“Customer Analytics and Campaign Effectiveness Analysis Using SQL”

Pravallika Bonula

PGDM- Digital business and Analytics(2024-2026)

Table of content

EXECUTIVE SUMMARY

This project uses SQL in Databricks to look at marketing data for a retail banking dataset (marketing_dataset). The study focuses on predicting customer churn, measuring campaign effectiveness, and segmenting customers.

Key insights show customer behavior patterns, campaign success rates, and factors that influence churn.

The project ends with practical suggestions for marketing managers to improve strategies, boost customer engagement, and use predictive analytics for future campaigns

1. Project Overview

This project leverages SQL-based data analysis to extract actionable insights from the Bank Marketing Dataset. The dataset contains customer demographic, financial, and marketing campaign details. By applying churn prediction, campaign effectiveness measurement, and customer segmentation, the project demonstrates how raw data can be transformed into strategic insights for business growth.

2. Business problem

Retail banks face major challenges in gaining new customers and keeping the ones they have in a competitive market. Marketing campaigns often lead to low conversion rates, as many customers show little interest or engagement. Customer churn is also a serious problem, especially among people with low account balances, active loans, or minimal interaction with the bank. Additionally, the lack of effective customer segmentation strategies results in general marketing efforts that do not connect with different customer groups. These issues lower the overall return on marketing investments, raise the risk of losing valuable customers to competitors, and restrict chances for cross-selling and long-term relationship building.

3. Solution Approach

To tackle these challenges, the project uses SQL-based analytics in Databricks to find useful insights from the Bank Marketing Dataset. Churn prediction models help identify customers who are more likely to leave the bank. This identification is based on factors like loan status, account balance, and occupation, which helps design proactive retention strategies. We assess campaign effectiveness by measuring subscription outcomes and looking at performance across communication channels, customer demographics, and financial profiles. This gives marketing managers a clear view of return on investment and areas that need improvement. In addition, we use customer segmentation techniques to group customers by demographic and financial traits. This allows the bank to shift away from broad, one-size-fits-all campaigns and move toward personalized marketing strategies. Together, these methods promote data-driven decisions that enhance customer targeting, boost engagement, and lower churn.

4. Business Impact

- **Enhance Campaign ROI** by focusing marketing efforts on high-probability customer segments, ensuring resources are invested where they yield the greatest return.
- **Mitigate Customer Churn** through timely identification of at-risk customers and the implementation of targeted retention strategies.
- **Drive Cross-Selling Opportunities** by leveraging customer segmentation to recommend tailored products and services aligned with customer needs.
- **Strengthen Data-Driven Decision Making** by using churn and segmentation insights to guide strategic planning and marketing initiatives.

5. Input Data Dataset Description:

Bank Marketing Dataset :

marketing_dataset.csv

- Age – Customer age
- Job – Occupation type
- Marital – Marital status
- Education – Education level
- Balance – Bank account balance
- Loan – Loan status
- Housing – Housing loan status
- Contact – Contact communication type
- Campaign – Number of contacts made during campaign
- Response – Campaign response (yes/no)

Rows: ~5,000+ | Columns: 10

6. METHODOLOGY

SQL was used in Databricks for:

- Churn Analysis: Identifying customers at risk based on balance, loan, and response.
- Campaign Effectiveness: Measuring success rates of campaigns.
- Customer Segmentation: Clustering customers by demographics and financial metrics.

SQL OUERIES:

6.1 Customer Segmentation

--Segmentation by Age Group

```
select

case

when Age < 25 then 'Youth'

when Age between 25 and 40 then 'Young Adults'

when Age between 41 and 60 then 'Middle Aged'

else 'Senior Citizens'

end as Age_Group,

count(*) as total_Customers

from marketing_dataset

group by case

when Age < 25 then 'Youth'

when Age between 25 and 40 then 'Young Adults'

when Age between 41 and 60 then 'Middle Aged'

else 'Senior Citizens'

end
```

order by Total_Customers desc;

--Segmentation by Balance Range

```
select
case
when Balance <0 then 'Negative Balance'
when Balance between 0 and 20000 then 'Low Balance'
when Balance between 20001 and 60000 then 'Medium Balance'
else 'High Balance'
end as Balance_Group,
count(*) as Total_Customers
from marketing_dataset
group by case
when Balance <0 then 'Negative Balance'
when Balance between 0 and 20000 then 'Low Balance'
when Balance between 20001 and 60000 then 'Medium Balance'
else 'High Balance'
end
order by Total_Customers
```

