Customer Churn Analysis Using Python:Uncovering Drivers Of Churn

In [28]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
```

In [29]:
```
df=pd.read_csv('/Users/deeps/Documents/projects/CUSTOMER CHURN/Customer C
```

In [30]:
```
df.shape
```

Out[30]:
```
(7043, 21)
```

In [31]:
```
df.head()
```

Out[31]:

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

5 rows × 21 columns

In [32]:
```
df.dtypes
```

Out[32]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

In [33]:
```
df.isnull().sum
```

Out[33]:
```
<bound method DataFrame.sum of       customerID  gender  SeniorCitizen
Partner  Dependents  tenure  \
0          False   False          False    False       False   False
1          False   False          False    False       False   False
2          False   False          False    False       False   False
3          False   False          False    False       False   False
4          False   False          False    False       False   False
...          ...     ...            ...      ...         ...     ...
7038       False   False          False    False       False   False
7039       False   False          False    False       False   False
7040       False   False          False    False       False   False
7041       False   False          False    False       False   False
7042       False   False          False    False       False   False

      PhoneService  MultipleLines  InternetService  OnlineSecurity  ...
\
0            False          False            False           False  ...
1            False          False            False           False  ...
2            False          False            False           False  ...
3            False          False            False           False  ...
4            False          False            False           False  ...
...            ...            ...              ...             ...  ...
7038         False          False            False           False  ...
7039         False          False            False           False  ...
7040         False          False            False           False  ...
7041         False          False            False           False  ...
7042         False          False            False           False  ...

      DeviceProtection  TechSupport  StreamingTV  StreamingMovies  Contr
act  \
0                False        False        False            False     Fa
lse
```

```
1                   False       False       False             False     Fa
lse
2                   False       False       False             False     Fa
lse
3                   False       False       False             False     Fa
lse
4                   False       False       False             False     Fa
lse
...                   ...         ...         ...               ...
...
7038                False       False       False             False     Fa
lse
7039                False       False       False             False     Fa
lse
7040                False       False       False             False     Fa
lse
7041                False       False       False             False     Fa
lse
7042                False       False       False             False     Fa
lse

      PaperlessBilling  PaymentMethod  MonthlyCharges  TotalCharges  Chu
rn
0                False          False           False         False  Fal
se
1                False          False           False         False  Fal
se
2                False          False           False         False  Fal
se
3                False          False           False         False  Fal
se
4                False          False           False         False  Fal
se
...                ...            ...             ...           ...
...
7038             False          False           False         False  Fal
se
7039             False          False           False         False  Fal
se
7040             False          False           False         False  Fal
se
7041             False          False           False         False  Fal
se
7042             False          False           False         False  Fal
se

[7043 rows x 21 columns]>
```

Total charges coulmn datatype is supposed to be float not object.However there is a blank space in the column which need to be addressed before changing data type

In [34]:
```
df['TotalCharges']=df['TotalCharges'].replace(' ','0')
```

In [12]:
```
df['TotalCharges']=df['TotalCharges'].astype('float64')
```

In [13]:
```
df['TotalCharges'].dtypes
```

Out[13]: dtype('float64')

In [35]:
```
df.isnull().sum()
```

Out[35]:
```
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 [36]:
```
df.duplicated().sum()
```

Out[36]: np.int64(0)

Double check duplicate values on basis of unique column in the data

In [37]:
```
df['customerID'].duplicated().sum()
```

Out[37]: np.int64(0)

