BUZZ MICROFINANCE BANK CHURN ANALYSIS

Date: 7th July 2025

Project Overview

This project aims to gain deeper insights into customer churn at Buzz Microfinance Bank, enabling the improvement of retention strategies and enhancement of customer satisfaction. The analysis provides actionable insights into why customers are leaving the bank and identifies high-risk segments.

Problem Statement

The provided customer dataset will help address the following key challenges:

1. Identify key factors (e.g., demographics, product usage, service complaints) leading to customer attrition
2. Allocate resources effectively by focusing on high-value or high-risk segments

Objectives

1. Investigate which age groups, income brackets, or tenure lengths have the highest churn rates.
2. Analyse which customers from certain geographical regions are more likely to leave.
3. Gain insight into whether low engagement (e.g., inactive digital banking) correlates with higher attrition by age group.

Data Description

The dataset appears to cover Customer and Account information across two tables.

Table 1: Customer Info

- CustomerId: A unique identifier to distinguish each customer, ensuring no duplicates in analysis.
- Surname: The customer's last name (this is not unique; may repeat across records).
- CreditScore: A numerical value (e.g., 300–850) reflecting creditworthiness. Lower scores may indicate higher churn risk.
- Geography: The customer's country (France, Spain, Germany), which helps identify regional churn trends.
- Gender: Male or Female. Used to analyse if churn rates differ by gender.
- Age: The customer's age in years. Younger/older customers may churn for different reasons.

- Tenure: Years the customer has stayed with the bank. Short tenure may signal higher attrition risk.

- EstimatedSalary: High-income customers may be more likely to churn due to offers from premium competitors.

Table 2: Account Info

- CustomerId: Same as Table 1
- Balance: The amount in the customer’s account. Near-zero balances may predict churn.
- NumOfProducts: The number of products the customer uses. Customers with fewer products may be more likely to churn.
- HasCrCard: Binary (1/0) indicating credit card ownership. Cardholders may be less likely to churn.
- Tenure: Same as in Customer Info
- IsActiveMember: Binary (1/0) showing account activity. Inactive customers are high-risk for churn.
- Exited: Binary (1/0) target variable. 1 = Churned, 0 = Retained. Critical for predictive modeling.

Data Cleaning and Transformation

The dataset was provided in two sheets: Customer_Info and Account_Info. To better analyse the bank's churn data, it was necessary to merge the two sheets into one.

Data Transformation

I duplicated the Customer_Info sheet and renamed it 'Cleaned_Data'.

FIG 1.1. Project Data Sheets

On the 'Cleaned_Data' sheet, I inserted new columns using the column headers from the 'Account_Info' sheet, excluding 'CustomerId'. The added columns were: NumOfProducts, HasCrCard, Tenure, IsActiveMember, and Exited.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
2	15634602	Hargrave	619	FRA	Female	42	2	€101348.88						
3	15647311	Hill	608	Spain	Female	41	1	€112542.58						

FIG 1.2. Customer Data Sheet New Columns

I used the VLOOKUP function on the 'CustomerId' column to merge the data from 'Account_Info' into the 'Cleaned_Data' sheet.

SUM | =VLOOKUP(A2,Account_Info!A2:G10003,2,FALSE)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
2	15634602	Hargrave	619	FRA	Female	42	2	€101348.88	=VLOOKUP(A2,Account_Info!A2:G10003,2,FALSE)					
3	15647311	Hill	608	Spain	Female	41	1	€112542.58	VLOOKUP(lookup_value, table_array, col_index_num, [range_lookup])					

FIG 1.3. VLOOKUP formula to fill data into new column in Fig.1.2.

I then filled down the formula to the rows below. For the other new columns, I replicated the same formula, adjusting the 'col_index_num' from 2 to 3, 4, 5, 6, and 7 according to the column positions in the 'Account_Info' sheet. Alternatively, a column reference number can be created for the 'Account_Info' sheet to replace the 'col_index_num' with a reference cell for quicker merging."

I then selected the entire data range and pasted it as values to remove the VLOOKUP formulas.

At this stage, I had successfully merged the 'Customer_Info' and 'Account_Info' sheets into the 'Cleaned_Data' sheet.

This left me with data cleaning, which is a crucial step in data analysis.