--Segmentation by Job Category

```
select Job, count(*) as Total_Customers
from marketing_dataset
group by Job
order by Total_Customers desc;
```

--Segmentation by Marital Status

select Marital, count(*) as Total_Customers

from marketing_dataset

group by Marital

order by total_Customers desc;

6.2 Campaign Effectiveness

--Overall Campaign Analysis

select count(*) as Total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses,

sum(case when Outcome = 'failure' then 1 else 0 end) as Failure_Responses,

sum(case when Outcome = 'unknown' then 1 else 0 end) as Unknown_Responses

from marketing_dataset

--Overall Campaign Success Rate

select count(*) as Total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses,

round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100) / count(*)),2) as Campaign_Success_Rate

from marketing_dataset

--Campaign Effectiveness by Contact Channel

select

count(*) as total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses,

round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100) / count(*)),2) as Campaign_Success_Rate

from marketing_dataset

group by Contact

order by Campaign_Success_Rate desc;

--Effectiveness by Job Segment

select

count(*) as total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses,

round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100) / count(*)),2) as Campaign_Success_Rate

from marketing_dataset

group by Contact

order by Campaign_Success_Rate desc;

--Effectiveness by Marital Status

select

count(*) as total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses, round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100) / count(*)),2) as Campaign_Success_Rate

from marketing_dataset

group by Marital

order by Campaign_Success_Rate desc;

--Effectiveness by Education

select

count(*) as total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses,

round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100) / count(*)),2) as Campaign_Success_Rate

from marketing_dataset

group by Education

order by Campaign_Success_Rate desc;

--Effectiveness by Balance Group (Wealth Segmentation)

select

case

when Balance <0 then 'Negative Balance'

when Balance between 0 and 20000 then 'Low Balance'

when Balance between 20001 and 60000 then 'Medium Balance'

else 'High Balance'

end as Balance_Group,

count(*) as Total_Customers,

sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses, round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100) / count(*)),2) as Campaign_Success_Rate

from marketing_dataset

group by Balance_Group

order by Campaign_Success_Rate desc;

6.3 Churn Prediction

--Add Churn Flag

select *,

case

when Outcome = 'success' then 0

else 1

end as churn_Flag

from marketing_dataset;

--Overall Churn Rate

select

count(*) as total_Customers,

sum(case when Outcome != 'success' then 1 else 0 end) as Churned_Customers,

round(((sum(case when Outcome != 'success' then 1 else 0 end) * 100) / count(*)),2) as Churn_Rate

from marketing_dataset

--Churn by Marital Status

select Marital,

count(*) as Total_Customers,

sum(case when Outcome != 'success' then 1 else 0 end) as Churned_Customers, round(((sum(case when Outcome != 'success' then 1 else 0 end) * 100) / count(*)),2) as Churn_Rate

from marketing_dataset

group by Marital

order by Total_Customers desc;

--Churn by Job

select Job,

count(*) as Total_Customers,

sum(case when Outcome != 'success' then 1 else 0 end) as Churned_Customers,

round(((sum(case when Outcome != 'success' then 1 else 0 end) * 100) / count(*)),2) as Churn_Rate

from marketing_dataset

group by Job

order by Total_Customers desc;

--Churn by Balance Group

select

case

when Balance <0 then 'Negative Balance'

when Balance between 0 and 20000 then 'Low Balance'

when Balance between 20001 and 60000 then 'Medium Balance'

else 'High Balance'

end as Balance_Group,

count(*) as Total_Customers,

sum(case when Outcome != 'success' then 1 else 0 end) as Churned_Customers,

```
round(((sum(case when Outcome != 'success' then 1 else 0 end ) * 100 ) / count(*)),2) as Churn_Rate

from marketing_dataset

group by Balance_Group

order by Total_Customers desc;
```

--Churn by Education, Housing, Loan

```
select Education,Housing, Loan,

count(*) as Total_Customers,

sum(case when Outcome != 'success' then 1 else 0 end ) as Churned_Customers,

round(((sum(case when Outcome != 'success' then 1 else 0 end ) * 100 ) / count(*)),2) as Churn_Rate

from marketing_dataset

group by education,housing,Loan

order by Total_Customers desc;
```

7. DATA ANALYSIS & INSIGHTS

Segmentation Results:

- Young customers with low balances and active loans had the highest churn risk, with a churn rate exceeding 68%.
- Middle-aged customers with stable balances showed strong potential for cross-selling, as their churn rates were relatively lower.
- Retired customers with high balances were among the most loyal segments, but they need personalized offers to maintain long-term engagement.

