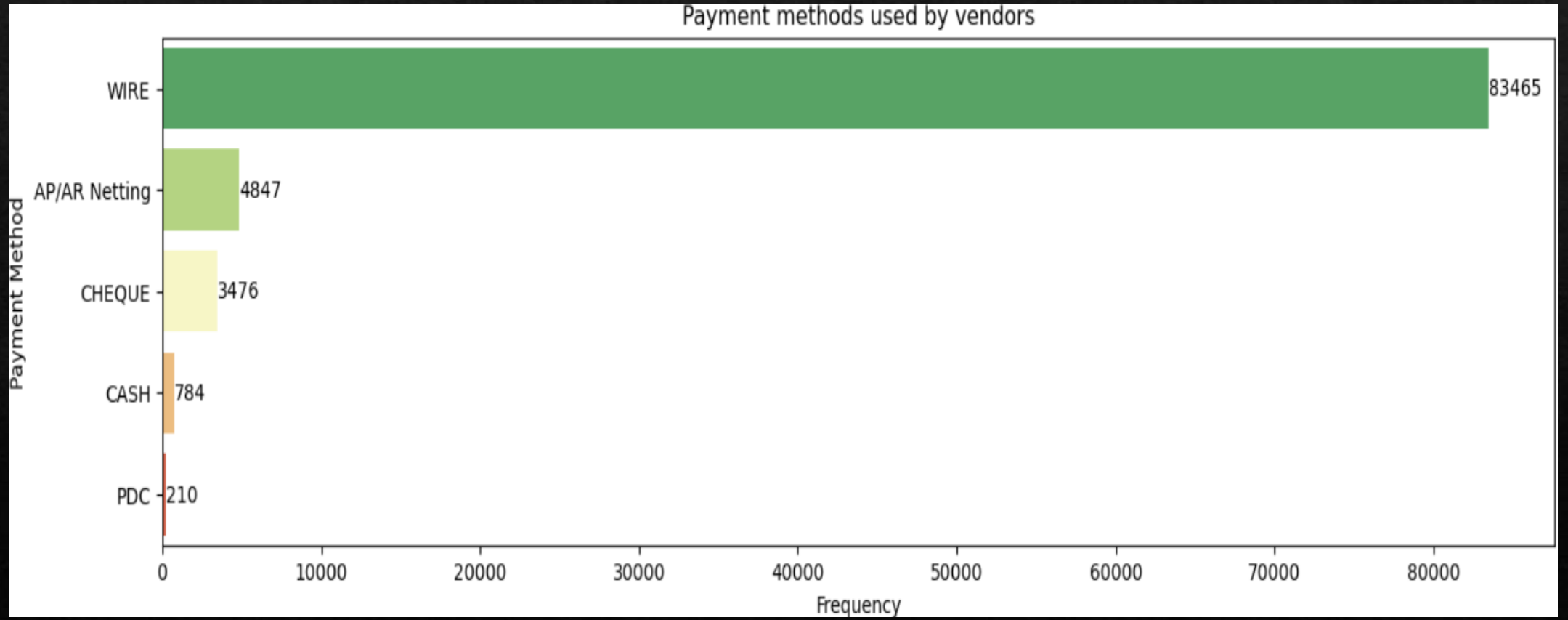


- USD Amount : USD amount can be considered as this is unique for all the transactions, also the data do not have any outlier which needs to be changed

