Device Insurance Attach Percentage Analysis

Jumbo & Company – Zopper Business Case

Objective

Analyze historical device insurance attach percentages across stores and branches, identify key performance drivers, and predict January attach percentages at the store level.

Dataset

Monthly attach percentage data (Aug–Dec) across 163 stores and multiple branches.

In [1]:
```python
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

# display settings
pd.set_option('display.max_columns', None)
plt.style.use('default')
```

In [2]:
```python
!pip install matplotlib seaborn
```

```
Requirement already satisfied: matplotlib in c:\users\armaan\appdata\local\prog
rams\python\python313\lib\site-packages (3.10.8)
Requirement already satisfied: seaborn in c:\users\armaan\appdata\local\program
s\python\python313\lib\site-packages (0.13.2)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\armaan\appdata\loca
l\programs\python\python313\lib\site-packages (from matplotlib) (1.3.3)
Requirement already satisfied: cycler>=0.10 in c:\users\armaan\appdata\local\pr
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Requirement already satisfied: fonttools>=4.22.0 in c:\users\armaan\appdata\loc
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Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\armaan\appdata\loc
al\programs\python\python313\lib\site-packages (from matplotlib) (1.4.9)
Requirement already satisfied: numpy>=1.23 in c:\users\armaan\appdata\local\pro
grams\python\python313\lib\site-packages (from matplotlib) (2.3.5)
Requirement already satisfied: packaging>=20.0 in c:\users\armaan\appdata\loca
l\programs\python\python313\lib\site-packages (from matplotlib) (25.0)
Requirement already satisfied: pillow>=8 in c:\users\armaan\appdata\local\progr
ams\python\python313\lib\site-packages (from matplotlib) (12.0.0)
Requirement already satisfied: pyparsing>=3 in c:\users\armaan\appdata\local\pr
ograms\python\python313\lib\site-packages (from matplotlib) (3.2.5)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\armaan\appdata\
local\programs\python\python313\lib\site-packages (from matplotlib) (2.9.0.post
0)
Requirement already satisfied: pandas>=1.2 in c:\users\armaan\appdata\local\pro
grams\python\python313\lib\site-packages (from seaborn) (2.3.3)
Requirement already satisfied: pytz>=2020.1 in c:\users\armaan\appdata\local\pr
ograms\python\python313\lib\site-packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in c:\users\armaan\appdata\local\
programs\python\python313\lib\site-packages (from pandas>=1.2->seaborn) (202
5.2)
Requirement already satisfied: six>=1.5 in c:\users\armaan\appdata\local\progra
ms\python\python313\lib\site-packages (from python-dateutil>=2.7->matplotlib)
(1.17.0)
```

In [3]:
```
!pip install xlrd
```

```
Requirement already satisfied: xlrd in c:\users\armaan\appdata\local\programs\p
ython\python313\lib\site-packages (2.0.2)
```

In [4]:
```
df = pd.read_excel(
    r"C:\Users\Armaan\Downloads\Jumbo & Company_ Attach % .xls",
    engine="xlrd"
)
```

In [5]:
```
df.head()
```

Out[5]:

	Branch	Store_Name	Dec	Nov	Oct	Sep	Aug
0	Delhi_Ncr	Delhi(Janakpuri) Br	0.23	0.17	0.16	0.25	0.24
1	Delhi_Ncr	Haryana(Gurgaon) Br	0.21	0.26	0.15	0.28	0.04
2	Delhi_Ncr	Up(Greater Noida) Br	0.25	0.36	0.30	0.41	0.43
3	Pune	Pune(Bhosari) Br	0.33	0.33	0.36	0.13	0.32
4	Gujarat	Ahmedabad(Maninagar) Br	0.19	0.11	0.14	0.21	0.17

In [6]:
```
df.shape
```

Out[6]:
```
(163, 7)
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 163 entries, 0 to 162
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Branch      163 non-null    object 
 1   Store_Name  163 non-null    object 
 2   Dec         163 non-null    float64
 3   Nov         163 non-null    float64
 4   Oct         163 non-null    float64
 5   Sep         163 non-null    float64
 6   Aug         163 non-null    float64
dtypes: float64(5), object(2)
memory usage: 9.0+ KB
```

In [8]:
```
df.describe()
```

Out[8]:

	Dec	Nov	Oct	Sep	Aug
count	163.000000	163.000000	163.000000	163.000000	163.000000
mean	0.217239	0.217117	0.170920	0.167301	0.128589
std	0.173270	0.131246	0.116125	0.134518	0.116640
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.095000	0.130000	0.100000	0.080000	0.035000
50%	0.200000	0.200000	0.160000	0.150000	0.110000
75%	0.300000	0.295000	0.240000	0.245000	0.190000
max	1.000000	0.700000	0.710000	0.800000	0.600000

Initial Observations

Dataset Overview

- Each row represents **one retail store**
- Total number of rows: **163 stores**
- Total number of columns: **7**
    - **2 categorical columns**
    - **5 numerical columns (monthly attach percentages)**

Column Descriptions

- **Branch**:
  Represents the geographical or organizational grouping of stores (e.g., Delhi_NCR, Pune, Gujarat).

- **Store_Name**:
  Unique identifier for each retail store within a branch.

- **Aug, Sep, Oct, Nov, Dec**:
  Monthly **insurance attach percentages**, indicating the proportion of device sales where an insurance plan was attached for that month.

Missing Values & Data Quality

- No obvious missing values observed in the initial data inspection.
- Attach percentage values fall within a reasonable range (0–1), indicating valid percentage data.
- Some stores exhibit **significant variation across months**, which may indicate:
    - Seasonal effects in insurance sales
    - Differences in store-level sales practices
    - Opportunities for targeted performance improvement initiatives

```
In [9]: df_long = df.melt(
            id_vars=["Branch", "Store_Name"],
            value_vars=["Aug", "Sep", "Oct", "Nov", "Dec"],
            var_name="Month",
            value_name="Attach_Percentage"
        )
```

```
In [10]: df_long.head()
```

Out[10]:

	Branch	Store_Name	Month	Attach_Percentage
0	Delhi_Ncr	Delhi(Janakpuri) Br	Aug	0.24
1	Delhi_Ncr	Haryana(Gurgaon) Br	Aug	0.04
2	Delhi_Ncr	Up(Greater Noida) Br	Aug	0.43
3	Pune	Pune(Bhosari) Br	Aug	0.32
4	Gujarat	Ahmedabad(Maninagar) Br	Aug	0.17

In [11]:
```
df_long.shape
```

Out[11]:
```
(815, 4)
```

In [12]:
```
df_long["Month"].value_counts()
```

Out[12]:
```
Month
Aug    163
Sep    163
Oct    163
Nov    163
Dec    163
Name: count, dtype: int64
```

In [13]:
```
df_long.describe()
```

Out[13]:

	Attach_Percentage
count	815.000000
mean	0.180233
std	0.139740
min	0.000000
25%	0.080000
50%	0.170000
75%	0.260000
max	1.000000

Data Structure After Reshaping

The dataset was converted from a wide format (one row per store with multiple month columns) to a long format where each row represents a single store-month combination.

Updated Structure

- **Branch**: Geographic grouping of stores
- **Store_Name**: Individual retail store identifier
- **Month**: Month of observation (Aug–Dec)
- **Attach_Percentage**: Insurance attach rate for that store in the given month

Why Reshaping Was Required

- Enables easier time-based analysis across months
- Simplifies aggregation at branch and store levels
- Supports trend analysis and visualization
- Prepares the data for forecasting future attach percentages

This structure is more suitable for exploratory analysis, store categorisation, and predictive modeling.

In [14]:
```
monthly_trend = (
    df_long
    .groupby("Month")["Attach_Percentage"]
    .mean()
    .reset_index()
)

monthly_trend
```

Out[14]:

	Month	Attach_Percentage
0	Aug	0.128589
1	Dec	0.217239
2	Nov	0.217117
3	Oct	0.170920
4	Sep	0.167301