Data Cleaning

I looked for and removed all duplicate rows from the 'Cleaned_Data' sheet. For example, rows 10001 and 10002 were duplicates, and only one was kept.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
2	15634602	Hargrave	619	FRA	Female	42	2	€101348.88	€0.0	1	Yes	2	Yes	1
3	15647311	Hill	608	Spain	Female	41	1	€112542.58	€83807.[illegible]	1	Yes	1	Yes	0
4	15619304	Onio	502	French	Female	42	8	€113931.57	€159660	3	No	8	No	1
5	15701354	Boni	699	FRA	Female	39	1	€93826.63	€0.0	2	No	1	No	0
6	15737888	Mitchell	850	Spain	Female	43	2	€79084.1	€125510	1	Yes	2	Yes	0
7	15574012	Chu	645	Spain	Male	44	8	€149756.71	€113755	2	No	8	No	1
8	15592531	Bartlett	822	France	Male	50	7	€10062.8	€0.0	2	Yes	7	Yes	0
9	15656148	Obinna	376	Germany	Female	29	4	€119346.88	€115046	4	No	4	No	1
10	15792365	He	501	French	Male	44	4	€74940.5	€142051	2	Yes	4	Yes	0
11	15592389	H?	684	France	Male	27	2	€71725.73	€134603	1	Yes	2	Yes	0
12	15767821	Bearce	528	French	Male	31	6	€80181.12	€102016	2	No	6	No	0
13	15737173	Andrews	497	Spain	Male	24	3	€76390.01	€0.0	2	No	3	No	0
14	15632264	Kay											No	0
15	15691483	Chin											No	0
16	15600882	Scott											Yes	0
17	15643966	Goforth											Yes	0
18	15737452	Romeo											No	1
19	15788218	Henderson											Yes	0
20	15661507	Muldrow	587	Spain	Male	45	6	€158684.81	€0.0	1	No	6	No	0
21	15568982	Hao	726	French	Female	24	6	€54724.03	€0.0	2	Yes	6	Yes	0
22	15577657	McDonald	732	French	Male	41	8	€170886.17	€0.0	2	Yes	8	Yes	0
23	15597945	Dellucci	636	Spain	Female	32	8	€138555.46	€0.0	2	No	8	No	0
24	15699309	Gerasimov	510	Spain	Female	38	4	€118913.53	€0.0	1	No	4	No	1
25	15725737	Mosman	669	France	Male	46	3	€8487.75	€0.0	2	Yes	3	Yes	0
26	15625047	Yen	846	FRA	Female	38	5	€187616.16	€0.0	1	Yes	5	Yes	0
27	15738191	Maclean	577	France	Male	25	3	€124508.29	€0.0	2	Yes	3	Yes	0
28	15736816	Young	756	Germany	Male	36	2	€170041.95	€136815	1	Yes	2	Yes	0
29	15700772	Nebechi	571	FRA	Male	44	9	€38433.35	€0.0	2	No	9	No	0
30	15728693		574	Germany	Female		3	-€999999	€141349	1	Yes	3	Yes	0
31	15656300	Lucciano	411	French	Male	29	0	€53483.21	€59697.[illegible]	2	Yes	0	Yes	0
32	15589475	Azikiwe	591	Spain	Female	39	3	€140469.38	€0.0	3	No	3	No	1
33	15706552	Odinakachukwu	533	France	Male	36	7	€156731.91	€85311.[illegible]	1	Yes	7	Yes	0
34	15750181	Sanderson	553	Germany	Male	41	9	€81898.81	€110112	2	No	9	No	0
35	15659428	Maggard	520	Spain	Female	42	6	€34410.55	€0.0	2	Yes	6	Yes	0
36	15732963	Clements	722	Spain	Female	29	9	€142033.07	€0.0	2	Yes	9	Yes	0
37	15794171	Lombardo	475	France	Female	45	0	€27822.99	€134264	1	No	0	No	1
38	15788448	Watson	490	Spain	Male	31	3	€114066.77	€145260	1	Yes	3	Yes	0

Microsoft Excel

1 duplicate values found and removed; 10000 unique values remain. Note that counts may include empty cells, spaces, etc.

OK

Cleaned_Data | Customer_Info | Account_Info

The 'Tenure' column also appeared duplicated after merging the 'Customer_Info' and 'Account_Info' sheets. Therefore, there was a need to remove one of these columns. Although this duplication did not affect the analysis, it was removed to maintain clean data.