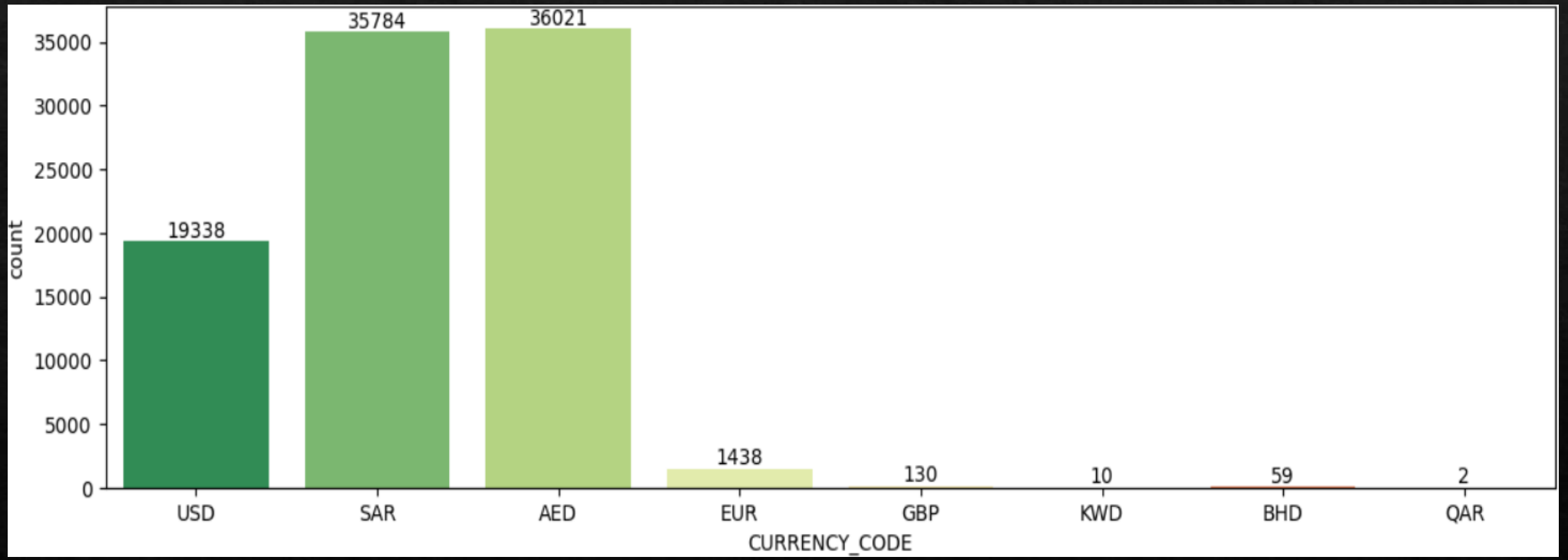




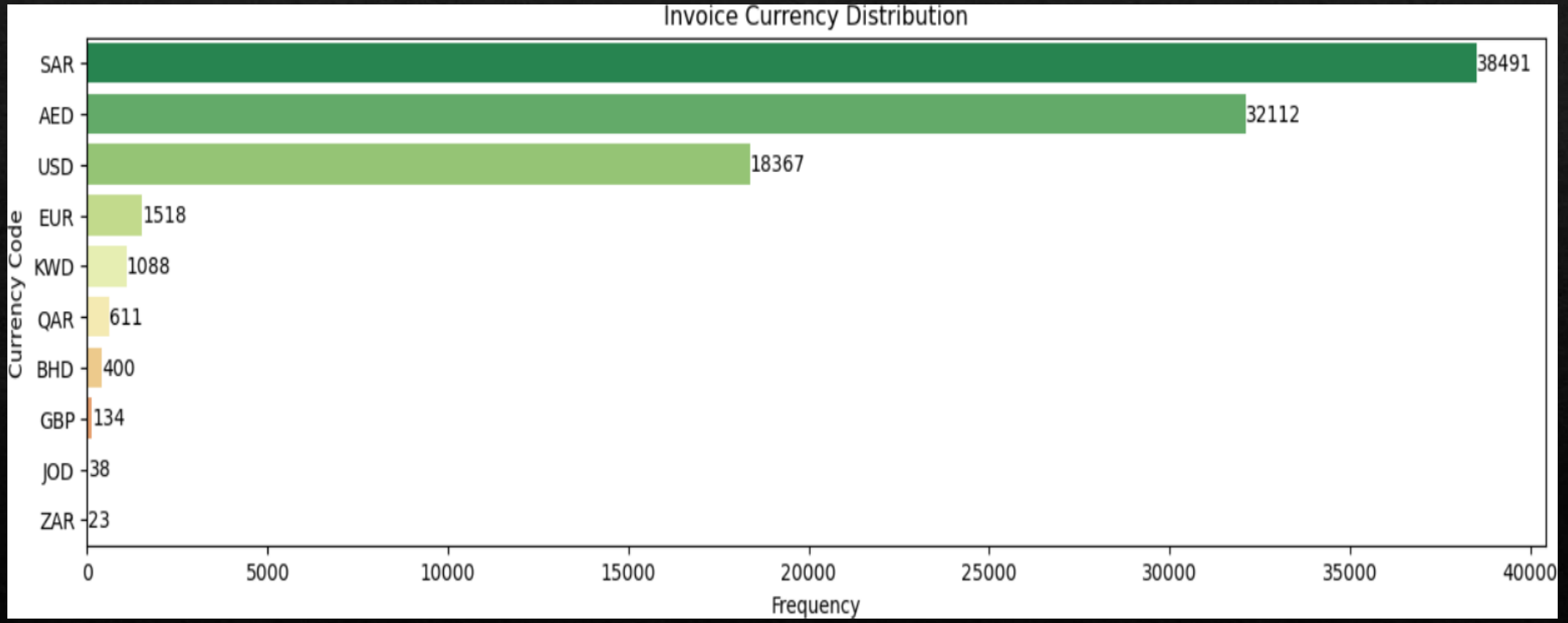
- **RECEIPT_METHOD :** The Most preferred method of payment is WIRE



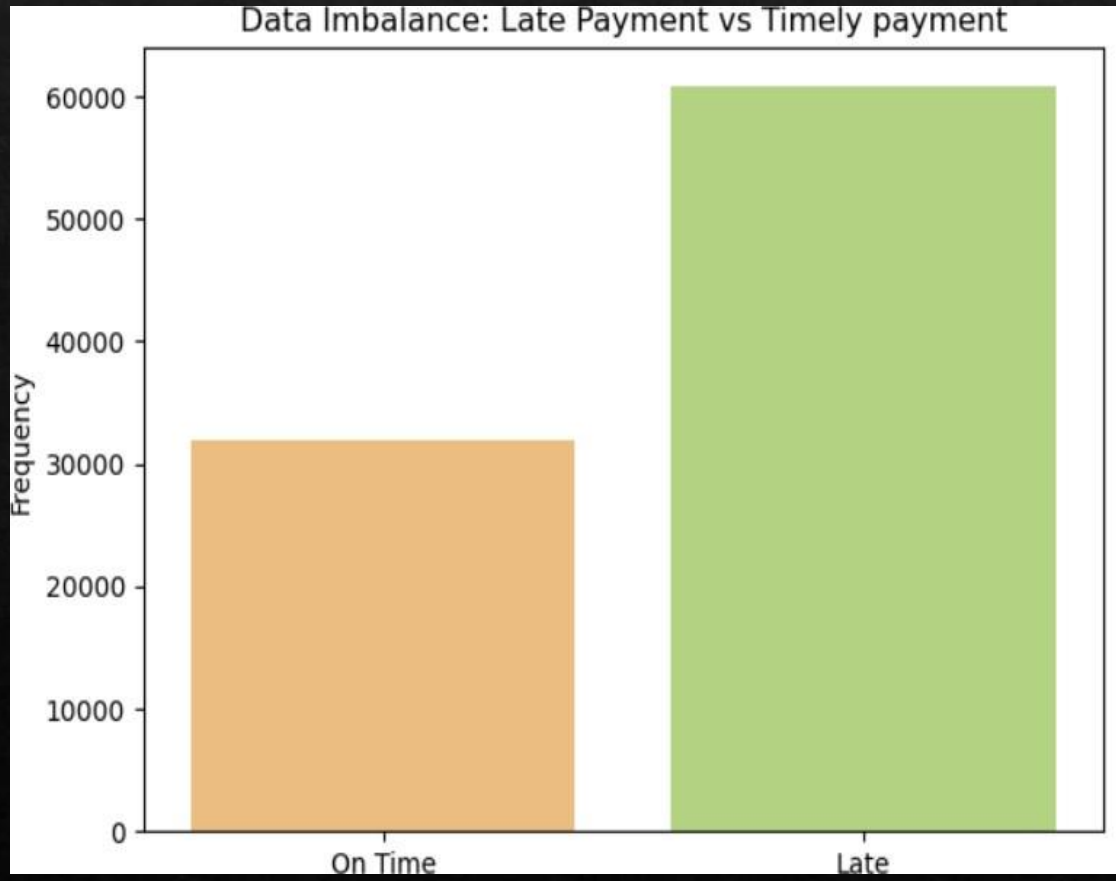
- **Currency_code :** The Most used currencies are SAR, AED & USD

