In [1]:
```python
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns
```

In [2]:
```python
data = pd.read_csv('./dataset/Telco-Customer-Churn.csv')
data.head()
```

Out[2]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneSe
0	7590-VHVEG	Female	0	Yes	No	1	
1	5575-GNVDE	Male	0	No	No	34	
2	3668-QPYBK	Male	0	No	No	2	
3	7795-CFOCW	Male	0	No	No	45	
4	9237-HQITU	Female	0	No	No	2	

5 rows × 21 columns

In [3]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
```

In [4]:
```
data['TotalCharges'] = data['TotalCharges'].replace(' ',0)
data['TotalCharges'] = data['TotalCharges'].astype(float)
```

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   float64
 20  Churn             7043 non-null   object 
dtypes: float64(2), int64(2), object(17)
memory usage: 1.1+ MB
```

In [6]:
```
data.describe()
```

Out[6]:

	SeniorCitizen	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692	2279.734304
std	0.368612	24.559481	30.090047	2266.794470
min	0.000000	0.000000	18.250000	0.000000
25%	0.000000	9.000000	35.500000	398.550000
50%	0.000000	29.000000	70.350000	1394.550000
75%	0.000000	55.000000	89.850000	3786.600000
max	1.000000	72.000000	118.750000	8684.800000

In [7]:
```
data.isnull().sum()
```

Out[7]:
```
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [8]:
```
data.duplicated().sum()
```

Out[8]:
```
np.int64(0)
```

In [9]:
```
data['customerID'].duplicated().sum()
```

Out[9]:
```
np.int64(0)
```

In [10]:
```
def convert(value):
    if value == 1:
        return 'Yes'
    else:
        return 'No'
data['SeniorCitizen'] = data['SeniorCitizen'].apply(convert)
```

In [11]:
```
data[data['SeniorCitizen'] == 'Yes'].head(2)
```

Out[11]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneS
20	8779-QRDMV	Male	Yes	No	No	1	
30	3841-NFECX	Female	Yes	Yes	No	71	

2 rows × 21 columns

In [12]:
```
data['tenureInYear'] = np.round(data['tenure']/12)
data.head()
```

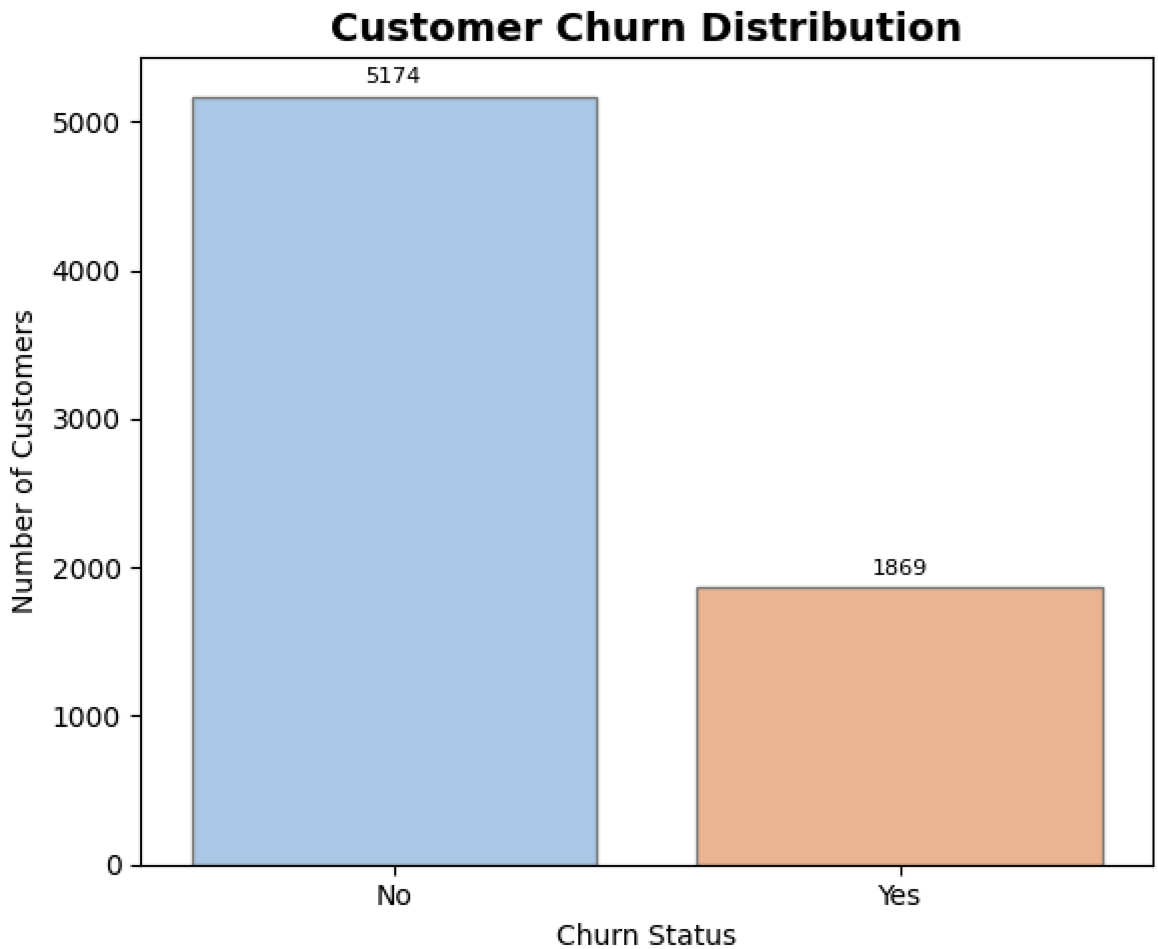
Out[12]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneSe
0	7590-VHVEG	Female	No	Yes	No	1	
1	5575-GNVDE	Male	No	No	No	34	
2	3668-QPYBK	Male	No	No	No	2	
3	7795-CFOCW	Male	No	No	No	45	
4	9237-HQITU	Female	No	No	No	2	

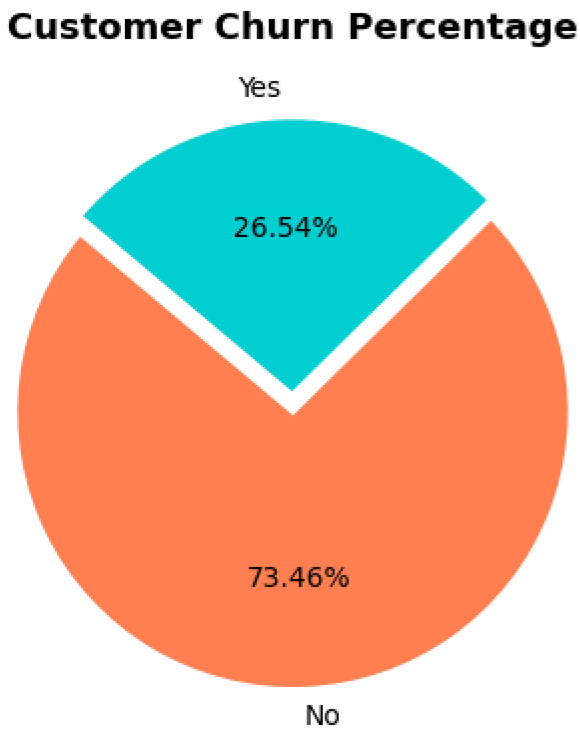
5 rows × 22 columns

In [13]:

```
# Create the plot with a pastel color palette
plt.figure(figsize=(6, 5))
ax = sns.countplot(x='Churn', data=data, hue = 'Churn',palette='pastel', edg
# Add value labels
ax.bar_label(ax.containers[0], fontsize=8, color='black', padding=3)
ax.bar_label(ax.containers[1], fontsize=8, color='black', padding=3)
# Improve title and axis labels
plt.title('Customer Churn Distribution', fontsize=14, fontweight='bold')
plt.xlabel('Churn Status', fontsize=10)
plt.ylabel('Number of Customers', fontsize=10)
# Tidy layout
plt.tight_layout()
plt.show()
```



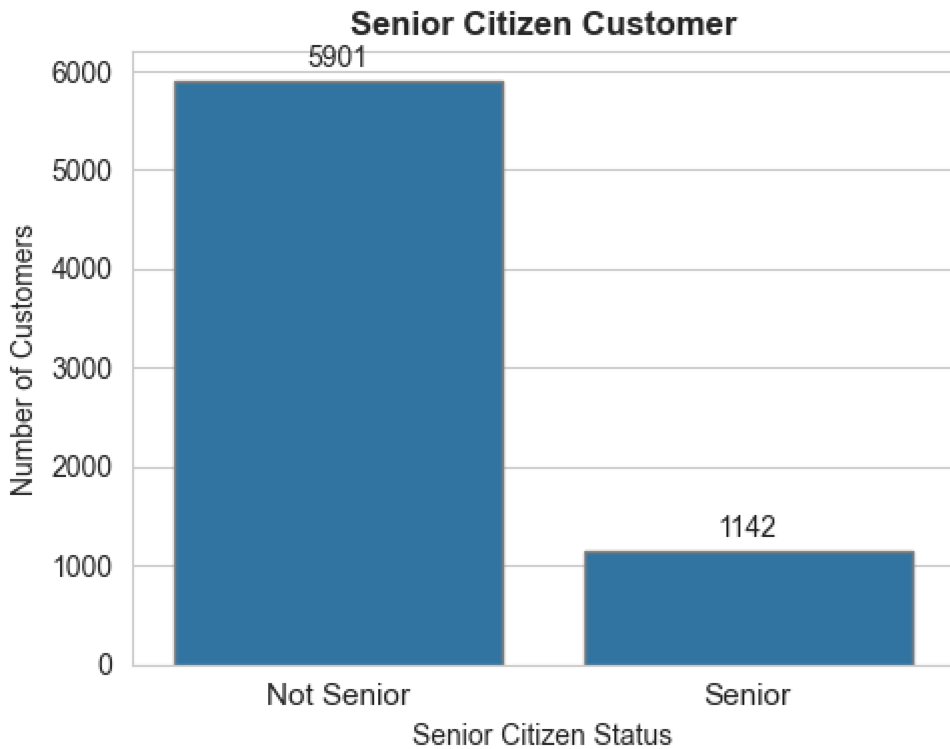
In [14]:
```
# Prepare data
gb = data.groupby('Churn')[['Churn']].count()
# Set up figure aesthetics
plt.figure(figsize=(4, 4))
colors = ['#FF7F50', '#00CED1']
explode = [0.03, 0.03]  # Slight pop-out for emphasis
# Plot pie chart
plt.pie(
    gb['Churn'],
    labels=gb.index,
    autopct='%1.2f%%',
    startangle=140,
    colors=colors,
    explode=explode,
    wedgeprops={'edgecolor': 'white', 'linewidth': 2}
)
# Add clean title
plt.title('Customer Churn Percentage', fontsize=13, fontweight='bold')
# Tidy layout
plt.tight_layout()
plt.show()
```



Insights from the Customer Churn Percentage Chart

- The pie chart visualizes the proportion of customers who have churned (`Yes`) versus those who have remained (`No`).
- **26.54%** of customers have churned, indicating that over a quarter of the customer base is not retained.
- **73.46%** of customers have stayed, suggesting that the majority are retained.
- Although the retention rate is relatively high, the **churn rate of 26.54% is still significant** and warrants investigation into possible reasons (e.g., customer service issues, product dissatisfaction, better competitor offerings).
- Reducing churn can lead to **higher customer lifetime value and increased revenue**, so strategies for improving customer retention should be prioritized.

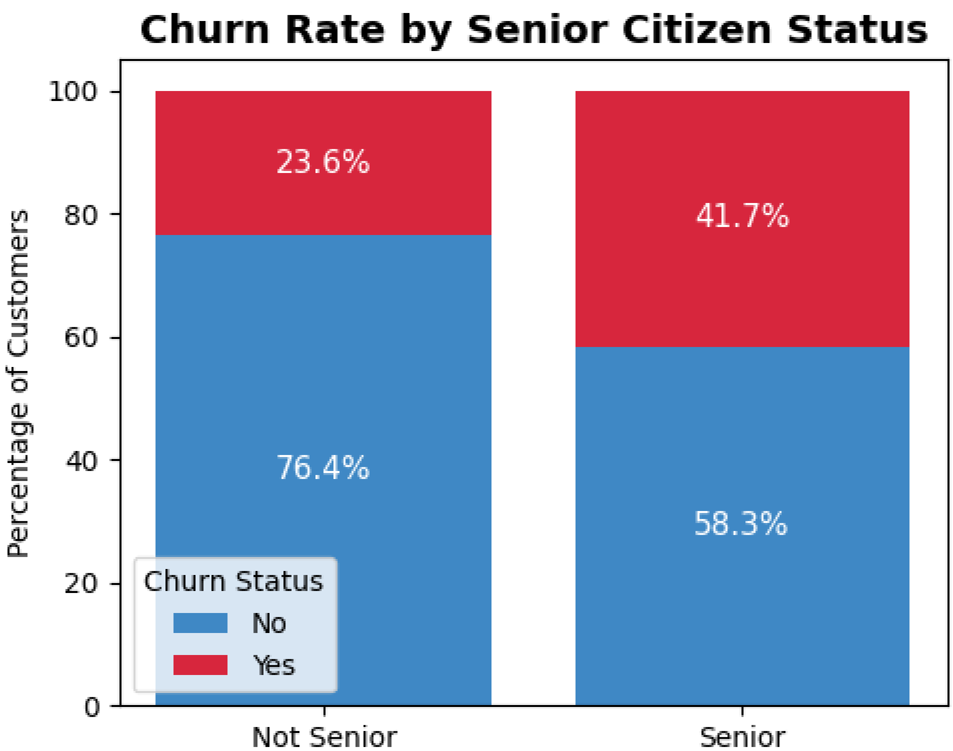
In [25]:
```
# Create the plot
plt.figure(figsize=(5, 4))
palette = {'Yes': '#DA264D', 'No': '#3F88C5'}  # Churn coloring
ax = sns.countplot(x='SeniorCitizen', data=data, edgecolor='gray')
ax.bar_label(ax.containers[0], fmt='%d', label_type='edge', padding=3)
# Title and axes polish
plt.title('Senior Citizen Customer', fontsize=12, fontweight='bold')
plt.xlabel('Senior Citizen Status', fontsize=10)
plt.ylabel('Number of Customers', fontsize=10)
plt.xticks([0, 1], ['Not Senior', 'Senior'], fontsize=11)
plt.tight_layout()
plt.show()
```



In [16]:

```
# Step 1: Prepare percentage data
grouped = data.groupby(['SeniorCitizen', 'Churn']).size().unstack(fill_value
percentage = grouped.div(grouped.sum(axis=1), axis=0) * 100
# Step 2: Plot stacked bar chart
plt.figure(figsize=(5, 4))
# Define colors
colors = ['#3F88C5', '#D7263D']  # Example: churn colors
# Plot each layer of the stack
bottom = None
for i, churn_status in enumerate(percentage.columns):
    plt.bar(
        percentage.index,
        percentage[churn_status],
        bottom=bottom,
        label=churn_status,
        color=colors[i]
    )
    bottom = (percentage[churn_status] if bottom is None else bottom + perce
# Step 3: Add percentage labels
for i in percentage.index:
    cumulative = 0
    for churn_status in percentage.columns:
        perc = percentage.loc[i, churn_status]
        if perc > 5:  # only label if slice is large enough
            plt.text(
                i,
                cumulative + perc / 2,
                f'{perc:.1f}%',
                ha='center',
                va='center',
                color='white',
                fontsize=11
```

```
        )
    cumulative += perc
# Final touches
plt.xticks([0, 1], ['Not Senior', 'Senior'])
plt.title('Churn Rate by Senior Citizen Status', fontsize=14, fontweight='bo
plt.ylabel('Percentage of Customers')
plt.legend(title='Churn Status')
plt.tight_layout()
plt.show()
```

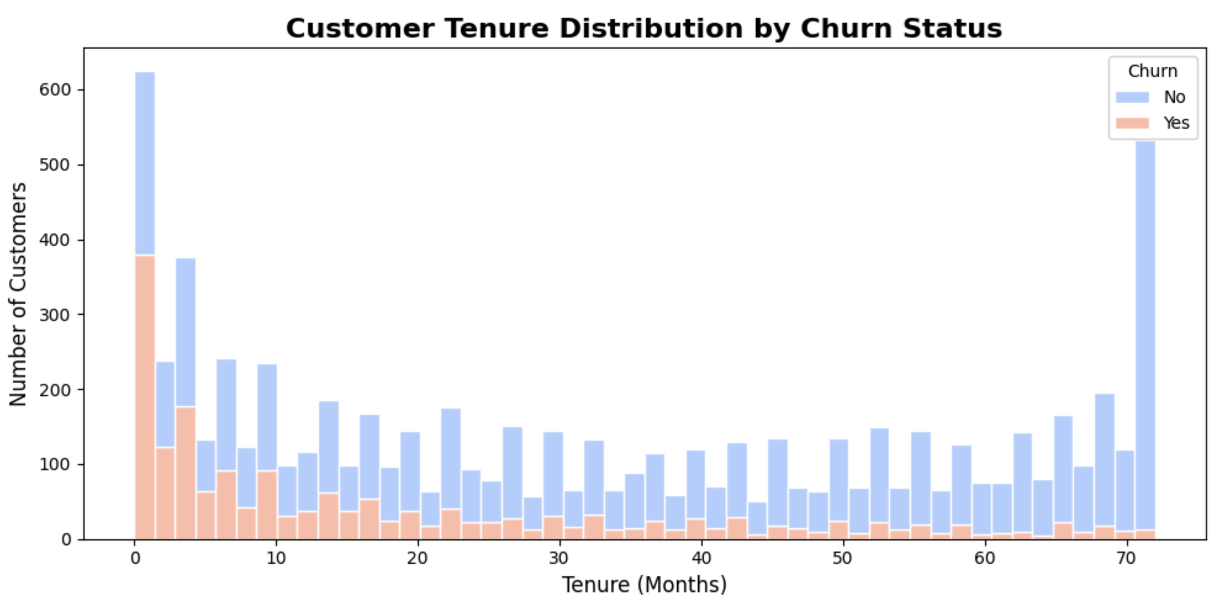


Insights from the Churn Rate by Senior Citizen Status Chart

- The chart compares customer churn rates between **Senior Citizens** and **Non-Senior Citizens**.
- Among **Non-Senior customers**, only **23.6%** have churned, while **76.4%** have stayed.
- Among **Senior customers**, a higher **41.7%** have churned, with **58.3%** retained.
- This indicates that **Senior Citizens are significantly more likely to churn** than Non-Senior customers.
- The increased churn among seniors suggests a need to explore targeted strategies to address their specific needs and concerns, such as:
  - Simplified services or billing processes
  - Better support and communication
  - Customized offerings for senior demographics

- Reducing churn in the senior group could improve overall retention and business sustainability.

In [17]:
```
# Create figure
plt.figure(figsize=(10, 5))