G1 Tenure

	rId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
2	34602	Hargrave	619	FRA	Female	42	2	€101348.88	€0.0	1	Yes	2	Yes	1
3	47311	Hill	608	Spain	Female	41	1	€112542.58	€83807.86	1	Yes	1	Yes	0
4	19304	Onio	502	French	Female	42	8	€113931.57	€159660.8	3	No	8	No	1
5	01354	Boni	699	FRA	Female	39	1	€93826.63	€0.0	2	No	1	No	0
6	37888	Mitchell	850	Spain	Female	43	2	€79084.1	€125510.82	1	Yes	2	Yes	0
7	74012	Chu	645	Spain	Male	44	8	€149756.71	€113755.78	2	No	8	No	1
8	92531	Bartlett	822	France	Male	50	7	€10062.8	€0.0	2	Yes	7	Yes	0
9	56148	Obinna	376	Germany	Female	29	4	€119346.88	€115046.74	4	No	4	No	1
10	92365	He	501	French	Male	44	4	€74940.5	€142051.07	2	Yes	4	Yes	0
11	92389	H?	684	France	Male	27	2	€71725.73	€134603.88	1	Yes	2	Yes	0
12	67821	Bearce	528	French	Male	31	6	€80181.12	€102016.72	2	No	6	No	0
13	37173	Andrews	497	Spain	Male	24	3	€76390.01	€0.0	2	No	3	No	0
14	32264	Kay	476	FRA	Female	34	10	€26260.98	€0.0	2	No	10	No	0
15	91483	Chin	549	France	Female	25	5	€190857.79	€0.0	2	No	5	No	0
16	00882	Scott	635	Spain	Female	35	7	€65951.65	€0.0	2	Yes	7	Yes	0
17	43966	Goforth	616	Germany	Male	45	3	€64327.26	€143129.41	2	Yes	3	Yes	0
18	37452	Romeo	653	Germany	Male	58	1	€5097.67	€132602.88	1	No	1	No	1
19	88218	Henderson	549	Spain	Female	24	9	€14406.41	€0.0	2	Yes	9	Yes	0
20	61507	Muldrow	587	Spain	Male	45	6	€158684.81	€0.0	1	No	6	No	0
21	68982	Hao	726	French	Female	24	6	€54724.03	€0.0	2	Yes	6	Yes	0
22	77657	McDonald	732	French	Male	41	8	€170886.17	€0.0	2	Yes	8	Yes	0
23	97945	Dellucci	636	Spain	Female	32	8	€138555.46	€0.0	2	No	8	No	0
24	99309	Gerasimov	510	Spain	Female	38	4	€118913.53	€0.0	1	No	4	No	1
25	25737	Mosman	669	France	Male	46	3	€8487.75	€0.0	2	Yes	3	Yes	0
26	25047	Yen	846	FRA	Female	38	5	€187616.16	€0.0	1	Yes	5	Yes	0
27	38191	Maclean	577	France	Male	25	3	€124508.29	€0.0	2	Yes	3	Yes	0
28	36816	Young	756	Germany	Male	36	2	€170041.95	€136815.64	1	Yes	2	Yes	0
29	00772	Nebechi	571	FRA	Male	44	9	€38433.35	€0.0	2	No	9	No	0
30	28693	Not_Available	574	Germany	Female	39	3	-€999999	€141349.43	1	Yes	3	Yes	0
31	56300	Lucciano	411	French	Male	29	0	€53483.21	€59697.17	2	Yes	0	Yes	0
32	89475	Azikiwe	591	Spain	Female	39	3	€140469.38	€0.0	3	No	3	No	1
33	06552	Odinakachukwu	533	France	Male	36	7	€156731.91	€85311.7	1	Yes	7	Yes	0
34	50181	Sanderson	553	Germany	Male	41	9	€81898.81	€110112.54	2	No	9	No	0
35	59428	Maggard	520	Spain	Female	42	6	€34410.55	€0.0	2	Yes	6	Yes	0
36	32963	Clements	722	Spain	Female	29	9	€142033.07	€0.0	2	Yes	9	Yes	0
37	94171	Lombardo	475	France	Female	45	0	€27822.99	€134264.04	1	No	0	No	1
38	88448	Watson	490	Spain	Male	31	3	€114066.77	€145260.23	1	Yes	3	Yes	0

Cleaned_Data Customer_Info Account_Info

Ready Accessibility: Good to go Average: 5.0128 Count: 20002 Sum: 100256

1. Handling missing values

Blank cells were observed on the 'Cleaned_Data' sheet under the 'Surname' and 'Age' columns.

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
30	15728693		574	Germany	Female		3	-€999999	€141349.43	1	Yes	3	Yes	0
123	15580203		674	Spain	Male		6	-€999999	€120193.42	1	No	6	No	0
9391	15756954		538	France	Female		2	-€999999	€0.0	1	Yes	2	Yes	0

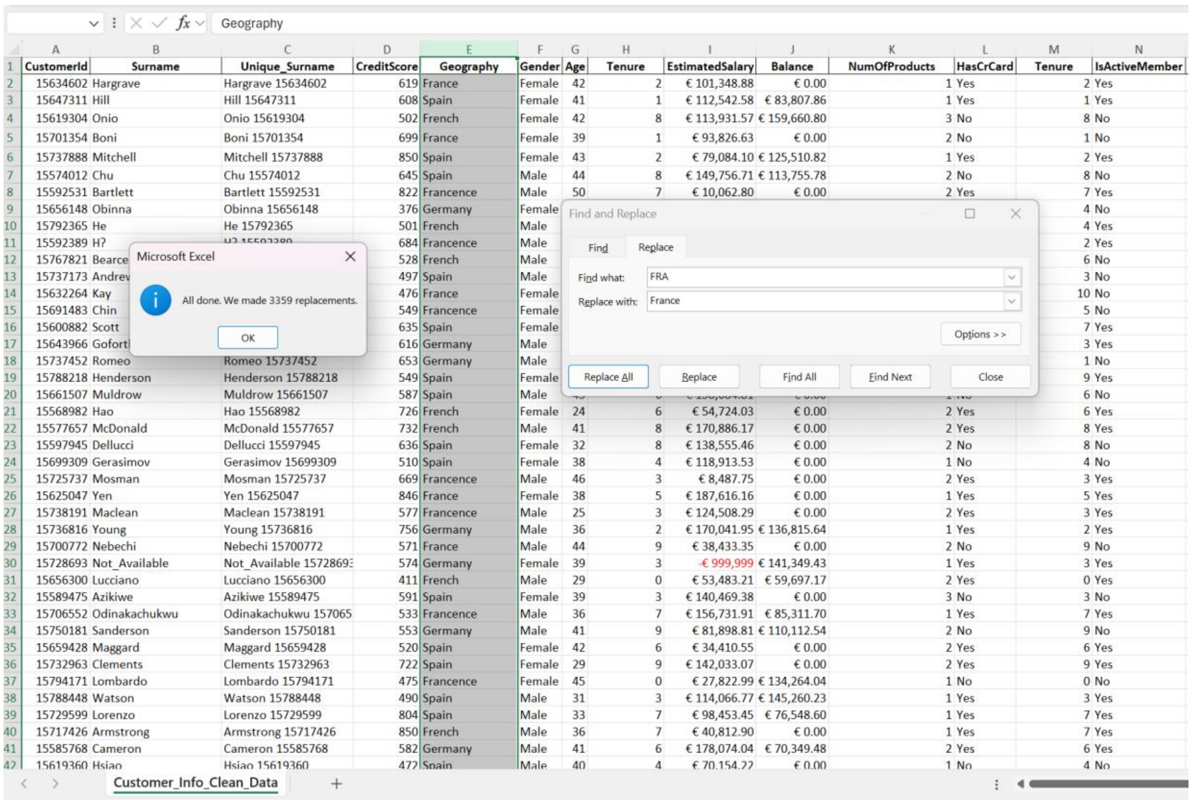
This indicates that Buzz Microfinance Bank should investigate how to prevent these errors to enhance data quality for analysis and for their database.