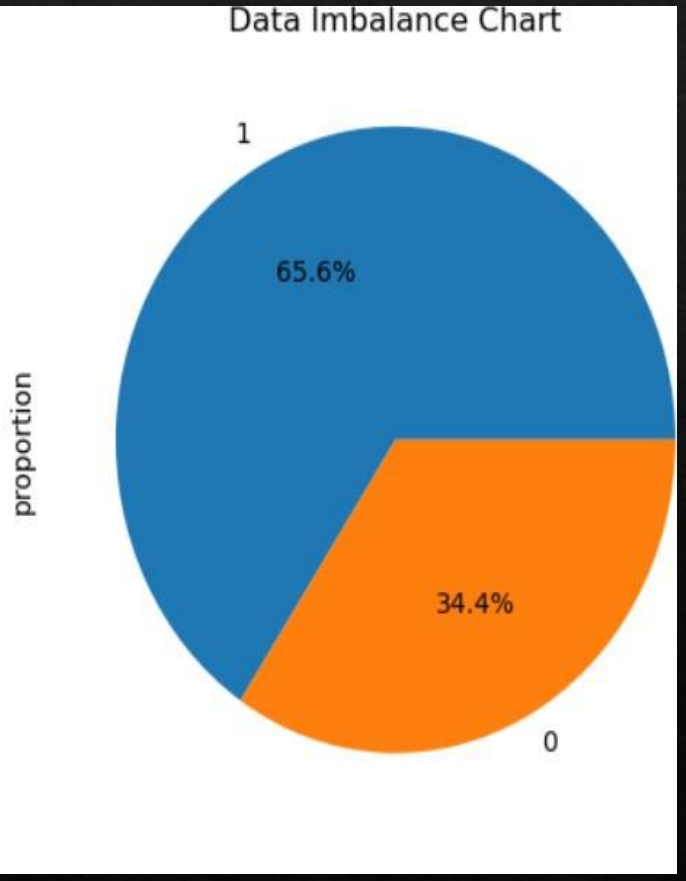


- **Invoice_Currency :** The Most used currencies are SAR, AED & USD, similar to Payment currencies



- **Checking Data imbalance between On-Time payment & Late payment**
  - There is no such data imbalance we can go ahead with the available data