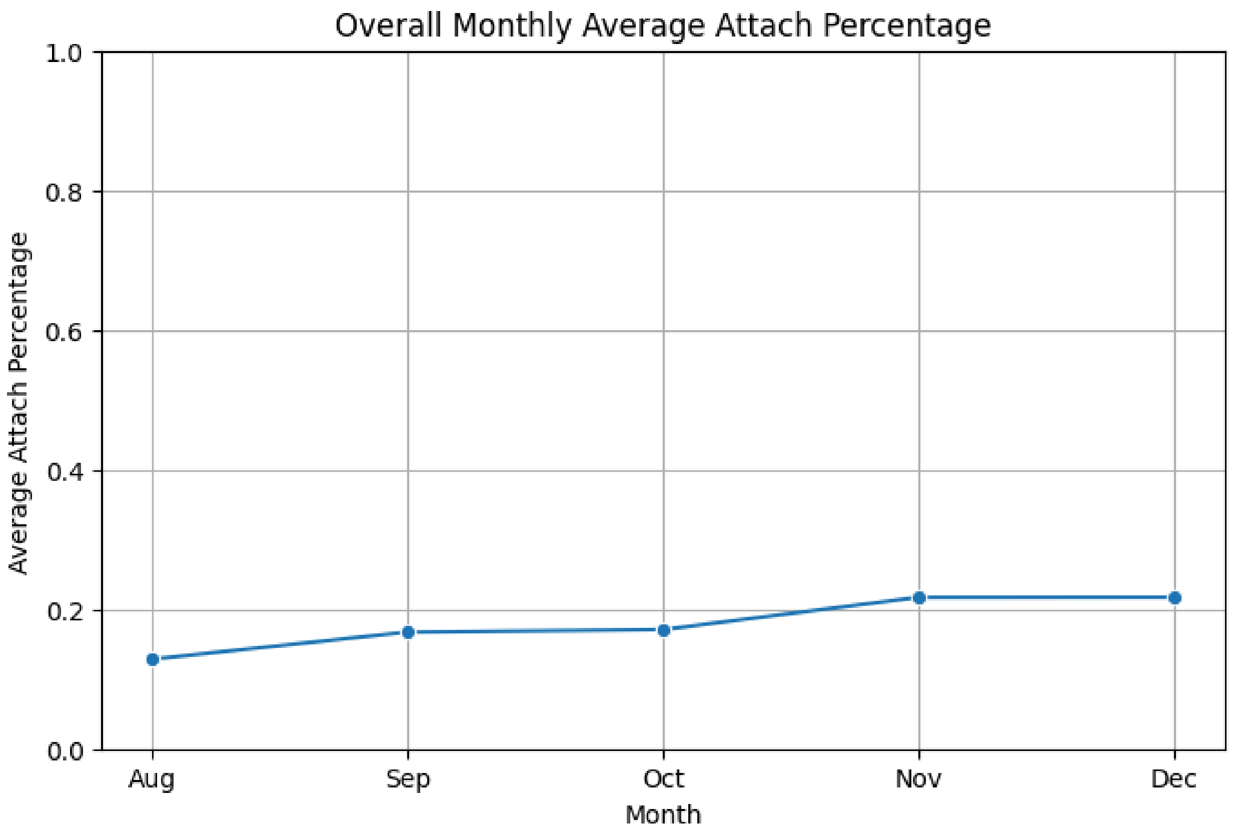
In [15]:
```
month_order = ["Aug", "Sep", "Oct", "Nov", "Dec"]

monthly_trend["Month"] = pd.Categorical(
    monthly_trend["Month"],
    categories=month_order,
    ordered=True
)

monthly_trend = monthly_trend.sort_values("Month")
monthly_trend
```

Out[15]:

	Month	Attach_Percentage
0	Aug	0.128589
4	Sep	0.167301
3	Oct	0.170920
2	Nov	0.217117
1	Dec	0.217239

In [16]:

```
plt.figure(figsize=(8, 5))
sns.lineplot(
    data=monthly_trend,
    x="Month",
    y="Attach_Percentage",
    marker="o"
)

plt.title("Overall Monthly Average Attach Percentage")
plt.xlabel("Month")
plt.ylabel("Average Attach Percentage")
plt.ylim(0, 1)
plt.grid(True)
plt.show()
```



Overall Monthly Attach Percentage Trend

The chart shows the average insurance attach percentage across all stores for each month.

Key Observations

- The overall attach percentage remains relatively stable across the observed months, ranging approximately between 13% and 22%.
- A gradual increase is observed from August to November, followed by stabilization towards December.
- The absence of sharp spikes or drops suggests consistent insurance attachment performance across months.
- This stability indicates that attach percentage may be driven more by store-level practices rather than strong seasonality effects.

Understanding this pattern helps shift focus towards branch and store-level optimization rather than purely seasonal strategies.