To address the blanks, I replaced the missing values in the 'Surname' column with 'Not_Available' using the Find and Replace function.

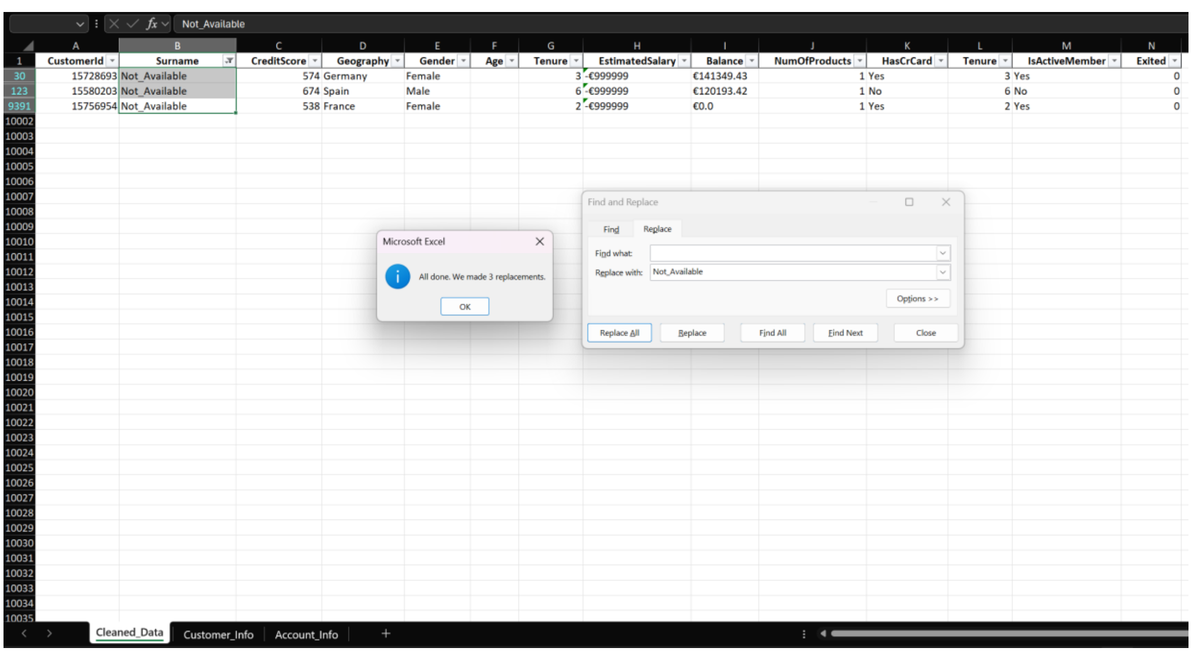
For the 'Age' column, I calculated the average age (using the formula =AVERAGE(F2:F10001), which was 38.92, rounded to 39) and replaced the blank cells with this average value. One might question why these rows were not removed. I advise against removal because these customers have associated 'Balance' figures and 'CustomerId's. Replacing the blank cells maintains data completeness as provided by Buzz Microfinance Bank.