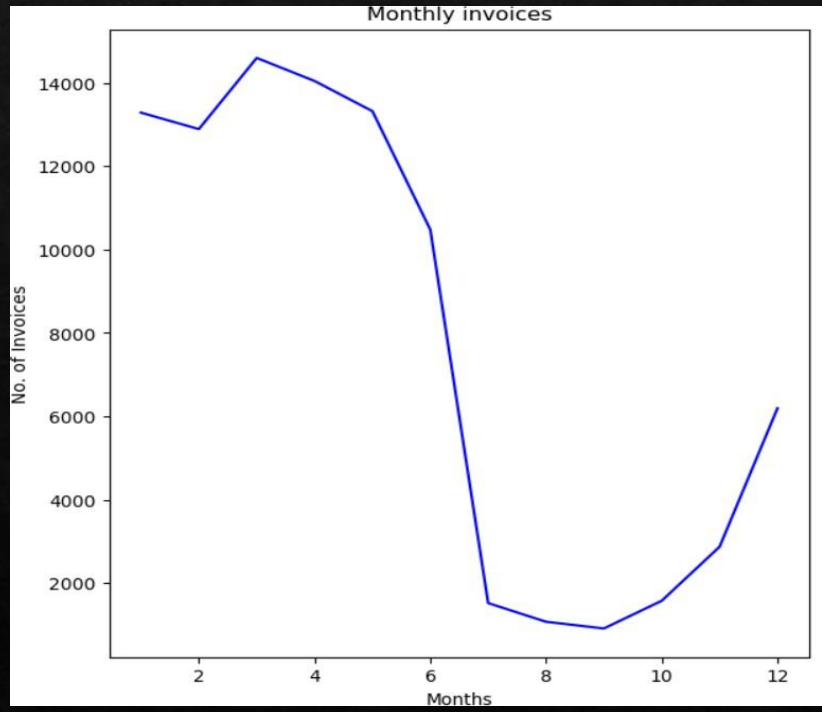


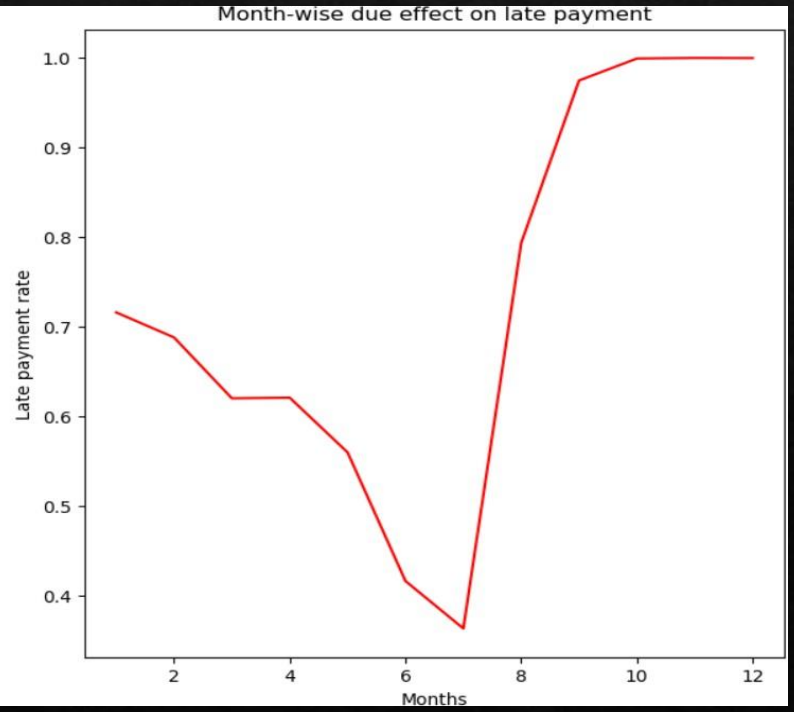


Bi-Variate Analysis

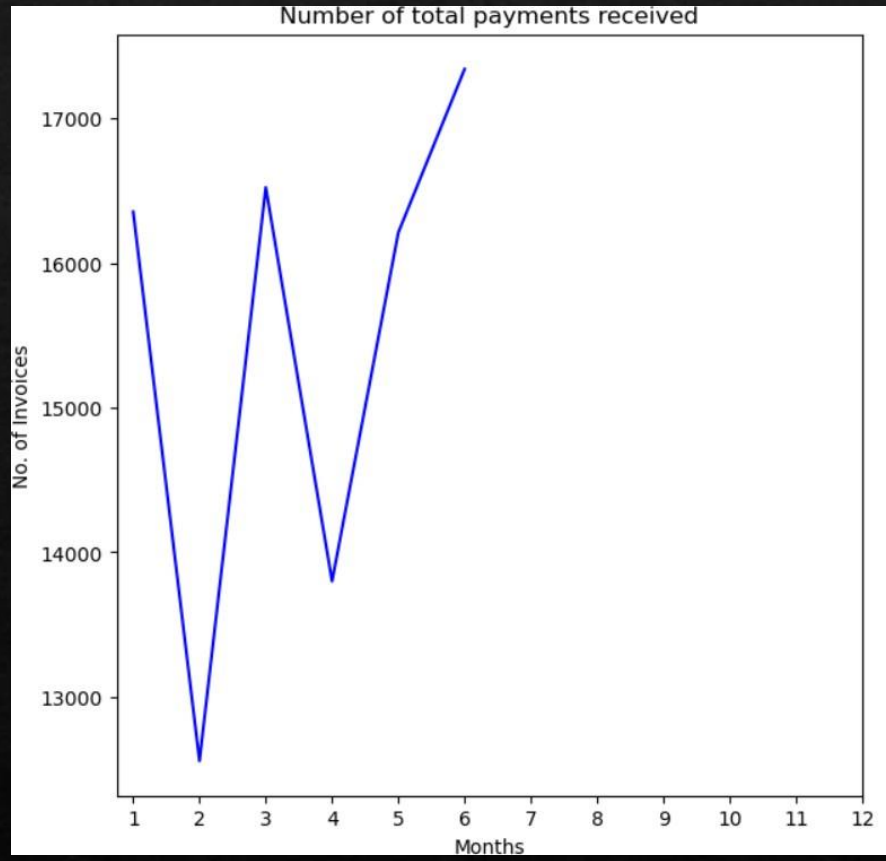
Basis of Due month :

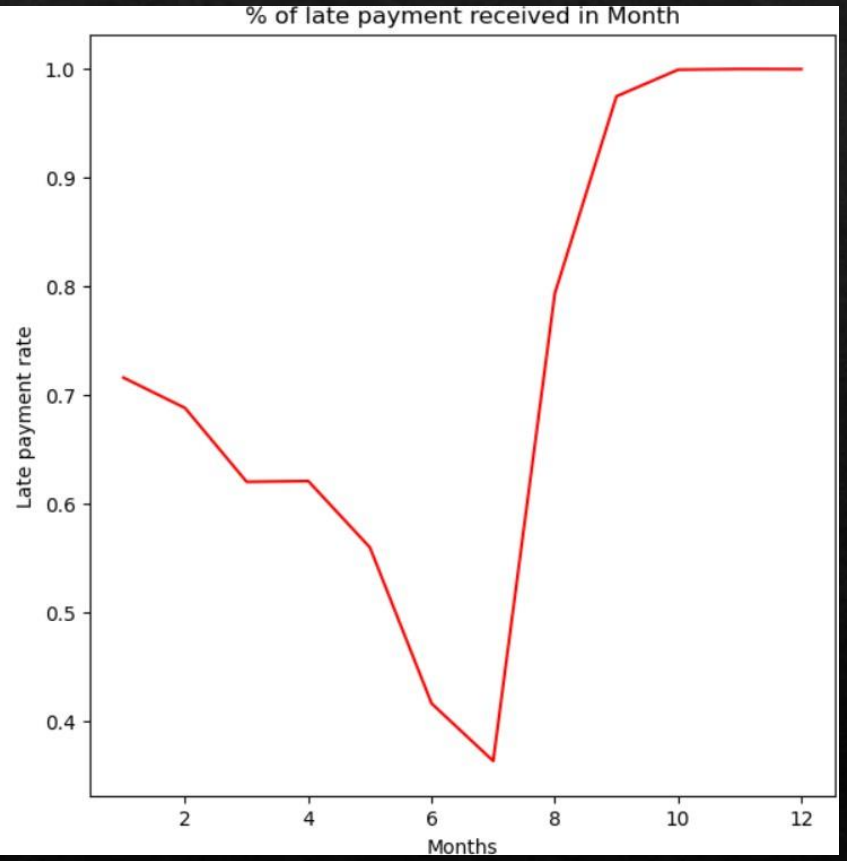
- For the 3rd month, the number of invoices is the highest and late payment rate is comparatively lower than other months with large number of invoices.
- Month 7 has the very low late payment rate, this can be because of the fact that the number of invoices is also low.
- In the 2nd half of the year, the late payment increases steeply from 7th month onwards. The number of invoices are comparatively lower than the first half of the year.