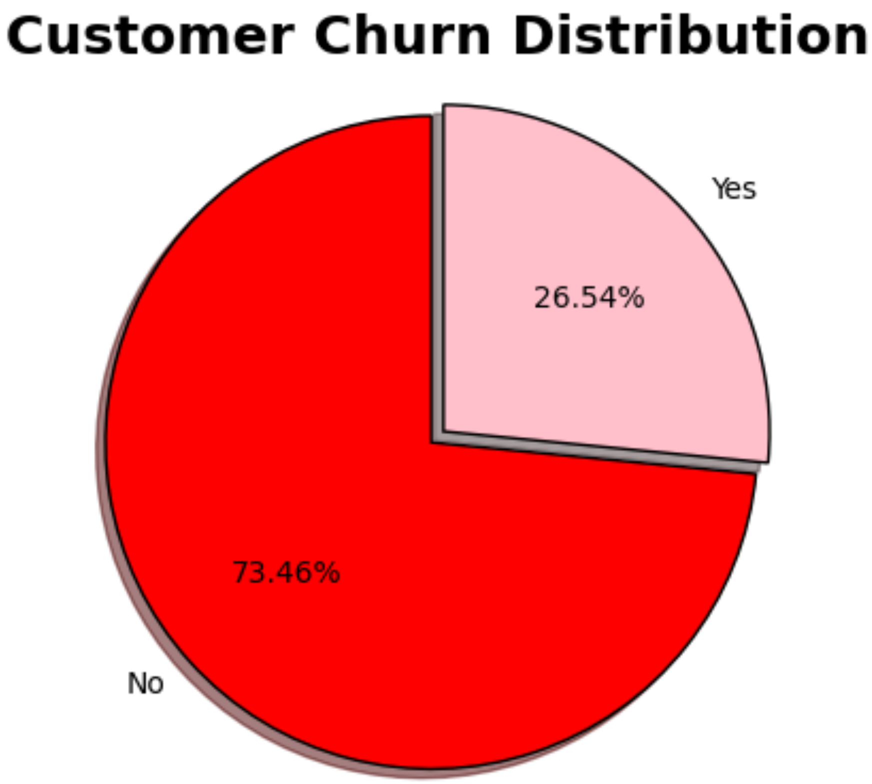
In [38]:
```
def convert(values):
    if values==1:
        return "yes"
    else:
        return "no"

df['SeniorCitizen']=df['SeniorCitizen'].apply(convert)
```

In [39]:
```
df['SeniorCitizen']
```

Out[39]:
```
0        no
1        no
2        no
3        no
4        no
        ...
7038     no
7039     no
7040     no
7041    yes
7042     no
Name: SeniorCitizen, Length: 7043, dtype: object
```

1. Customer Churn Distribution

In [59]:
```
plt.figure(figsize=(6, 4))

churn_counts = df['Churn'].value_counts()
labels = churn_counts.index

plt.pie(churn_counts,
        labels=labels,
        autopct='%1.2f%%',  #2 decimal places
        startangle=90,
        colors=['red', 'pink'],
        explode=[0.05, 0],
        shadow=True,
        wedgeprops={'edgecolor': 'black'}) #slice seperation

plt.title('Customer Churn Distribution', fontsize=18, weight='bold')
plt.axis('equal')  #  ensures pie is circular
plt.tight_layout()
plt.show()
```



Insights:

- 26.54% of customers have churned.
- 73.46% of customers have remained loyal.

Interpretation:

- While a majority of customers are retained, the churn rate is still **significant**.
- Losing over 1 in 4 customers can have a **substantial impact** on revenue and growth.
- This warrants further analysis into why customers are leaving and how to prevent it.

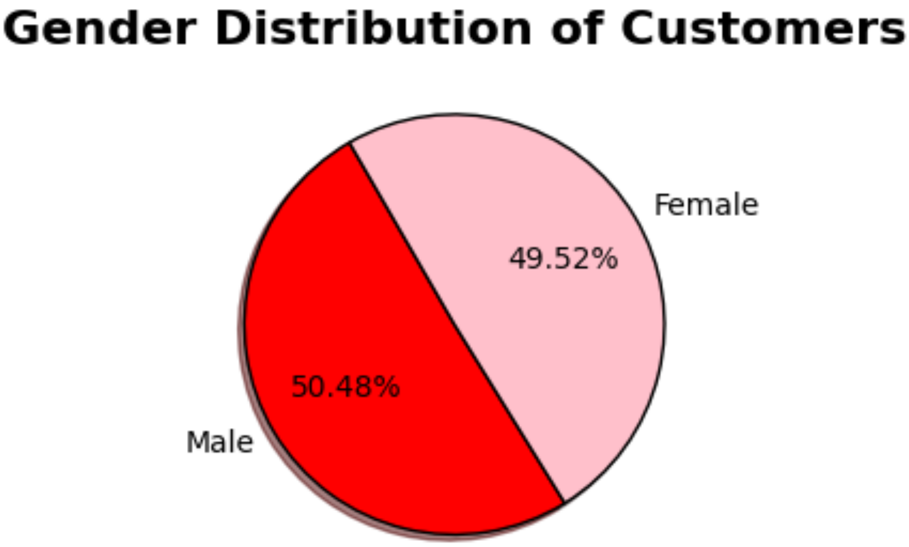
Recommendations:

- Focus on understanding churn drivers (high charges, poor support, short contracts,etc.).
- Investigate if churn is concentrated in specific customer segments (seniors, monthly users, etc.).