Branch-wise Performance Analysis,

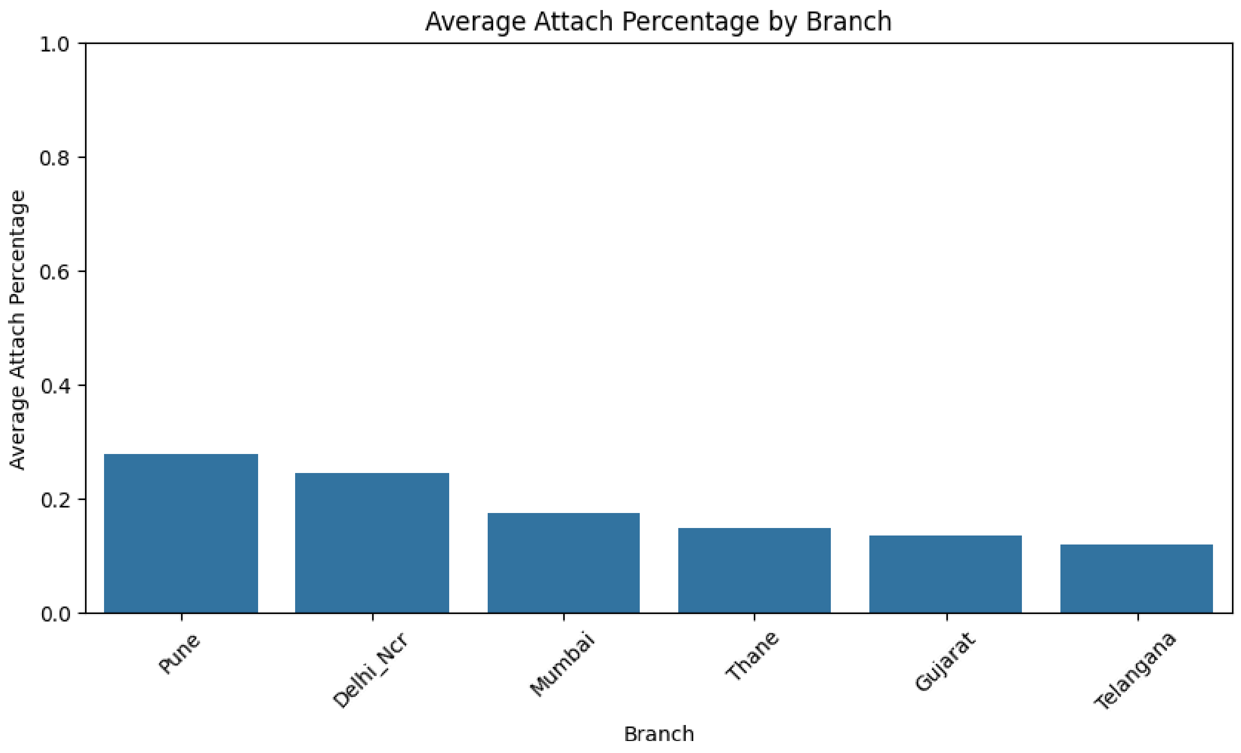
This answers: Which regions are driving Zopper's business, and which need intervention?

In [17]:
```
branch_performance = (
    df_long
    .groupby("Branch")["Attach_Percentage"]
    .mean()
    .reset_index()
    .sort_values("Attach_Percentage", ascending=False)
)

branch_performance
```

Out[17]:

	Branch	Attach_Percentage
3	Pune	0.276500
0	Delhi_Ncr	0.243682
2	Mumbai	0.173474
5	Thane	0.148600
1	Gujarat	0.134583
4	Telangana	0.118350

```
In [18]: plt.figure(figsize=(10, 5))
sns.barplot(
    data=branch_performance,
    x="Branch",
    y="Attach_Percentage"
)

plt.title("Average Attach Percentage by Branch")
plt.xlabel("Branch")
plt.ylabel("Average Attach Percentage")
plt.ylim(0, 1)
plt.xticks(rotation=45)
plt.show()
```



Branch-wise Attach Percentage Performance

The chart compares the average insurance attach percentage across different branches.

Key Observations

- **Pune** emerges as the highest-performing branch in terms of attach percentage, indicating strong adoption of insurance plans at the store level.
- **Delhi_NCR** also shows relatively strong performance, suggesting effective sales practices or higher customer acceptance.

- **Telangana** records the lowest average attach percentage, highlighting a potential area for improvement.
- The noticeable variation across branches suggests that attach performance is influenced more by regional or operational factors than by overall seasonality.

Business Implications

- High-performing branches such as Pune can serve as benchmarks for best practices.
- Low-performing branches like Telangana may benefit from targeted interventions such as staff training, revised incentive structures, or focused promotional campaigns.