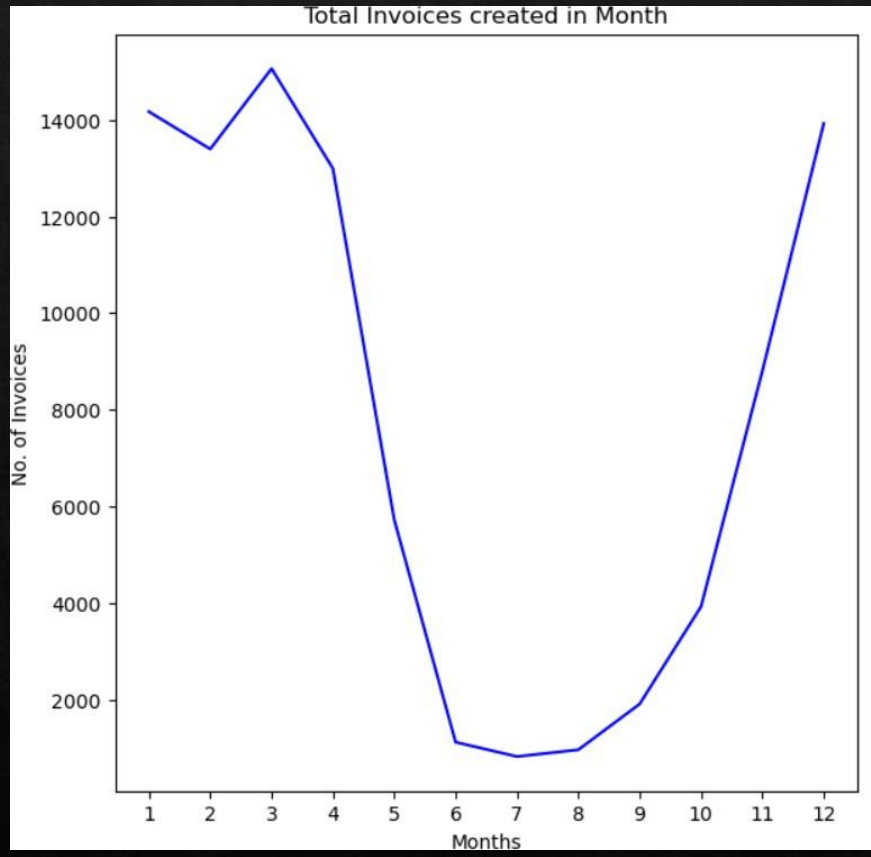


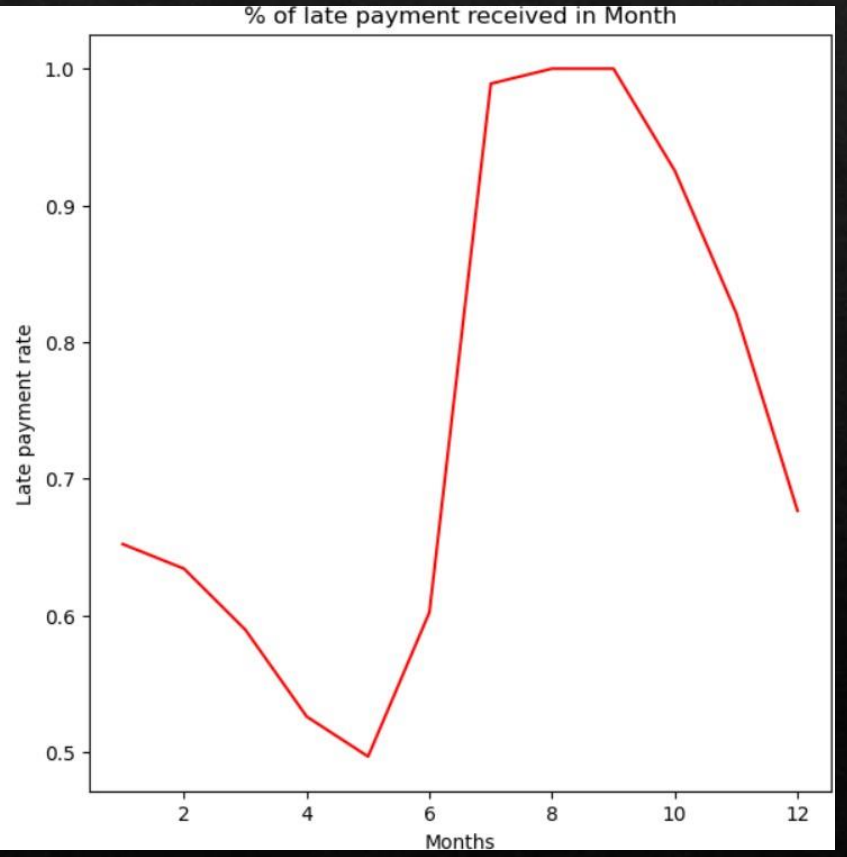
- **Bi-Variate Analysis**
  - **2. Analysis on Basis of Receipt Months :**
    - No payment received against any invoices from 7th month onwards even having due.





- **Bi-Variate Analysis**
  - **3. Analysis on Basis of Invoice Creation Months** :
    - Late payment rate is decreases from 1st to 5th month.
    - For the months 7, 8 and 9, the late payment rate is very high.