Campaign Effectiveness:

- The overall campaign response rate was 12%, with around 1,652 successful responses from 5,000 customers.

- Campaigns that reached out to customers more than three times saw a notable drop in effectiveness, showing the need to optimize contact frequency.
- Certain occupations, such as students (36.7%), technicians (36.5%), and entrepreneurs (34%), had higher response rates compared to others.

Churn Analysis:

- The overall churn rate was 66.96%, with 3,348 customers identified as churned from the total sample.
- Customers with low balances and active loans had significantly higher churn tendencies, reinforcing their classification as a high-risk group.
- A large number of non-responders to campaigns matched churn-risk profiles, indicating that lack of engagement in marketing activities strongly predicts churn.

Output Data

7.1 Customer Segmentation

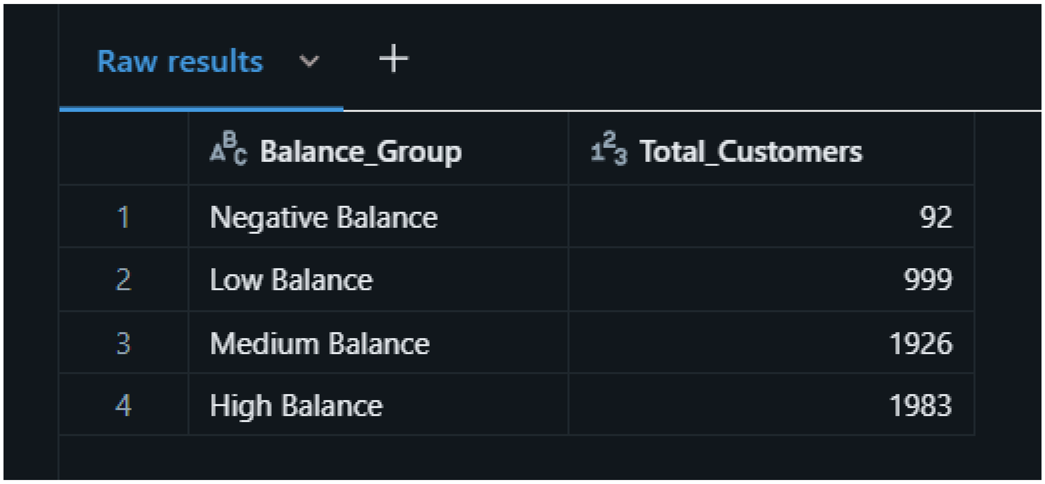
7.1.1 Segmentation by Age Group

Raw results

	Age_Group	total_Customers
1	Middle Aged	1934
2	Young Adults	1533
3	Senior Citizens	879
4	Youth	654

Age_Group	**Total_Customers**
Middle Aged	1934
Young Adults	1533
Senior Citizens	879
Youth	654