In [19]:
```python
store_performance = (
    df_long
    .groupby(["Branch", "Store_Name"])["Attach_Percentage"]
    .mean()
    .reset_index()
    .sort_values("Attach_Percentage", ascending=False)
)

store_performance.head(10)
```

Out[19]:

	Branch	Store_Name	Attach_Percentage
9	Delhi_Ncr	Delhi(Hauz Khas)	0.622
92	Pune	Pune(Hadapsar)	0.586
94	Pune	Pune(Kondhawa)	0.414
3	Delhi_Ncr	Delhi(Budh Vihar)	0.390
5	Delhi_Ncr	Delhi(Daryaganj)	0.386
90	Pune	Pune(Dange Chowk)	0.368
145	Thane	Bhiwandi Br	0.362
18	Delhi_Ncr	Delhi(Narela)	0.358
35	Delhi_Ncr	Haryana(Mewla M.) Br	0.352
41	Delhi_Ncr	Up(Greater Noida) Br	0.350

Store-level Attach Percentage Performance

The table ranks stores based on their average insurance attach percentage across all observed months.

Key Observations

- The top-performing store is **Delhi (Hauz Khas)**, which records the highest average attach percentage.
- A majority of the top 10 stores belong to **Pune** and **Delhi_NCR**, indicating strong and consistent performance within these branches.
- High-performing branches tend to have multiple stores with strong attach rates rather than reliance on a single standout store.

Business Implications

- Best practices from top-performing stores in Pune and Delhi_NCR can be identified and replicated across other regions.
- Consistency across multiple stores suggests robust branch-level processes and effective sales strategies.

In [20]:
```
store_performance["Performance_Category"] = pd.qcut(
    store_performance["Attach_Percentage"],
    q=3,
    labels=["Low Performer", "Medium Performer", "High Performer"]
)
```

In [21]:
```
store_performance["Performance_Category"].value_counts()
```

Out[21]:
```
Performance_Category
Medium Performer    55
Low Performer       54
High Performer      54
Name: count, dtype: int64
```

Store Performance Categorisation

Stores were categorised into three performance groups based on their average attach percentage using percentile-based thresholds.

Category Distribution

- **High Performers**: 54 stores
- **Medium Performers**: 55 stores
- **Low Performers**: 54 stores

Key Insights

- The balanced distribution indicates a wide variation in store-level attach performance.
- High-performing stores significantly outperform the overall average and represent best-in-class execution.
- Low-performing stores present clear opportunities for improvement through targeted interventions.

This categorisation enables focused strategy formulation, allowing business teams to prioritize actions by store performance tier.

In [22]:
```
branch_category_dist = (
    store_performance
    .groupby(["Branch", "Performance_Category"], observed=True)
    .size()
    .reset_index(name="Store_Count")
)

branch_category_dist
```

Out[22]:

	Branch	Performance_Category	Store_Count
0	Delhi_Ncr	Low Performer	6
1	Delhi_Ncr	Medium Performer	10
2	Delhi_Ncr	High Performer	28
3	Gujarat	Low Performer	11
4	Gujarat	Medium Performer	11
5	Gujarat	High Performer	2
6	Mumbai	Low Performer	5
7	Mumbai	Medium Performer	6
8	Mumbai	High Performer	8
9	Pune	Low Performer	1
10	Pune	Medium Performer	4
11	Pune	High Performer	11
12	Telangana	Low Performer	23
13	Telangana	Medium Performer	15
14	Telangana	High Performer	2
15	Thane	Low Performer	8
16	Thane	Medium Performer	9
17	Thane	High Performer	3

Branch-wise Distribution of Store Performance Categories

The table shows the distribution of store performance categories across branches.