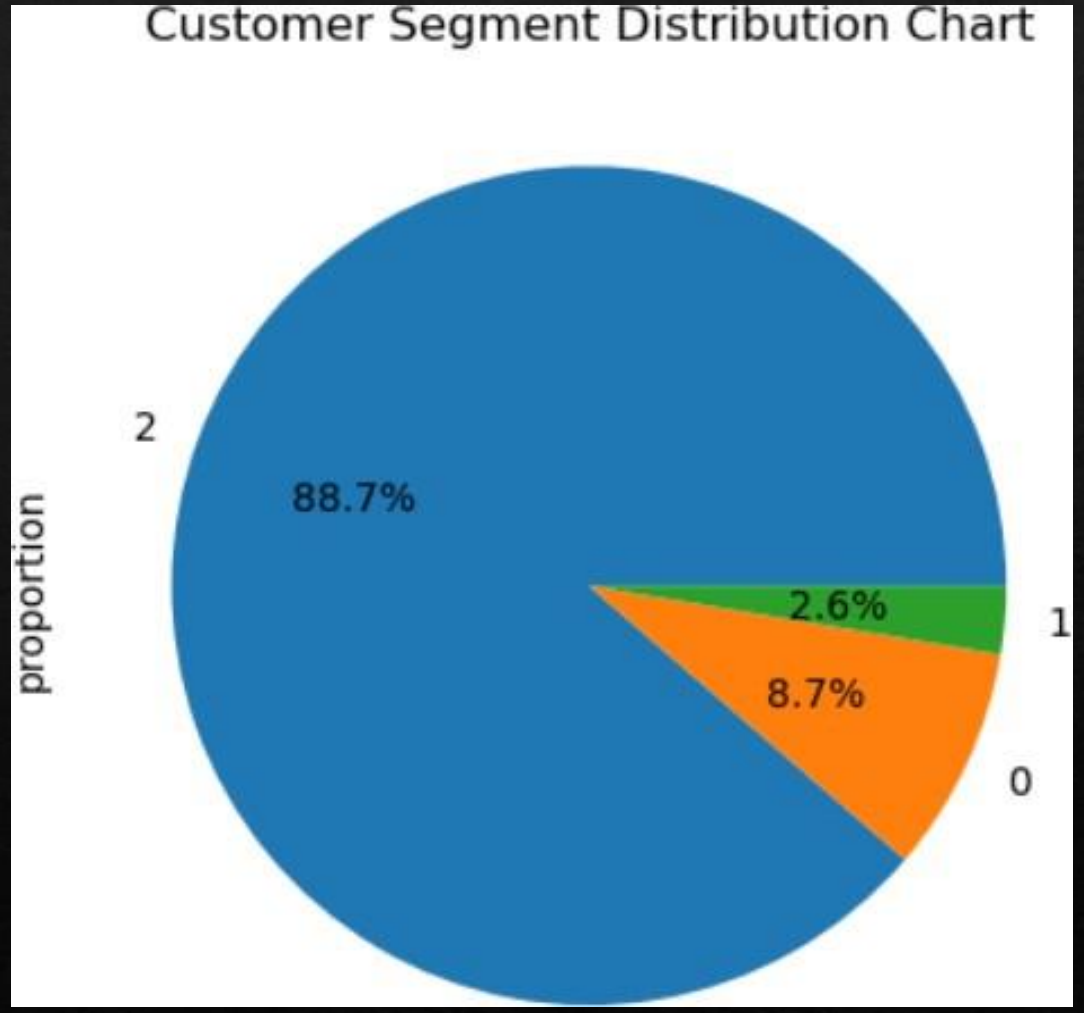




ANALYSIS ON OPEN_INVOICE_DATA" DATASET

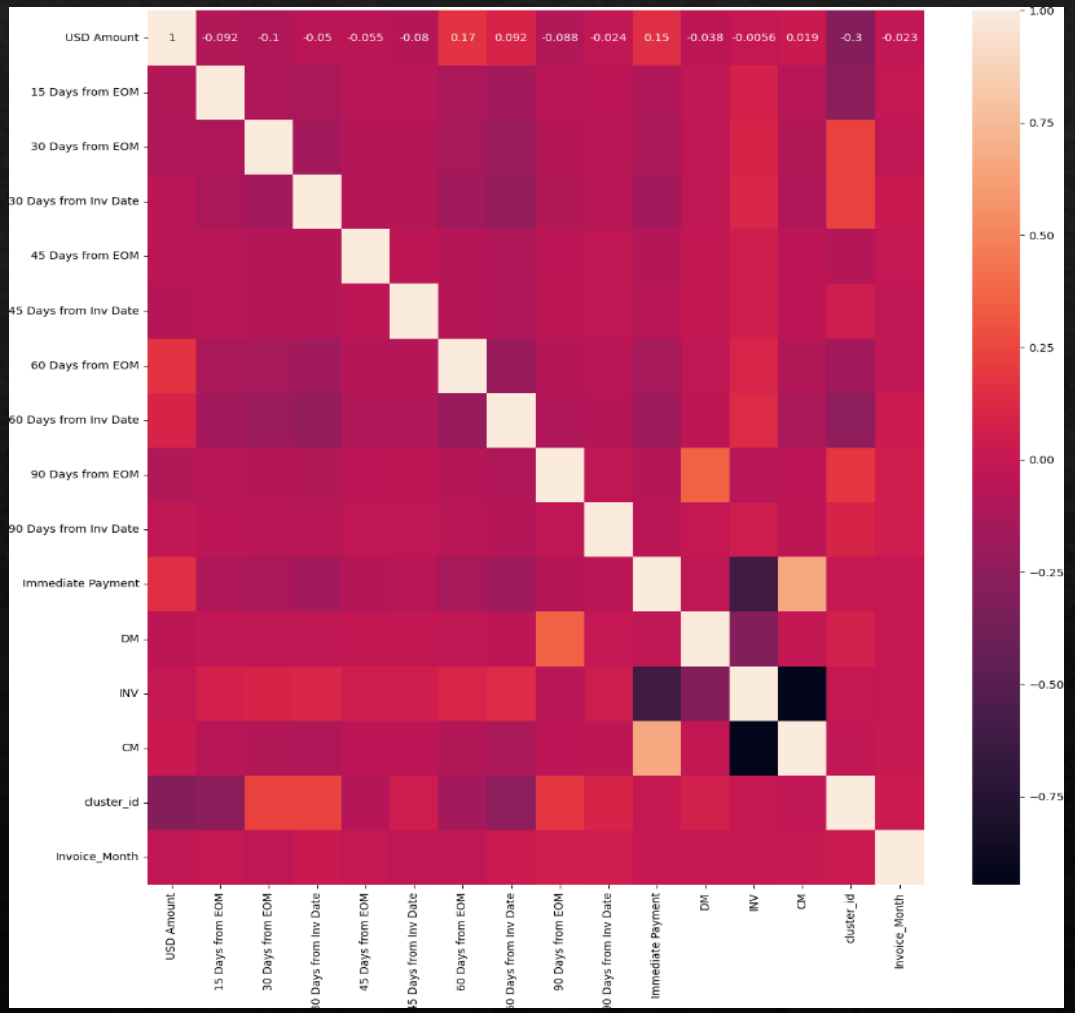
- **Customer Segmentation**
  - '1' Cluster -- Prolonged Invoice Payment
  - '2' Cluster -- Early Invoice Payment
  - '0' Cluster -- Medium Invoice
  - Payment