2. Replacing Inconsistent Entries

Inconsistent entries for France (such as 'FRA', 'Francence', and 'FRENCH') were observed in the 'Geography' column. I used the Find and Replace function to replace these with 'France'.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CustomerId	Surname	Unique_Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember
2	15634602	Hargrave	Hargrave 15634602	619	France	Female	42	2	€ 101,348.88	€ 0.00	1	Yes	2	Yes
3	15647311	Hill	Hill 15647311	608	Spain	Female	41	1	€ 112,542.58	€ 83,807.86	1	Yes	1	Yes
4	15619304	Onio	Onio 15619304	502	French	Female	42	8	€ 113,931.57	€ 159,660.80	3	No	8	No
5	15701354	Boni	Boni 15701354	699	France	Female	39	1	€ 93,826.63	€ 0.00	2	No	1	No
6	15737888	Mitchell	Mitchell 15737888	850	Spain	Female	43	2	€ 79,084.10	€ 125,510.82	1	Yes	2	Yes
7	15574012	Chu	Chu 15574012	645	Spain	Male	44	8	€ 149,756.71	€ 113,755.78	2	No	8	No
8	15592531	Bartlett	Bartlett 15592531	822	Francence	Male	50	7	€ 10,062.80	€ 0.00	2	Yes	7	Yes
9	15656148	Obinna	Obinna 15656148	376	Germany	Female							4	No
10	15792365	He	He 15792365	501	French	Male							4	Yes
11	15592389	H?		684	Francence	Male							2	Yes
12	15767821	Bearce		528	French	Male							6	No
13	15737173	Andrev		497	Spain	Male							3	No
14	15632264	Kay		476	France	Female							10	No
15	15691483	Chin		549	Francence	Female							5	No
16	15600882	Scott		635	Spain	Female							7	Yes
17	15643966	Gofortl		616	Germany	Male							3	Yes
18	15737452	Romeo	Romeo 15737452	653	Germany	Male							1	No
19	15788218	Henderson	Henderson 15788218	549	Spain	Female							9	Yes
20	15661507	Muldrow	Muldrow 15661507	587	Spain	Male							6	No
21	15568982	Hao	Hao 15568982	726	French	Female	24	6	€ 54,724.03	€ 0.00	2	Yes	6	Yes
22	15577657	McDonald	McDonald 15577657	732	French	Male	41	8	€ 170,886.17	€ 0.00	2	Yes	8	Yes
23	15597945	Dellucci	Dellucci 15597945	636	Spain	Female	32	8	€ 138,555.46	€ 0.00	2	No	8	No
24	15699309	Gerasimov	Gerasimov 15699309	510	Spain	Female	38	4	€ 118,913.53	€ 0.00	1	No	4	No
25	15725737	Mosman	Mosman 15725737	669	Francence	Male	46	3	€ 8,487.75	€ 0.00	2	Yes	3	Yes
26	15625047	Yen	Yen 15625047	846	France	Female	38	5	€ 187,616.16	€ 0.00	1	Yes	5	Yes
27	15738191	Maclean	Maclean 15738191	577	Francence	Male	25	3	€ 124,508.29	€ 0.00	2	Yes	3	Yes
28	15736816	Young	Young 15736816	756	Germany	Male	36	2	€ 170,041.95	€ 136,815.64	1	Yes	2	Yes
29	15700772	Nebechi	Nebechi 15700772	571	France	Male	44	9	€ 38,433.35	€ 0.00	2	No	9	No
30	15728693	Not_Available	Not_Available 1572869:	574	Germany	Female	39	3	-€ 999,999	€ 141,349.43	1	Yes	3	Yes
31	15656300	Lucciano	Lucciano 15656300	411	French	Male	29	0	€ 53,483.21	€ 59,697.17	2	Yes	0	Yes
32	15589475	Azikiwe	Azikiwe 15589475	591	Spain	Female	39	3	€ 140,469.38	€ 0.00	3	No	3	No
33	15706552	Odinakachukwu	Odinakachukwu 157065	533	Francence	Male	36	7	€ 156,731.91	€ 85,311.70	1	Yes	7	Yes
34	15750181	Sanderson	Sanderson 15750181	553	Germany	Male	41	9	€ 81,898.81	€ 110,112.54	2	No	9	No
35	15659428	Maggard	Maggard 15659428	520	Spain	Female	42	6	€ 34,410.55	€ 0.00	2	Yes	6	Yes
36	15732963	Clements	Clements 15732963	722	Spain	Female	29	9	€ 142,033.07	€ 0.00	2	Yes	9	Yes
37	15794171	Lombardo	Lombardo 15794171	475	Francence	Female	45	0	€ 27,822.99	€ 134,264.04	1	No	0	No
38	15788448	Watson	Watson 15788448	490	Spain	Male	31	3	€ 114,066.77	€ 145,260.23	1	Yes	3	Yes
39	15729599	Lorenzo	Lorenzo 15729599	804	Spain	Male	33	7	€ 98,453.45	€ 76,548.60	1	Yes	7	Yes
40	15717426	Armstrong	Armstrong 15717426	850	French	Male	36	7	€ 40,812.90	€ 0.00	1	Yes	7	Yes
41	15585768	Cameron	Cameron 15585768	582	Germany	Male	41	6	€ 178,074.04	€ 70,349.48	2	Yes	6	Yes
42	15619360	Hsiao	Hsiao 15619360	472	Spain	Male	40	4	€ 70,154.22	€ 0.00	1	No	4	No



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	EstimatedSalary	Balance	NumOfProducts	HasCrCard	Tenure	IsActiveMember	Exited
30	15728693	Not_Available	574	Germany	Female		3	-€999999	€141349.43	1	Yes	3	Yes	0
123	15580203	Not_Available	674	Spain	Male		6	-€999999	€120193.42	1	No	6	No	0
9391	15756954	Not_Available	538	France	Female		2	-€999999	€0.0	1	Yes	2	Yes	0