Key Observations

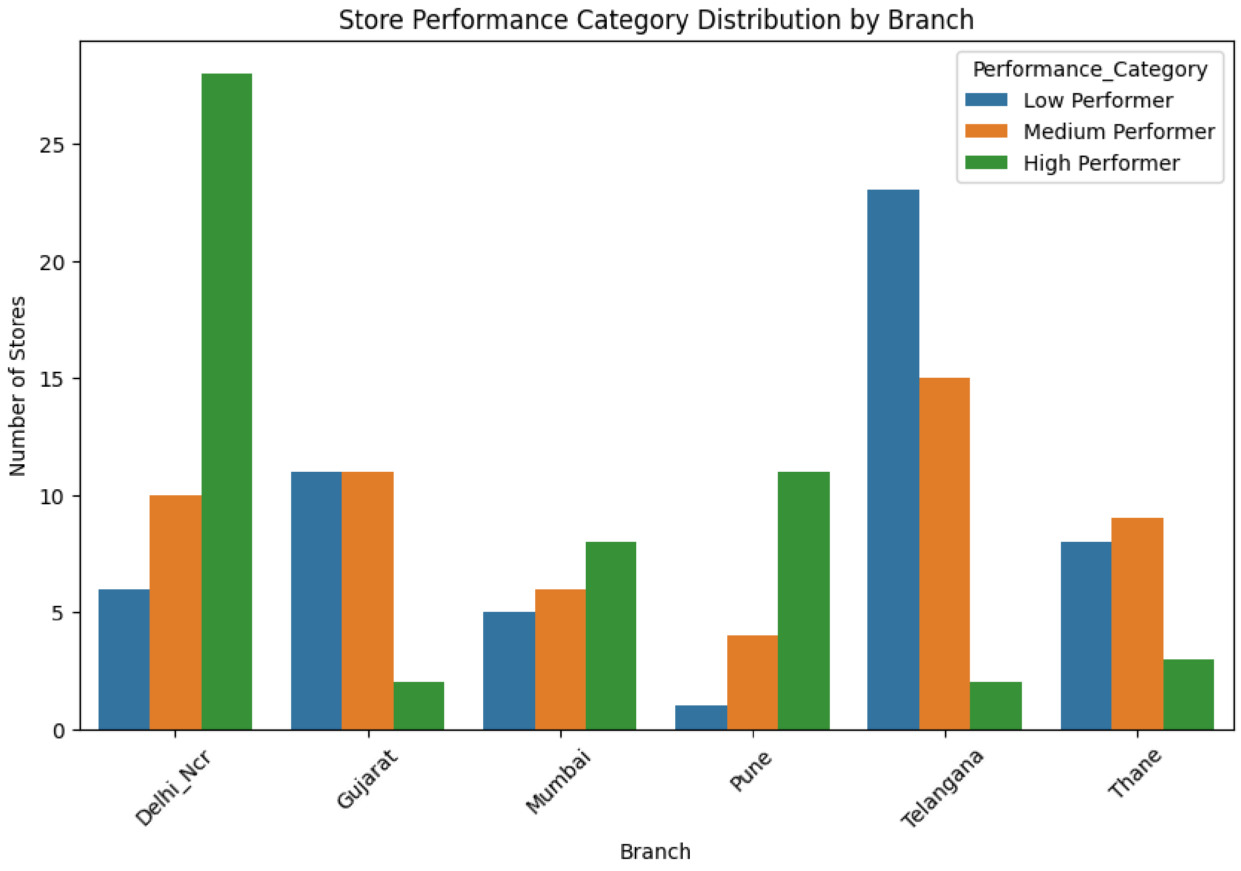
- **Delhi_NCR** stands out with a large concentration of **high-performing stores**, indicating strong and consistent execution across the branch.
- **Pune** also shows a healthy performance profile, with most stores falling in the high or medium performer categories.
- **Telangana** has a high number of **low-performing stores** and very few high performers, highlighting a significant opportunity for improvement.
- **Gujarat** and **Thane** show a skew towards low and medium performers,

with limited representation in the high-performance category.

Business Implications

- Best practices from high-performing branches such as Delhi_NCR and Pune can be identified and replicated in underperforming regions.
- Low-performing branches may benefit from focused interventions including training, sales enablement, and targeted incentive programs.

In [23]:
```
plt.figure(figsize=(10, 6))
sns.barplot(
    data=branch_category_dist,
    x="Branch",
    y="Store_Count",
    hue="Performance_Category"
)

plt.title("Store Performance Category Distribution by Branch")
plt.xlabel("Branch")
plt.ylabel("Number of Stores")
plt.xticks(rotation=45)
plt.show()
```



In [24]:
```
month_mapping = {
    "Aug": 1,
    "Sep": 2,
    "Oct": 3,
    "Nov": 4,
    "Dec": 5
}

df_long["Month_Index"] = df_long["Month"].map(month_mapping)
df_long.head()
```

Out[24]:

	Branch	Store_Name	Month	Attach_Percentage	Month_Index
0	Delhi_Ncr	Delhi(Janakpuri) Br	Aug	0.24	1
1	Delhi_Ncr	Haryana(Gurgaon) Br	Aug	0.04	1
2	Delhi_Ncr	Up(Greater Noida) Br	Aug	0.43	1
3	Pune	Pune(Bhosari) Br	Aug	0.32	1
4	Gujarat	Ahmedabad(Maninagar) Br	Aug	0.17	1

In [25]:
```
!pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in c:\users\armaan\appdata\local\pr
ograms\python\python313\lib\site-packages (1.8.0)
Requirement already satisfied: numpy>=1.24.1 in c:\users\armaan\appdata\local\p
rograms\python\python313\lib\site-packages (from scikit-learn) (2.3.5)
Requirement already satisfied: scipy>=1.10.0 in c:\users\armaan\appdata\local\p
rograms\python\python313\lib\site-packages (from scikit-learn) (1.16.3)
Requirement already satisfied: joblib>=1.3.0 in c:\users\armaan\appdata\local\p
rograms\python\python313\lib\site-packages (from scikit-learn) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.2.0 in c:\users\armaan\appdata\
local\programs\python\python313\lib\site-packages (from scikit-learn) (3.6.0)
```

In [26]:
```
from sklearn.linear_model import LinearRegression

def predict_january(store_df):
    X = store_df[["Month_Index"]]
    y = store_df["Attach_Percentage"]

    model = LinearRegression()
    model.fit(X, y)

    jan_index = pd.DataFrame({"Month_Index": [6]})  # January
    jan_pred = model.predict(jan_index)[0]

    return max(0, min(1, jan_pred))
```

In [27]:
```
jan_index = pd.DataFrame({"Month_Index": [6]})
```

In [28]:
```
def predict_january(store_df):
    X = store_df[["Month_Index"]]
    y = store_df["Attach_Percentage"]

    model = LinearRegression()
    model.fit(X, y)

    # Use DataFrame to preserve feature name
    jan_index = pd.DataFrame({"Month_Index": [6]})
    jan_pred = model.predict(jan_index)[0]

    return max(0, min(1, jan_pred))
```

In [29]:
```
january_predictions = (
    df_long
    .groupby(["Branch", "Store_Name"])
    .apply(predict_january, include_groups=False)
    .reset_index(name="Predicted_Jan_Attach_Percentage")
)
```

In [30]:
```
january_predictions.head()
```

Out[30]:

	Branch	Store_Name	Predicted_Jan_Attach_Percentage
0	Delhi_Ncr	DELHI(ASHOK VIHAR)	0.211
1	Delhi_Ncr	DELHI(KRISHNA NAGAR)	0.200
2	Delhi_Ncr	DELHI(ROHINI Sector-16)	0.154
3	Delhi_Ncr	Delhi(Budh Vihar)	0.552
4	Delhi_Ncr	Delhi(Burari)	0.418

In [31]:
```
january_predictions = january_predictions.merge(
    store_performance[["Branch", "Store_Name", "Performance_Category"]],
    on=["Branch", "Store_Name"],
    how="left"
)

january_predictions.head()
```

Out[31]:

	Branch	Store_Name	Predicted_Jan_Attach_Percentage	Performance_Categ
0	Delhi_Ncr	DELHI(ASHOK VIHAR)	0.211	Low Perfo
1	Delhi_Ncr	DELHI(KRISHNA NAGAR)	0.200	Medium Perfo
2	Delhi_Ncr	DELHI(ROHINI Sector-16)	0.154	Low Perfo
3	Delhi_Ncr	Delhi(Budh Vihar)	0.552	High Perfo
4	Delhi_Ncr	Delhi(Burari)	0.418	High Perfo

Summary & Key Takeaways

- Attach percentage performance varies significantly across branches and individual stores.
- Delhi_NCR and Pune consistently outperform other regions, driven by a higher concentration of high-performing stores.
- Store-level categorisation highlights clear opportunities for targeted improvement in low-performing branches such as Telangana and Gujarat.
- A trend-based forecasting approach was used to predict January attach percentages at the store level.
- The predictions align with historical performance patterns and provide actionable insights for proactive planning.

Recommendations

- Replicate best practices from high-performing stores in Delhi_NCR and Pune.
- Focus training and incentive programs on low-performing stores and branches.
- Use predicted January attach percentages to prioritize stores requiring immediate attention.