- We can say that Early payers comprise of 88.7% of customers whereas medium and prolonged payers are 11.3% in total



STEPS FOR MODEL BUILIDNG

- 1. Data Preparation
- 2. Train Test Split - 70:30 Spilt
- 3. Feature Scaling
- 4. Plotting Heatmap for Correlation matrix
  - "CM" & "INV", "INV" & "Immediate Payment", "DM" & "90 days" from "EOM" has high multicollinearity, hence dropping these columns.



MODEL BUILDING - LOGISITIC REGRESSION

Generalized Linear Model Regression Results

Dep. Variable:	Default	**No. Observations:**	64947
Model:	GLM	**Df Residuals:**	64933
Model Family:	Binomial	**Df Model:**	13
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-30170.
Date:	Mon, 06 May 2024	**Deviance:**	60339.
Time:	10:13:39	**Pearson chi2:**	6.34e+04
No. Iterations:	7	**Pseudo R-squ. (CS):**	0.3012
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.7495	0.050	15.124	0.000	0.652	0.847
USD Amount	-0.1054	0.012	-8.748	0.000	-0.129	-0.082
15 Days from EOM	2.6146	0.108	24.267	0.000	2.403	2.826
30 Days from EOM	-2.2548	0.052	-42.950	0.000	-2.358	-2.152
30 Days from Inv Date	0.2638	0.052	5.102	0.000	0.162	0.365
45 Days from EOM	0.3968	0.070	5.704	0.000	0.260	0.533
45 Days from Inv Date	-0.3347	0.063	-5.338	0.000	-0.458	-0.212
60 Days from EOM	-2.2158	0.053	-41.704	0.000	-2.320	-2.112
60 Days from Inv Date	-0.2641	0.051	-5.219	0.000	-0.363	-0.165
90 Days from EOM	-0.4898	0.062	-7.953	0.000	-0.611	-0.369
90 Days from Inv Date	-1.0483	0.069	-15.203	0.000	-1.183	-0.913
Immediate Payment	3.0618	0.103	29.634	0.000	2.859	3.264
cluster_id	-0.1355	0.012	-11.123	0.000	-0.159	-0.112
Invoice_Month	0.0978	0.003	38.542	0.000	0.093	0.103

First Model

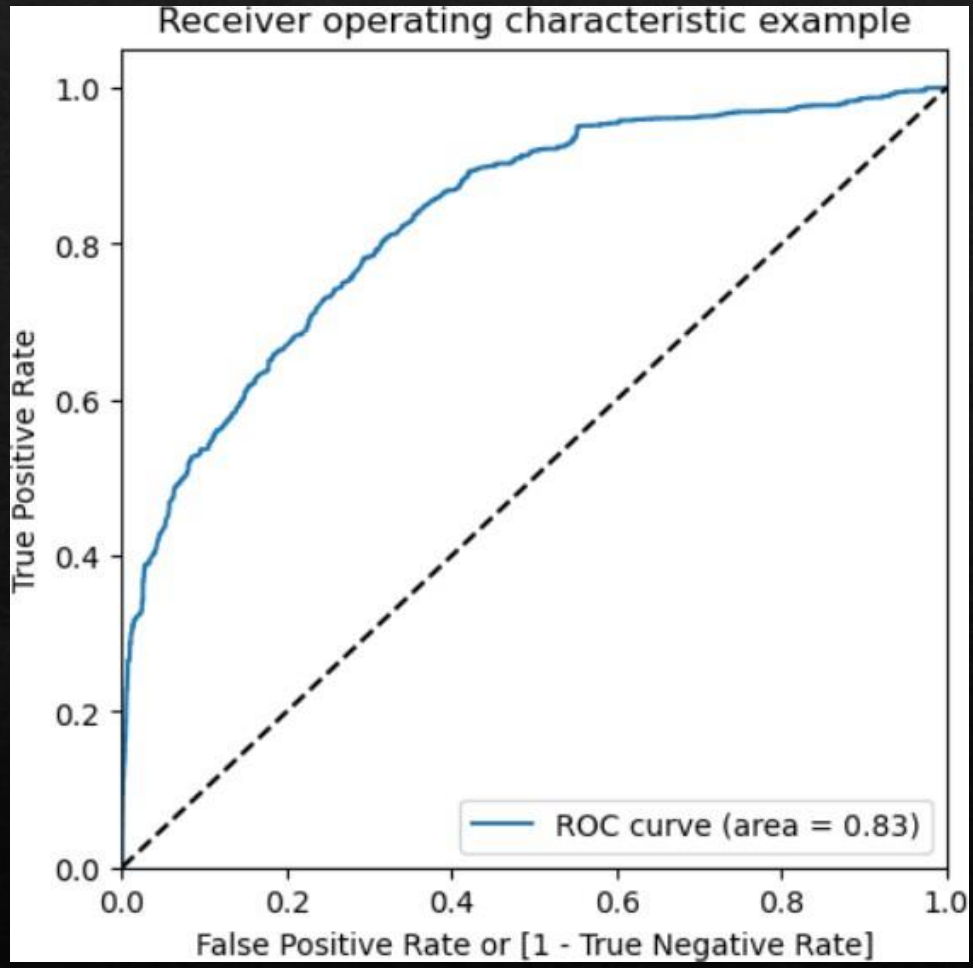
Both the "p-value" and "VIF" are in acceptable range, hence going ahead with this model.