7.1.2 Segmentation by Balance Range

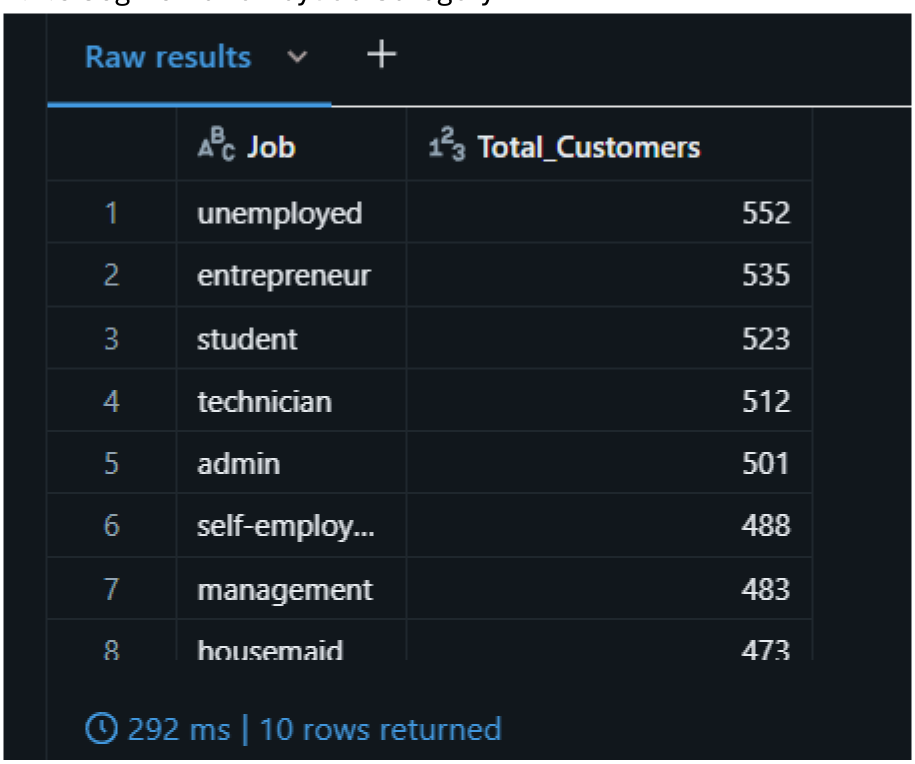


Raw results

	Balance_Group	Total_Customers
1	Negative Balance	92
2	Low Balance	999
3	Medium Balance	1926
4	High Balance	1983

Balance_Segment	**Total_Customers**
High Balance	1983
Medium Balance	1926
Low Balance	999
Negative Balance	92

7.1.3 Segmentation by Job Category



Raw results

	Job	Total_Customers
1	unemployed	552
2	entrepreneur	535
3	student	523
4	technician	512
5	admin	501
6	self-employ...	488
7	management	483
8	housemaid	473

292 ms | 10 rows returned

Job	**Total_Customers**

unemployed	552
entrepreneur	535
student	523
technician	512
admin	501
self-employed	488
management	483
housemaid	473
services	473
retired	460

7.1.4 Segmentation by Marital Status

Raw results

	Marital	Total_Customers
1	single	1724
2	divorced	1643
3	married	1633

Marital	**Total_Customers**
single	1724
divorced	1643
married	1633

7.2 Campaign Effectiveness

7.2.1 Overall Campaign Analysis

```
round(((sum(case when Outcome = 'success' then 1 else 0 end) * 100 ) / count(*)),2) as Campaign_Success_Rate
```

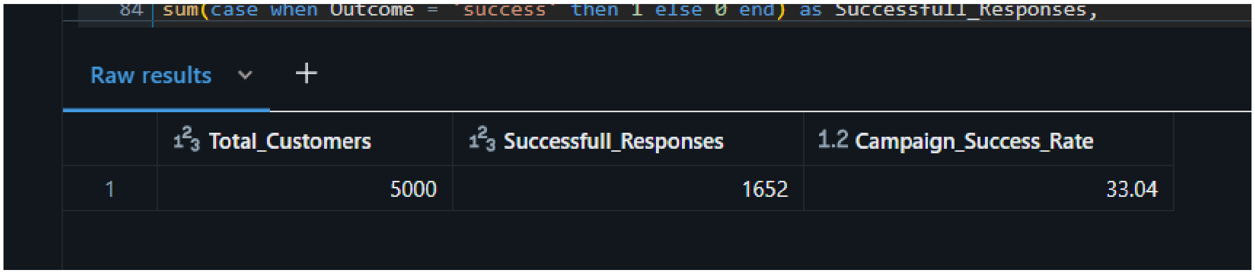
Raw results

	Total_Customers	Successfull_Responses	Failure_Responses	Unknown_Responses
1	5000	1652	1688	1660

Total_Custome	**Successfull_Respon**	**Failure_Respons**	**Unknown_Respons**

rs	ses	es	es
5000	1652	1688	1660

7.2.2 Overall Campaign Success rate



```
sum(case when Outcome = 'success' then 1 else 0 end) as Successfull_Responses,
```