# Draw histogram with stack and auto-handled legend
ax = sns.histplot(
    data=data,
    x='tenure',
    bins=50,
    hue='Churn',
    multiple='stack',
    palette='coolwarm',
    edgecolor='white',
    alpha=0.85
)

# Add title and axis labels
plt.title('Customer Tenure Distribution by Churn Status', fontsize=16, fontw
plt.xlabel('Tenure (Months)', fontsize=12)
plt.ylabel('Number of Customers', fontsize=12)

# Tidy up layout
plt.tight_layout()
plt.show()
```



Insights from the Customer Tenure Distribution by Churn Status Chart

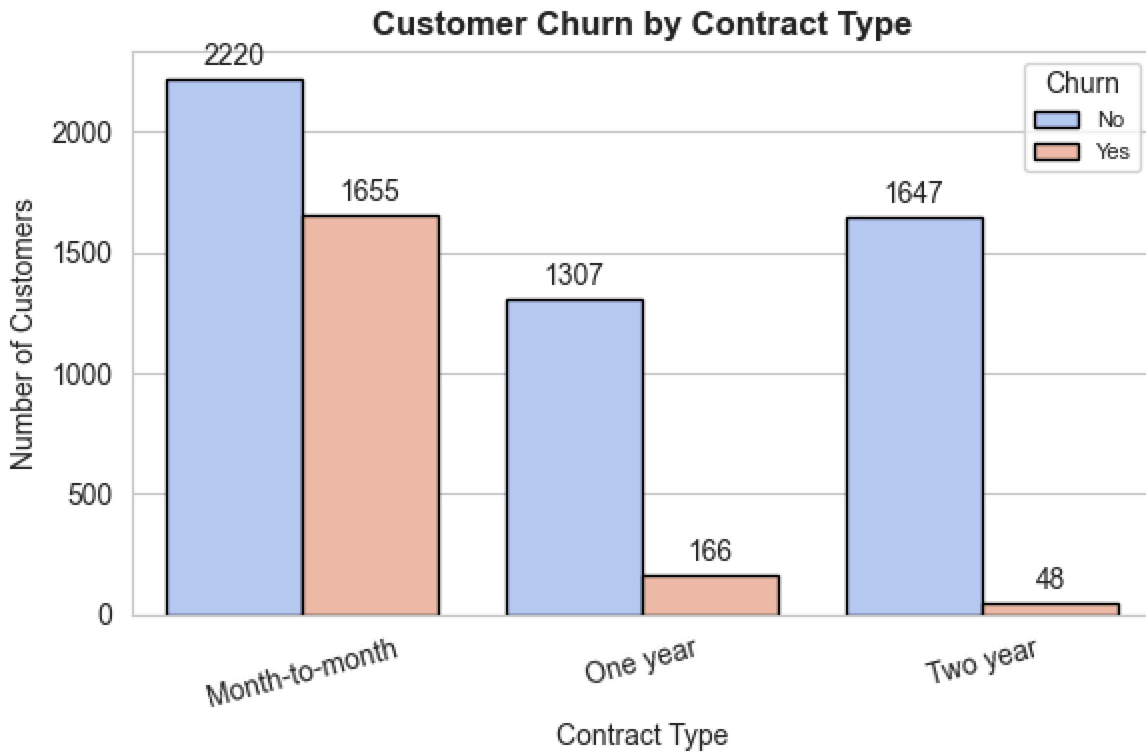
- The chart illustrates how customer churn varies based on their **tenure (in months)**.
- A large number of churned customers are observed within the **first few months (0–10 months)** of tenure.

- This suggests that many customers churn **early in their subscription period**, possibly due to dissatisfaction or unmet expectations.

- As tenure increases, the number of churned customers **decreases gradually**, indicating that **longer-tenured customers are more likely to stay**.
- Very few customers with **tenure greater than 60 months** have churned, highlighting a trend of strong loyalty among long-term users.
- The spikes at **tenure = 0 and 72 months** could be due to new customers joining recently and long-standing customers still being active.
- These patterns suggest that:
  - Improving the **onboarding experience** and **early customer support** could significantly reduce churn.
  - **Loyalty programs** or **long-term benefits** might be effective in retaining customers for extended periods.

In [18]:

```python
# Set a clean style
sns.set_style("whitegrid")
plt.figure(figsize=(6, 4))

# Create the count plot
ax = sns.countplot(
    x='Contract',
    data=data,
    hue='Churn',
    palette='coolwarm',  # Choose a pleasant color palette
    edgecolor='black'
)
# Add bar labels to both hues
for container in ax.containers:
    ax.bar_label(container, fmt='%d', label_type='edge', padding=3)
# Add title and axis labels with styling
plt.title('Customer Churn by Contract Type', fontsize=12, fontweight='bold')
plt.xlabel('Contract Type', fontsize=10)
plt.ylabel('Number of Customers', fontsize=10)
# Improve legend
plt.legend(title='Churn', title_fontsize='10', fontsize='8')
# Rotate x-axis labels if needed
plt.xticks(rotation=15)
# Tight layout for better spacing
plt.tight_layout()
plt.show()
```



Insights from the Chart: Customer Churn by Contract Type

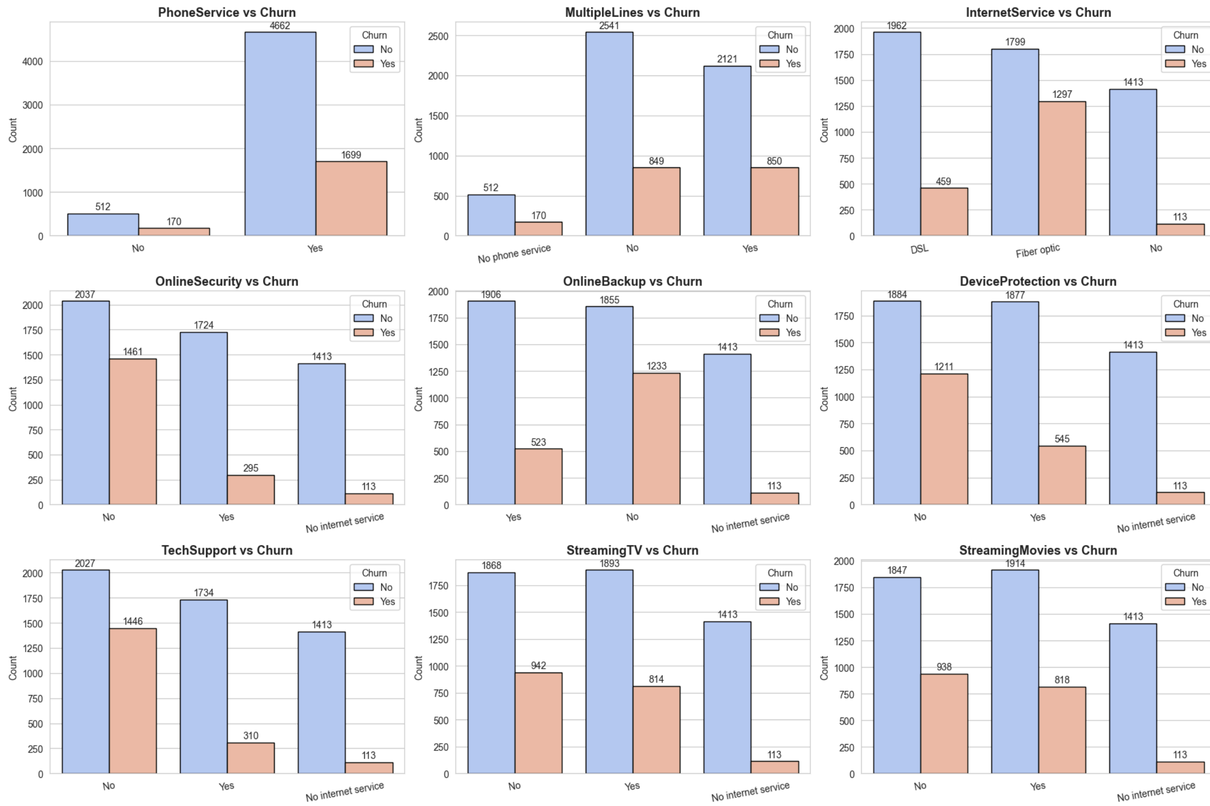
1. *Month-to-Month Contracts Have the Highest Churn:*
   - This represents the highest churn rate among all contract types, indicating that customers with flexible, short-term contracts are more likely to leave.
2. *Longer Contracts Have Significantly Lower Churn:*
   - Only *166* out of *1,473* one-year contract customers have churned.
   - Just *48* out of *1,695* two-year contract customers have churned.
   - This shows that customers on longer-term contracts are more likely to stay, possibly due to commitment, incentives, or penalties for early termination.
3. *Business Implication:*
   - To reduce churn, businesses may consider promoting *longer-term contracts* through *discounts, loyalty programs,* or other incentives.

In [19]:
```
data.columns
```

Out[19]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn',
       'tenureInYear'],
      dtype='object')
```