	Features	VIF
12	Invoice_Month	2.67
11	cluster_id	2.60
3	30 Days from Inv Date	1.66
2	30 Days from EOM	1.52
7	60 Days from Inv Date	1.45
10	Immediate Payment	1.36
6	60 Days from EOM	1.31
8	90 Days from EOM	1.25
0	USD Amount	1.20
1	15 Days from EOM	1.14
9	90 Days from Inv Date	1.12
5	45 Days from Inv Date	1.10
4	45 Days from EOM	1.08

MODEL BUILDING - LOGISITIC REGRESSION

First Model

```
Accuracy is 0.7723369858092329
Precision is 0.8089661576557986
Recall is 0.8565089799272215
```



- AUC = 0.83 which shows the model is good.

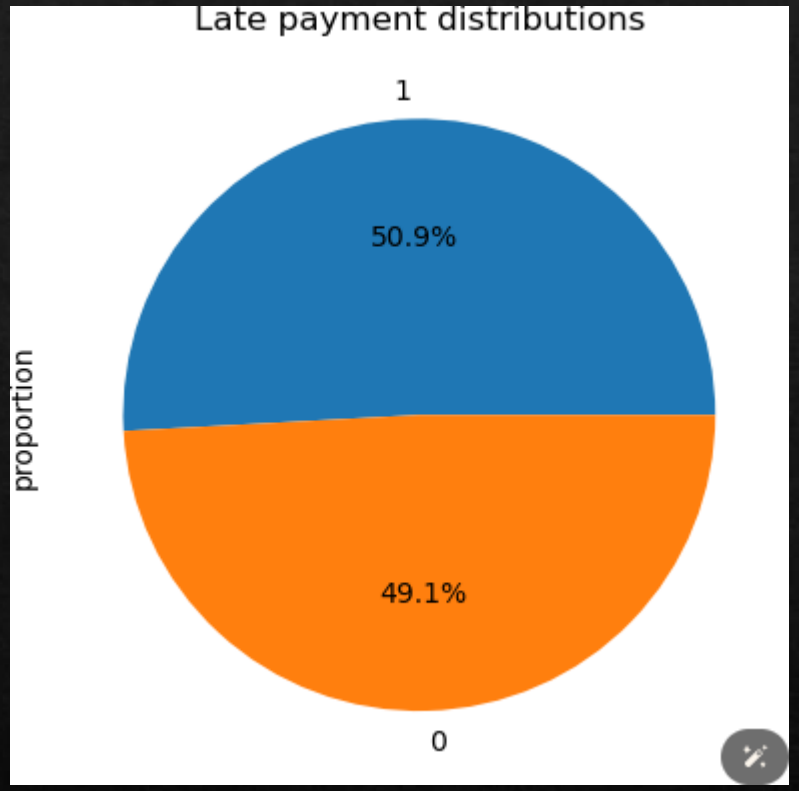
- With this model our train and test accuracy is almost same around 77.2 %

MODEL BUILDING - RANDOM FOREST (CLASSIFICATION MODEL)

Second Model

	precision	recall	f1-score	support
0	0.97	0.91	0.94	22352
1	0.95	0.98	0.97	42595
accuracy			0.96	64947
macro avg	0.96	0.95	0.95	64947
weighted avg	0.96	0.96	0.96	64947

Accuracy is : 0.9572882504195729



From the above pie chart, we can observe that 50.9% payments in the open invoice data with AGE value negative(indicating due date not crossed)

Recommendations

•**Credit Note Payments**:
•Credit Note Payments experience the highest delay rate compared to Debit Note and Invoice type classes. Therefore, it is recommended that the company implement stricter payment collection policies for Credit Note invoices.
•**Goods Type Invoices**:
•Goods type invoices have significantly higher payment delay rates than non-goods types. As a result, stricter payment policies should be applied to goods type invoices.
•**Lower Value Payments**:
•Lower value payments make up the majority of transactions and exhibit a higher incidence of late payments. It is recommended that the company focus more on these lower value payments.
•**Penalty System**:
•The company could implement a penalty system based on the billing amount, where smaller bills incur a higher percentage penalty for late payments. This approach should be used as a last resort.

- **Customer Segmentation**:
- Customers were grouped into three categories based on payment duration:
    - Cluster 0: Medium payment duration
    - Cluster 1: Prolonged payment duration
    - Cluster 2: Early payment duration
- **Focus on Cluster 1**:
- Customers in Cluster 1 (prolonged payment duration) exhibited significantly higher delay rates compared to those with early and medium payment durations. Therefore, extensive focus should be given to Cluster 1 customers to manage and reduce payment delays.
- **High-Risk Companies**:
- Companies with the highest probability of delayed payments, as well as high total and delayed payment counts, should be prioritized. These companies should receive additional attention due to their high likelihood of payment delays.