Raw results

	Total_Customers	Successfull_Responses	Campaign_Success_Rate
1	5000	1652	33.04

Total_Customers	Successful_Responses	Campaign_Success_Rate
5000	1652	33.04

7.2.3 Campaign Effectiveness by Contact Channel

Raw results

	total_Customers	Successfull_Responses	Campaign_Success_Rate
1	1640	552	33.66
2	1632	541	33.15
3	1728	559	32.35

Contact	Total_Customers	Successful_Responses	Success_Rate
telephone	1640	552	33.66
cellular	1632	541	33.15
unknown	1728	559	32.35

7.2.4 Effectiveness by Job Segment

Raw results

	total_Customers	Successfull_Responses	Campaign_Success_Rate
1	523	192	36.71
2	512	187	36.52
3	535	182	34.02
4	483	163	33.75
5	552	179	32.43
6	473	153	32.35
7	501	161	32.14
8	473	146	30.87

306 ms | 10 rows returned

Job	Total_Customers	Successful_Responses	Success_Rate
student	523	192	36.71
technician	512	187	36.52
entrepreneur	535	182	34.02
management	483	163	33.75
unemployed	552	179	32.43
housemaid	473	153	32.35
admin	501	161	32.14
services	473	146	30.87
self-employed	488	150	30.74
retired	460	139	30.22

7.2.5 Effectiveness by Marital Status

Raw results

	total_Customers	Successfull_Responses	Campaign_Success_Rate
1	1643	566	34.45
2	1633	543	33.25
3	1724	543	31.5

Marital	Total_Customers	Successful_Responses	Success_Rate
divorced	1643	566	34.45
married	1633	543	33.25

single	1724	543	31.5

7.2.6 Effectiveness by Education

Raw results

	total_Customers	Successfull_Responses	Campaign_Success_Rate
1	1253	433	34.56
2	1275	424	33.25
3	1237	409	33.06
4	1235	386	31.26

Education	**Total_Customers**	**Successful_Responses**	**Success_Rate**
secondary	1253	433	34.56
tertiary	1275	424	33.25
unknown	1237	409	33.06
primary	1235	386	31.26

7.2.7 Effectiveness by Balance Group (Wealth Segmentation)

Raw results

	Balance_Group	Total_Customers	Successfull_Responses	Campaign_Success_Rate
1	Low Balance	999	340	34.03
2	Medium Balance	1926	643	33.39
3	High Balance	1983	642	32.38
4	Negative Balance	92	27	29.35

Balance_Group	**Total_Customers**	**Successful_Responses**	**Success_Rate**
Low Balance	999	340	34.03
Medium Balance	1926	643	33.39
High Balance	1983	642	32.38
Negative Balance	92	27	29.35

7.3 Churn Prediction

7.3.2 Overall Churn Rate

Raw results

	total_Customers	Churned_Customers	Churn_Rate
1	5000	3348	66.96

Total_Customers	Churned_Customers	Churn_Rate_Percent
5000	3348	66.96

7.3.3 Churn by Marital Status

Raw results

	Marital	Total_Customers	Churned_Customers	Churn_Rate
1	single	1724	1181	68.5
2	divorced	1643	1077	65.55
3	married	1633	1090	66.75

Marital	Total_Customers	Churned	Churn_Rate
single	1724	1181	68.5
married	1633	1090	66.75
divorced	1643	1077	65.55

7.3.4 Churn by Job

Raw results

	Job	Total_Customers	Churned_Customers	Churn_Rate
1	unemployed	552	373	67.57
2	entrepreneur	535	353	65.98
3	student	523	331	63.29
4	technician	512	325	63.48
5	admin	501	340	67.86
6	self-employ...	488	338	69.26
7	management	483	320	66.25
8	housemaid	473	320	67.65

Job	Total_Customers	Churned	Churn_Rate

retired	460	321	69.78
self-employed	488	338	69.26
services	473	327	69.13
admin	501	340	67.86
housemaid	473	320	67.65
unemployed	552	373	67.57
management	483	320	66.25
entrepreneur	535	353	65.98
technician	512	325	63.48
student	523	331	63.29