2.Churn Rate by Gender

In [49]:
```
plt.figure(figsize=(5, 3))
df['gender'].value_counts().plot.pie(
    autopct='%1.2f%%',
    colors=['red', 'pink'],
```

```
    startangle=120,
    wedgeprops={'edgecolor': 'black'},
    shadow=True,
    labels=['Male', 'Female']
)

plt.title('Gender Distribution of Customers', fontsize=16, weight='bold')
plt.ylabel('')  # Remove gender label
plt.tight_layout()
plt.show()
```

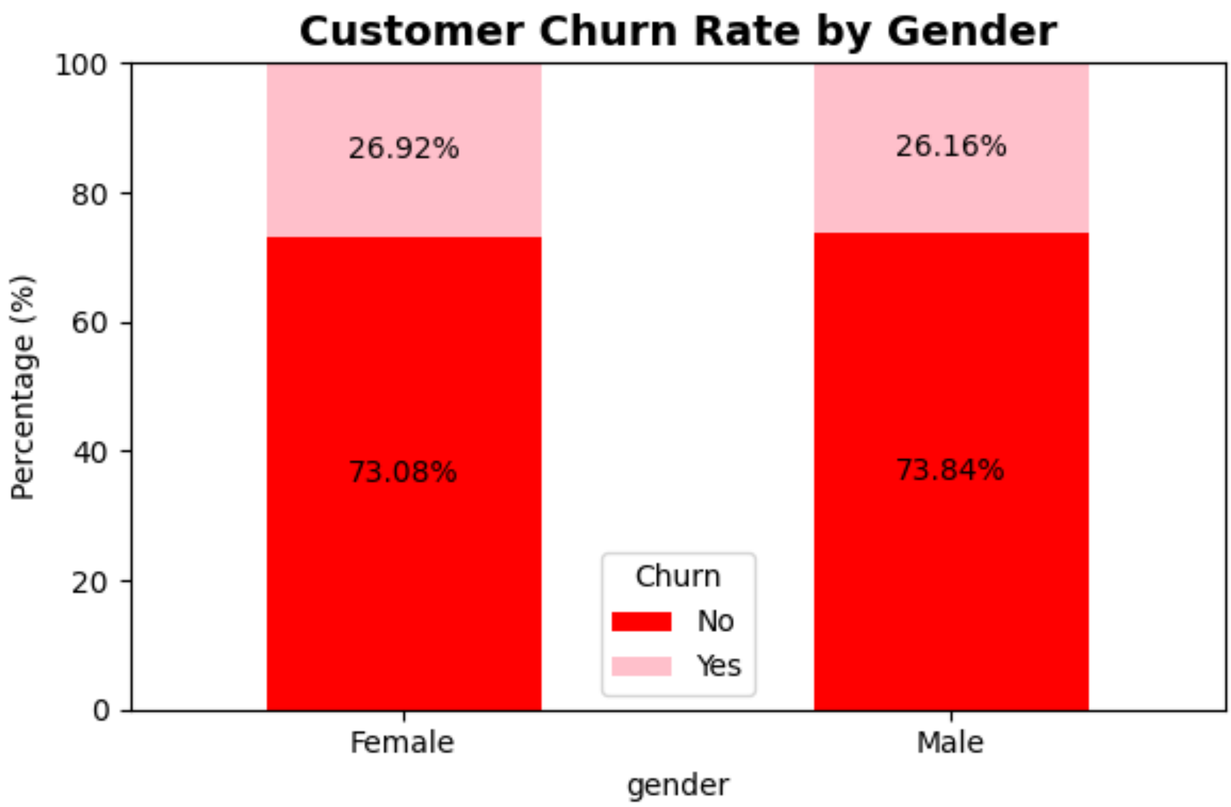


Insight:

- The dataset has a nearly equal distribution of male and female customers.
- This suggests there is no major gender bias in the customer base.

In [53]:

```
gender_churn = pd.crosstab(df['gender'], df['Churn'], normalize='index')
gender_churn = gender_churn.round(2)

gc = gender_churn.plot(
    kind='bar',
    stacked=True,
    color=['red', 'pink'],
    figsize=(6, 4)
)

plt.title('Customer Churn Rate by Gender', fontsize=14, weight='bold')
plt.ylabel('Percentage (%)')
plt.xticks(rotation=0)
plt.ylim(0, 100)
plt.legend(title='Churn')

for container in gc.containers:
    gc.bar_label(container, fmt='%.2f%%', label_type='center')

plt.tight_layout()
plt.show()
```



Interpretation:

- Churn rates are **very similar** across genders.
- Female customers have a slightly higher churn rate (26.92%) than male customers (26.16%), but the difference is marginal (only 0.76 percentage points).
- This suggests that gender is not a strong factor influencing churn in this dataset.