3. Calculated Columns

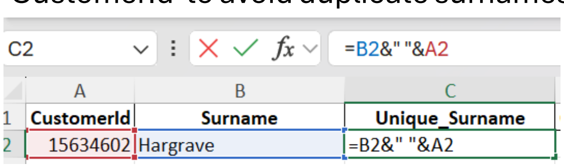
I created calculated columns based on 'Age' and 'CreditScore' to derive new information, such as trends, patterns, and variations across different groups. These columns can reveal important insights about customer behaviour and trends.

a. I grouped the 'Age' column into categories in a new column called 'AgeByGroup'. The groups are:

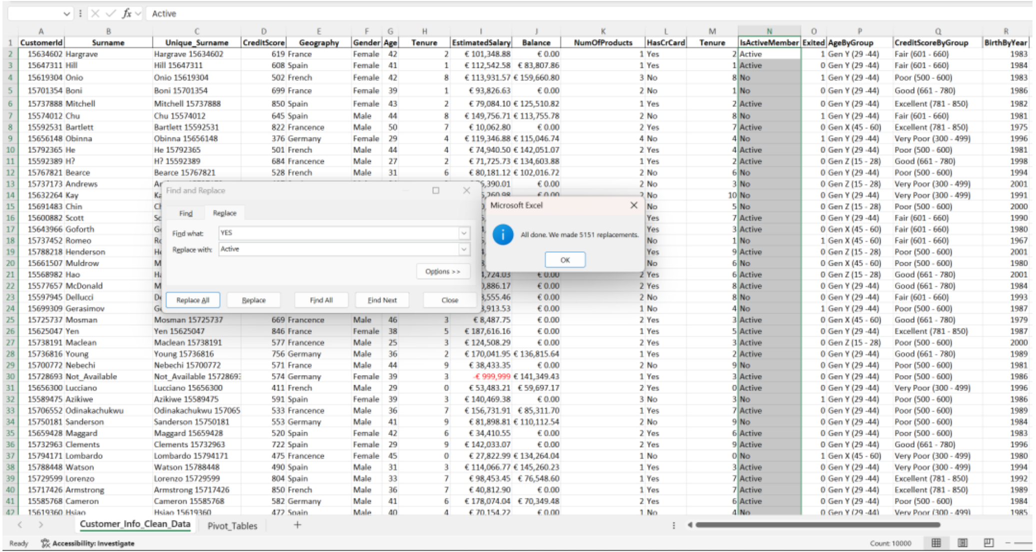
Generations	Age
Silent Generation	80 – 97
Baby Boomers	61 – 79
Gen X	45 – 60
Gen Y	29 – 44
Gen Z	15 – 28

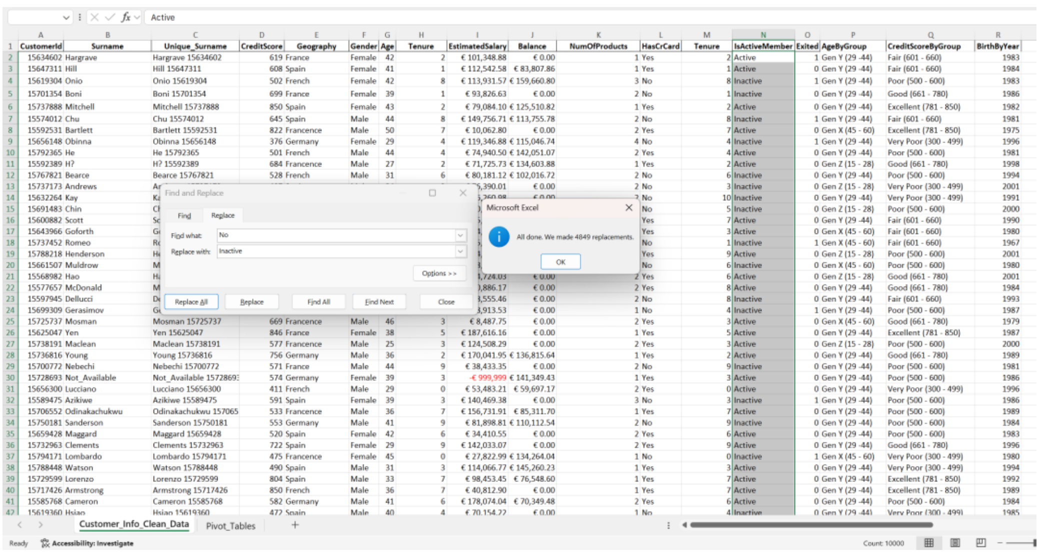
b. I grouped the 'CreditScore' column into ranges (from poor to excellent) based on the FICO® Score model, which is widely recognised for representing past borrowing and payment behaviour. Note that there are many credit scoring models, but FICO is the most recognised.

c. I created a new column 'Unique_Surname' by combining 'Surname' and 'CustomerId' to avoid duplicate surnames (since surnames alone are not unique).