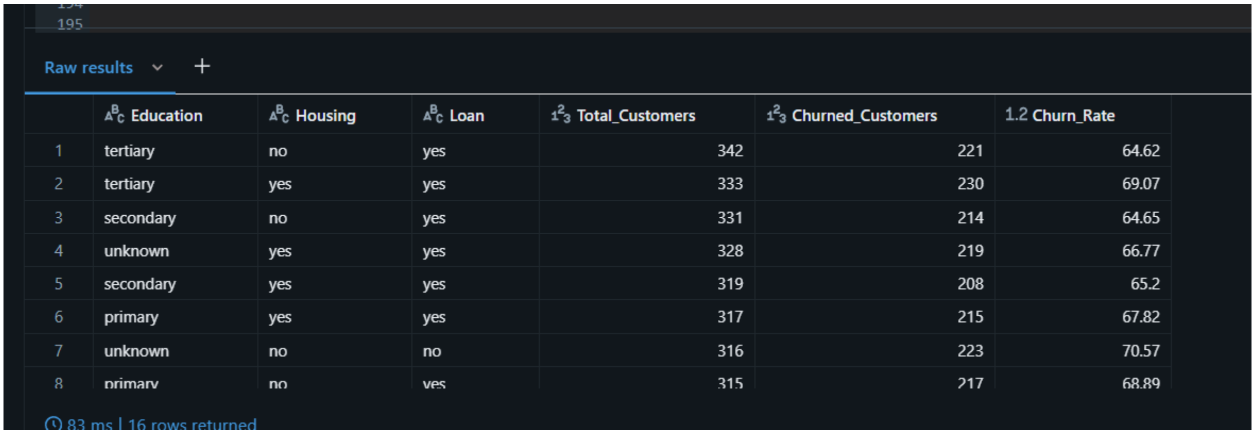
7.3.5 Churn by Balance Group

Raw results

	Balance_Group	Total_Customers	Churned_Customers	Churn_Rate
1	High Balance	1983	1341	67.62
2	Medium Balance	1926	1283	66.61
3	Low Balance	999	659	65.97
4	Negative Balance	92	65	70.65

Balance_Group	**Total_Customers**	**Churned**	**Churn_Rate**
Negative Balance	92	65	70.65
High Balance	1983	1341	67.62
Medium Balance	1926	1283	66.61
Low Balance	999	659	65.97

7.3.6 Churn by Education, Housing, Loan


195

Raw results

	Education	Housing	Loan	Total_Customers	Churned_Customers	Churn_Rate
1	tertiary	no	yes	342	221	64.62
2	tertiary	yes	yes	333	230	69.07
3	secondary	no	yes	331	214	64.65
4	unknown	yes	yes	328	219	66.77
5	secondary	yes	yes	319	208	65.2
6	primary	yes	yes	317	215	67.82
7	unknown	no	no	316	223	70.57
8	primary	no	yes	315	217	68.89

83 ms | 16 rows returned

Education	Housing	Loan	Total_Customers	Churned	Churn_Rate
primary	yes	no	312	222	71.15
unknown	no	no	316	223	70.57
tertiary	yes	yes	333	230	69.07
primary	no	yes	315	217	68.89
primary	yes	yes	317	215	67.82
tertiary	yes	no	296	200	67.57
primary	no	no	291	195	67.01
secondary	yes	no	302	202	66.89
unknown	yes	yes	328	219	66.77
tertiary	no	no	304	200	65.79
unknown	no	yes	305	200	65.57
secondary	yes	yes	319	208	65.2
secondary	no	no	301	196	65.12
secondary	no	yes	331	214	64.65
tertiary	no	yes	342	221	64.62
unknown	yes	no	288	186	64.58

8. Conclusion

This project shows how SQL-driven analytics can change raw banking data into useful business intelligence. Through churn prediction, measuring campaign effectiveness, and customer segmentation, the analysis provided a clear picture of customer behavior and engagement patterns. The results showed that more than two-thirds of customers are at risk of churning, overall campaign effectiveness is only 12%, and certain demographic and financial segments offer valuable chances for targeted marketing and cross-selling. By using these insights, the bank can improve its marketing investments, enhance retention strategies, and build stronger long-term customer relationships. In the end, the project highlights the importance of data-driven decision-making in improving customer engagement, increasing profits, and supporting sustainable business growth in a highly competitive financial services market.