Recommendation:

- Focus on other variables like contract type, payment method, or service usage to find stronger churn predictors.

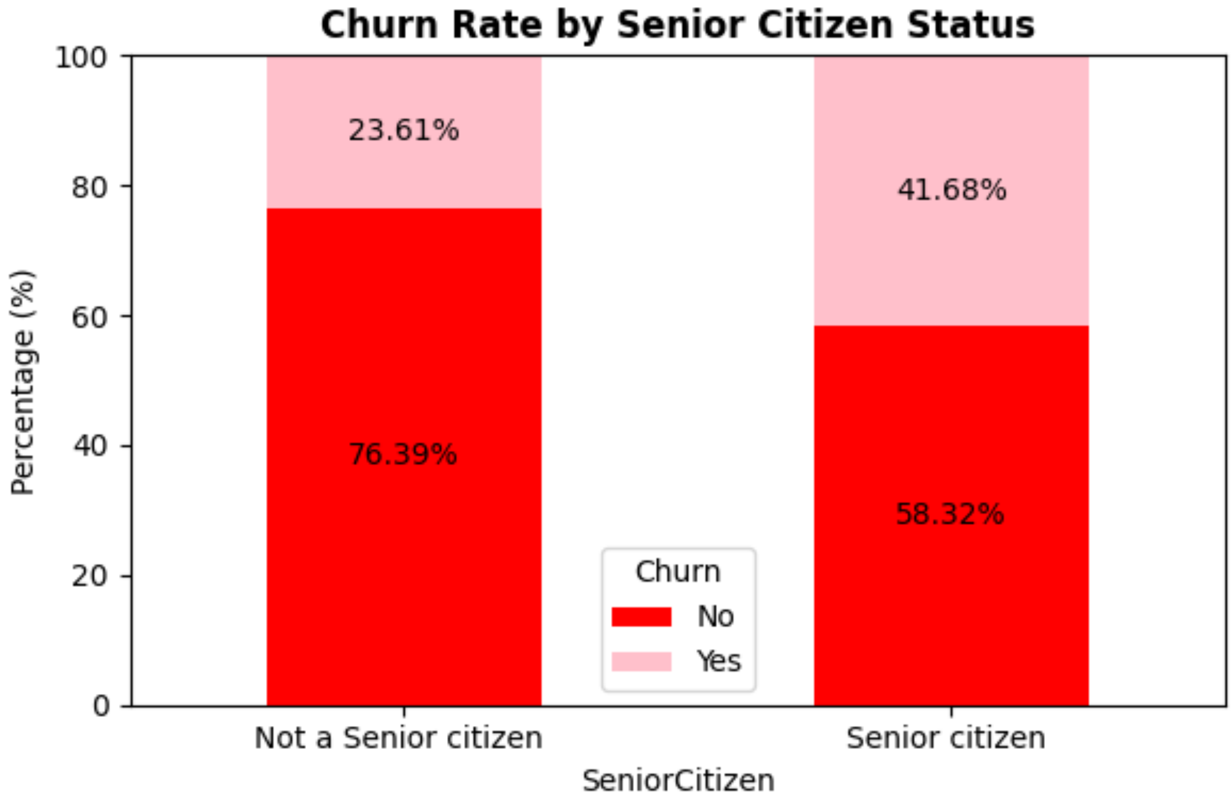
3. Churn Rate by senior sitizen status

In [54]:

```
senior_churn = pd.crosstab(df['SeniorCitizen'], df['Churn'], normalize='i
senior_churn = senior_churn.round(2)
print(senior_churn)


sc = senior_churn.plot(kind='bar', stacked=True, color=['red', 'pink'], f
plt.title('Churn Rate by Senior Citizen Status', fontsize=12, weight='bol
plt.ylabel('Percentage (%)')
plt.xticks(ticks=[0, 1], labels=['Not a Senior citizen ', 'Senior citizen
plt.ylim(0, 100)
plt.legend(title='Churn')
```

```python
for container in sc.containers:
    sc.bar_label(container, fmt='%.2f%%', label_type='center')

plt.tight_layout()
plt.show()
```

```
Churn              No    Yes
SeniorCitizen
no              76.39  23.61
yes             58.32  41.68
```



Interpretation:

- Senior citizens are **much more likely** to churn (41.68%) compared to non-seniors (23.61%).
- This is a significant difference of 18.07 percentage points.
- Senior status is a strong predictor of customer churn in this dataset.