d. I replaced the values in the 'IsActiveMember' column: 'YES' became 'ACTIVE' and 'NO' became 'INACTIVE'. Similarly, I created another 'Exited' column and replaced the previous column header as 'ExitedByNum'. On the new 'Exited' column, 1 was replaced with 'Churned' and 0 with 'Retained'. This enhances clarity for stakeholders and for using slicers in dashboards





e. I also added a new column titled TenurebyGroup. This group the customer tenure into the following categories:

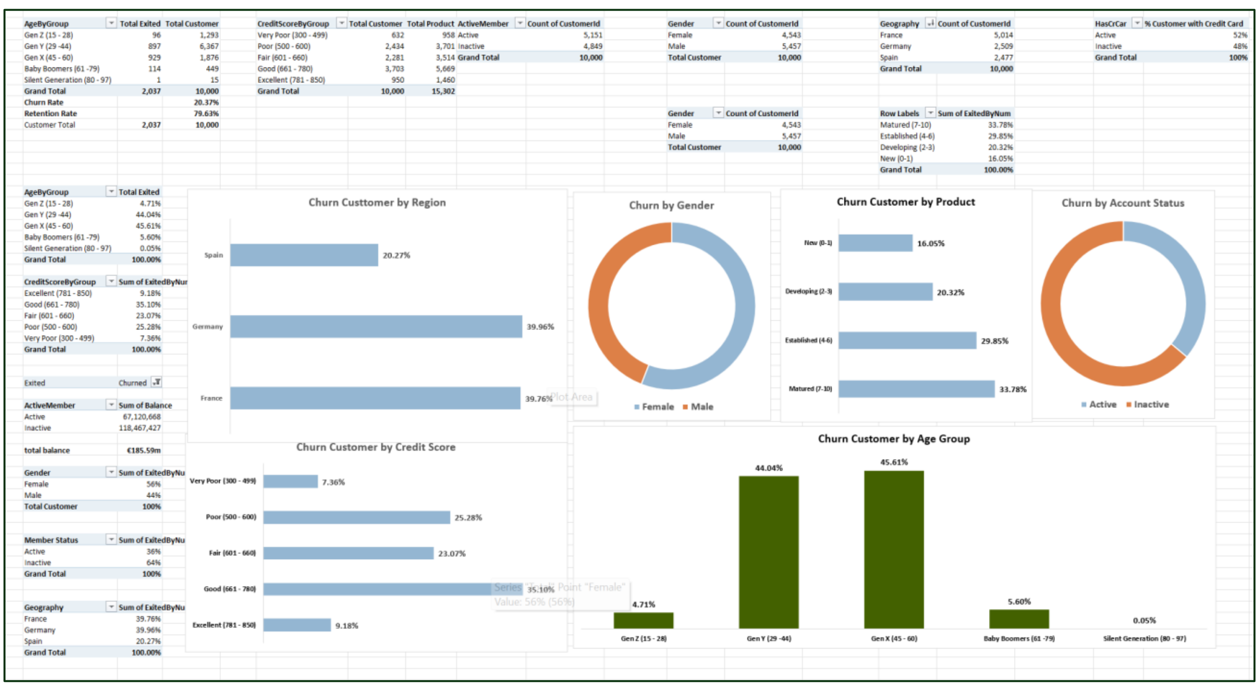
Group Title	**Group Range**
New (0-1)	0 -1
Developing (2-3)	2-3
Established (4-6)	4-6
Matured (7-10)	7-10

At this point, I had completed data cleaning, which is a crucial stage of data analysis. It serves as the foundation for building dashboards for presentations to stakeholders. Without proper data cleaning, any subsequent analysis or dashboard may be unreliable.