In [20]:

```python
columns_to_plot = [
    'PhoneService', 'MultipleLines', 'InternetService',
    'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
    'TechSupport', 'StreamingTV', 'StreamingMovies'
]

# Step 2: Set a clean background style
sns.set_style("whitegrid")

# Step 3: Create 3x3 subplot grid (9 plots)
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(18, 12))
axes = axes.flatten()  # Convert 2D axes to 1D list for easy access

# Step 4: Loop through each column and create a countplot
for i, col in enumerate(columns_to_plot):
    ax = axes[i]
    sns.countplot(
        data=data,
        x=col,
        hue='Churn',
        palette='coolwarm',  # Use a visually distinct color palette
        edgecolor='black',
        ax=ax
    )

    ax.set_title(f'{col} vs Churn', fontsize=13, fontweight='bold')
    ax.set_xlabel('')  # Hide x-axis label (optional)
    ax.set_ylabel('Count')

    # Rotate x-axis labels for better readability
    ax.tick_params(axis='x', rotation=10)

    # Add count labels on top of bars
    for container in ax.containers:
        ax.bar_label(container, fmt='%d', label_type='edge', padding=2)

# Step 5: Remove any unused subplots (in case of extra grid space)
for j in range(len(columns_to_plot), len(axes)):
    fig.delaxes(axes[j])

# Step 6: Adjust layout for better spacing
plt.tight_layout()
plt.show()
```



Insights from the Chart: Services vs Customer Churn

- **Phone Service:** Most customers use phone service; churn is present but proportionally lower.
- **Multiple Lines:** Has minimal impact on churn; behavior is similar with or without it.
- **Internet Service:**
  - *Fiber optic* users show higher churn than *DSL* users.
  - *No internet service* group has the lowest churn.
- **Online Security & Backup:**
  - Customers without these services show higher churn.
  - Indicates these features support retention.
- **Device Protection & Tech Support:**
  - Churn is significantly higher among customers lacking these services.
  - Tech support especially plays a strong role in retention.
- **Streaming TV & Movies:**
  - Users of streaming services show slightly lower churn.
  - Suggests entertainment options contribute to loyalty.

Overall Conclusion:

Customers using **value-added services** (e.g., tech support, security, streaming) are **less likely to churn**, highlighting the importance of **enhancing**

service offerings to improve **customer retention**.

In [21]:
```
for col in columns_to_plot:
    print(f'\n📊 Churn analysis for: {col}')

    # Group by column and churn, get count
    churn_counts = data.groupby(col)['Churn'].value_counts().unstack().fillr

    # Calculate percentages
    churn_percentages = data.groupby(col)['Churn'].value_counts(normalize=Tr

    # Combine count and percentage into one DataFrame
    combined = pd.DataFrame()
    combined['No (Count)'] = churn_counts.get('No', 0).astype(int)
    combined['Yes (Count)'] = churn_counts.get('Yes', 0).astype(int)
    combined['No (%)'] = churn_percentages.get('No', 0).round(2)
    combined['Yes (%)'] = churn_percentages.get('Yes', 0).round(2)

    print(combined)
```

📊 Churn analysis for: PhoneService

PhoneService	No (Count)	Yes (Count)	No (%)	Yes (%)
No	512	170	75.07	24.93
Yes	4662	1699	73.29	26.71

📊 Churn analysis for: MultipleLines

MultipleLines	No (Count)	Yes (Count)	No (%)	Yes (%)
No	2541	849	74.96	25.04
No phone service	512	170	75.07	24.93
Yes	2121	850	71.39	28.61

📊 Churn analysis for: InternetService

InternetService	No (Count)	Yes (Count)	No (%)	Yes (%)
DSL	1962	459	81.04	18.96
Fiber optic	1799	1297	58.11	41.89
No	1413	113	92.60	7.40

📊 Churn analysis for: OnlineSecurity

OnlineSecurity	No (Count)	Yes (Count)	No (%)	Yes (%)
No	2037	1461	58.23	41.77
No internet service	1413	113	92.60	7.40
Yes	1724	295	85.39	14.61

📊 Churn analysis for: OnlineBackup

OnlineBackup	No (Count)	Yes (Count)	No (%)	Yes (%)
No	1855	1233	60.07	39.93
No internet service	1413	113	92.60	7.40
Yes	1906	523	78.47	21.53