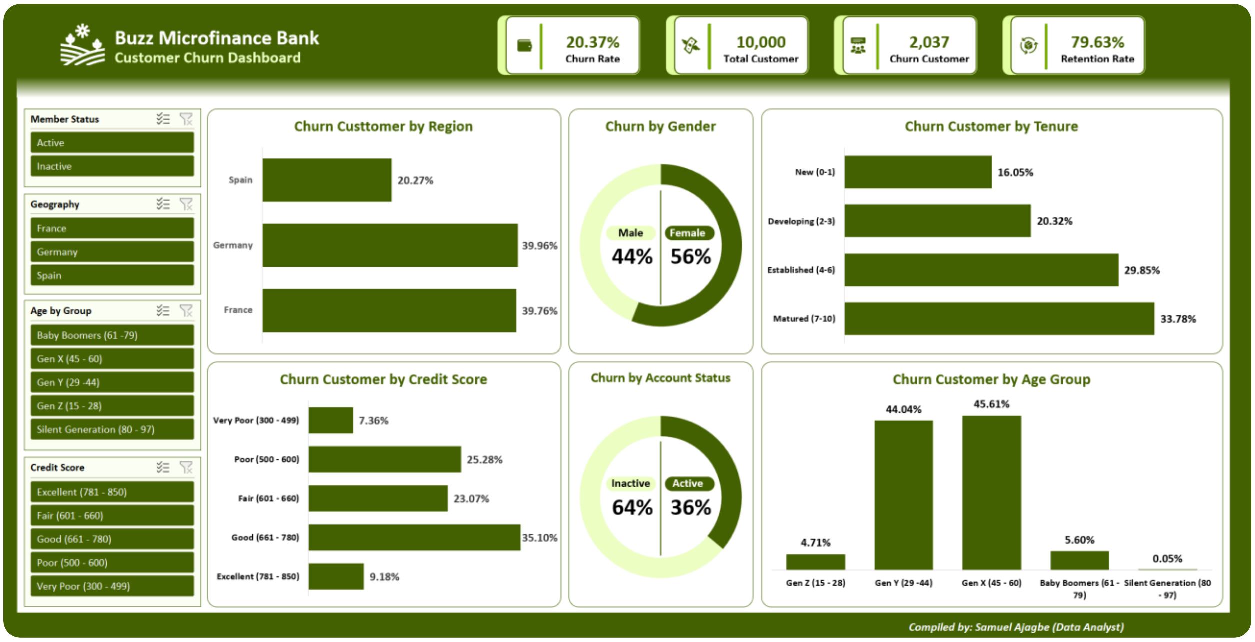
Data Analysis through Pivoting

I employed pivot tables to transform the cleaned dataset into structured summaries, enabling targeted exploration of churn drivers. Key pivot tables were designed to segment data by critical variables, with Exited (Churned/Retained) as the core filter. Below are the pivot configurations and insights generated:

a. Overall Churn Rate: Pivot table showing total customers and churn rate.
b. Churn by Activity Status: Active vs. Inactive members and their churn rates.
c. Regional Churn Analysis: Churn rates by country (Germany, France, Spain).
d. Gender-Based Churn: Churn rates by gender.
e. Age Group Analysis: Churn rates by generation (Gen Z, Gen Y, Gen X, Baby Boomers).
f. Credit Card Usage and Churn: Churn by card activity (inactive card users).



Data Visualization and Dashboard Development



Key Performance Indicators KPIs

Churn Rate: The percentage of customers who discontinued services from the bank within the time dataset was presented.

Churn Customer: The absolute total number of customers who exited the bank.

Total Customer: Track changes in customer numbers by region and churn status.

Retention Rate: The percentage of customers retained within the period was presented for analysis.

CHURNED INSIGHT

Total Customers: Out of 10,000 customers total, 2,037 customers churned, representing 20.4%. This means 1 in 5 customers left the bank. Examining the Retained vs. Active Customers, I note that 'Adams 15709136' has no credit balance but is currently active, while 'Johnstone 15682834' has only 40,170 in credit balance. These cases highlight a potential factor in customer churn: customers may not receive instant credit line replenishment before their current credit is exhausted. This pattern is also evident among inactive churned customers, indicating a critical trend.

Active vs. Inactive: 36% of churned customers were Active at the time of churn, while 64% were Inactive. This indicates that inactive customers (from whom no deposits were received) are more prone to churn. However, without implementing proactive measures, even active customers may become inactive and eventually churn.

Region: The Germany region shows an alarming churn rate of 32.4% (814 churned out of 2,509 customers). This is significantly higher than France (16.2%, 810 out of 5,014) and Spain (16.7%, 413 out of 2,477). This disparity may be due to intense local competition offering better products or promotions.

Gender: Females exhibit a higher churn rate compared to males, across all regions. This might indicate that the current product offerings are less suitable for the female demographic.

Age & Tenure Risks: I observe a high churn rate among Gen X (45-60) and Baby Boomers (61-79) relative to their proportion in the customer base. In contrast, Gen Y (29-44) shows a low churn rate. It is essential to analyze the factors contributing to the retention of Gen Y customers and replicate successful strategies in other regions and age groups.

Credit Card Usage: 64% of churned customers were inactive card users. Specifically, 517 churned customers from Germany and 512 from France were inactive card users, indicating a strong correlation between card inactivity and churn.

RECOMMENDATION

1. Credit Line Management: Implement an automated system for proactive credit line replenishment to prevent customers from exhausting their available credit, thereby reducing a key churn trigger.

2. Inactive Customer Engagement: Launch targeted reactivation campaigns for inactive customers, including personalized offers and communication, to prevent churn.

3. Regional Strategy in Germany: Conduct a thorough competitive analysis in the German market and adjust product features, pricing, and promotional offers to better compete with local players.

4. Gender-Specific Products: Undertake research to understand the financial needs and preferences of female customers and develop tailored products and services for this demographic.

5. Age Group Retention Strategies: Investigate the reasons for high retention among Gen Y customers and adapt these strategies (e.g., digital engagement, product features) for Gen X and Baby Boomers.

6. Card Usage Incentives: Introduce reward programs and usage-based benefits to encourage active card usage, which may reduce churn among inactive cardholders.

CONCLUSIION

This churn analysis has identified several critical areas requiring immediate attention, including credit management, customer engagement, regional competitiveness, product suitability for different genders and age groups, and card activity. By implementing the recommended strategies, the bank can address the root causes of churn, enhance customer satisfaction, and significantly improve retention rates across all segments.

Signed,

Samuel Ajagbe

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