📊 Churn analysis for: DeviceProtection

DeviceProtection	No (Count)	Yes (Count)	No (%)	Yes (%)
No	1884	1211	60.87	39.13
No internet service	1413	113	92.60	7.40
Yes	1877	545	77.50	22.50

📊 Churn analysis for: TechSupport

TechSupport	No (Count)	Yes (Count)	No (%)	Yes (%)
No	2027	1446	58.36	41.64
No internet service	1413	113	92.60	7.40
Yes	1734	310	84.83	15.17

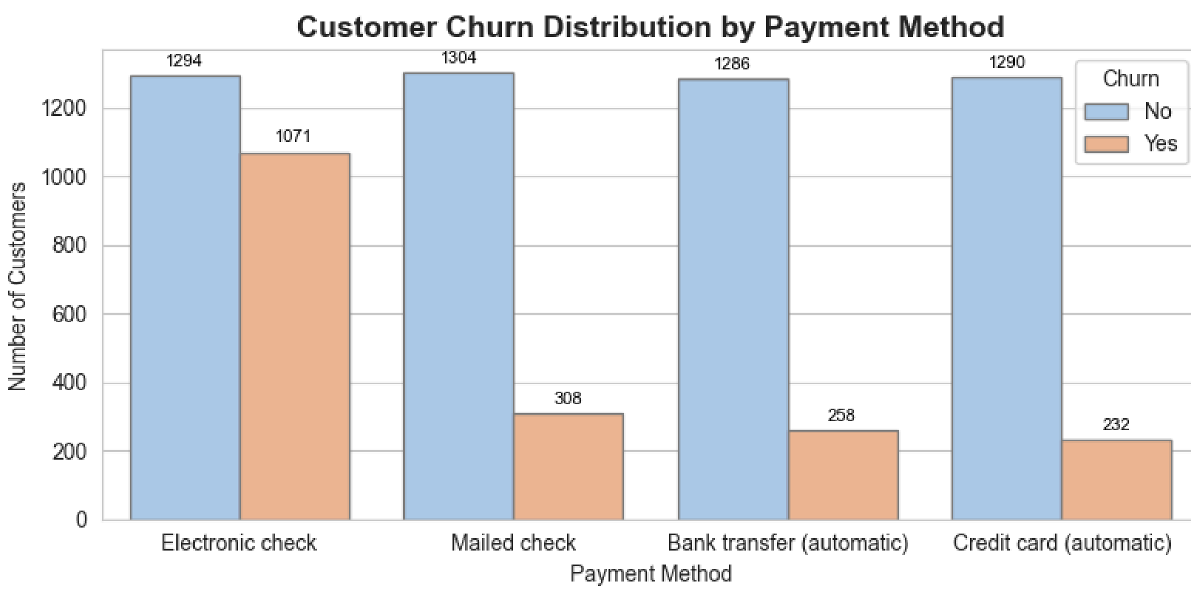
📊 Churn analysis for: StreamingTV

StreamingTV	No (Count)	Yes (Count)	No (%)	Yes (%)
No	1868	942	66.48	33.52
No internet service	1413	113	92.60	7.40
Yes	1893	814	69.93	30.07

📊 Churn analysis for: StreamingMovies

```
                     No (Count)  Yes (Count)  No (%)  Yes (%)
StreamingMovies
No                         1847          938   66.32    33.68
No internet service        1413          113   92.60     7.40
Yes                        1914          818   70.06    29.94
```

In [26]:
```python
# Create the plot with a pastel color palette
plt.figure(figsize=(8, 4))
ax = sns.countplot(x='PaymentMethod', data=data, hue = 'Churn',palette='past
# Add value labels
ax.bar_label(ax.containers[0], fontsize=8, color='black', padding=3)
ax.bar_label(ax.containers[1], fontsize=8, color='black', padding=3)
# Improve title and axis labels
plt.title('Customer Churn Distribution by Payment Method', fontsize=14, font
plt.xlabel('Payment Method', fontsize=10)
plt.ylabel('Number of Customers', fontsize=10)
# Tidy layout
plt.tight_layout()
plt.show()
```



Insights from the Chart: Customer Churn Distribution by Payment Method

1. *Highest Churn with Electronic Check:*
   - 1071 out of 2365 customers using electronic checks have churned — the highest among all methods.
2. *Lowest Churn with Automatic Payments:*
   - Bank transfer (258 churn) and credit card (232 churn) show much lower churn rates.
   - Indicates that automatic payments help retain customers.
3. *Mailed Checks Show Moderate Churn:*

- 308 churned out of 1612 mailed check users — better than electronic check but worse than automatic methods.

Conclusion:

- *Automatic payment methods* lead to better retention.
- *Electronic check users* are more likely to churn.
- Promoting *auto-pay options* can help reduce churn.

In [ ]:

```

```