Recommendation:

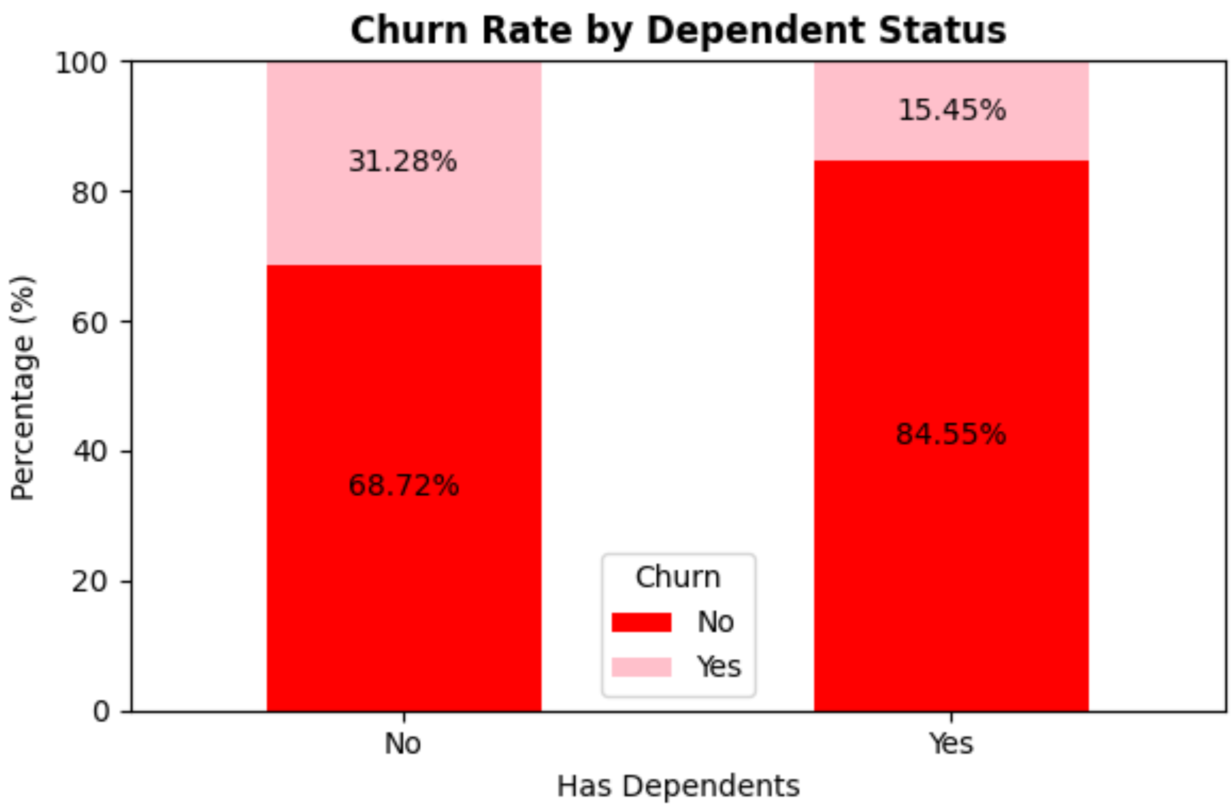
- Provide a simplified user experience for senior customers
- Offer dedicated phone support with trained agents who handle common senior citizen's concerns
- Create custom, affordable plans tailored to seniors

4.Churn Rate by Dependents

In [55]:
```python
dependents_churn = pd.crosstab(df['Dependents'], df['Churn'], normalize='
dependents_churn = dependents_churn.round(2)
```

```python
print(dependents_churn)

dc = dependents_churn.plot(
    kind='bar',
    stacked=True,
    color=['red', 'pink'],
    figsize=(6, 4)
)

plt.title('Churn Rate by Dependent Status', fontsize=12, weight='bold')
plt.ylabel('Percentage (%)')
plt.xlabel('Has Dependents')
plt.xticks(rotation=0)
plt.ylim(0, 100)
plt.legend(title='Churn')

for container in dc.containers:
    dc.bar_label(container, fmt='%.2f%%', label_type='center')

plt.tight_layout()
plt.show()
```

```
Churn          No    Yes
Dependents
No          68.72  31.28
Yes         84.55  15.45
```



Interpretation:

- Customers **without dependents** are more than twice as likely to churn.
- Having dependents may indicate greater responsibility or a more stable lifestyle, making customers less likely to switch providers.

Recommendation:

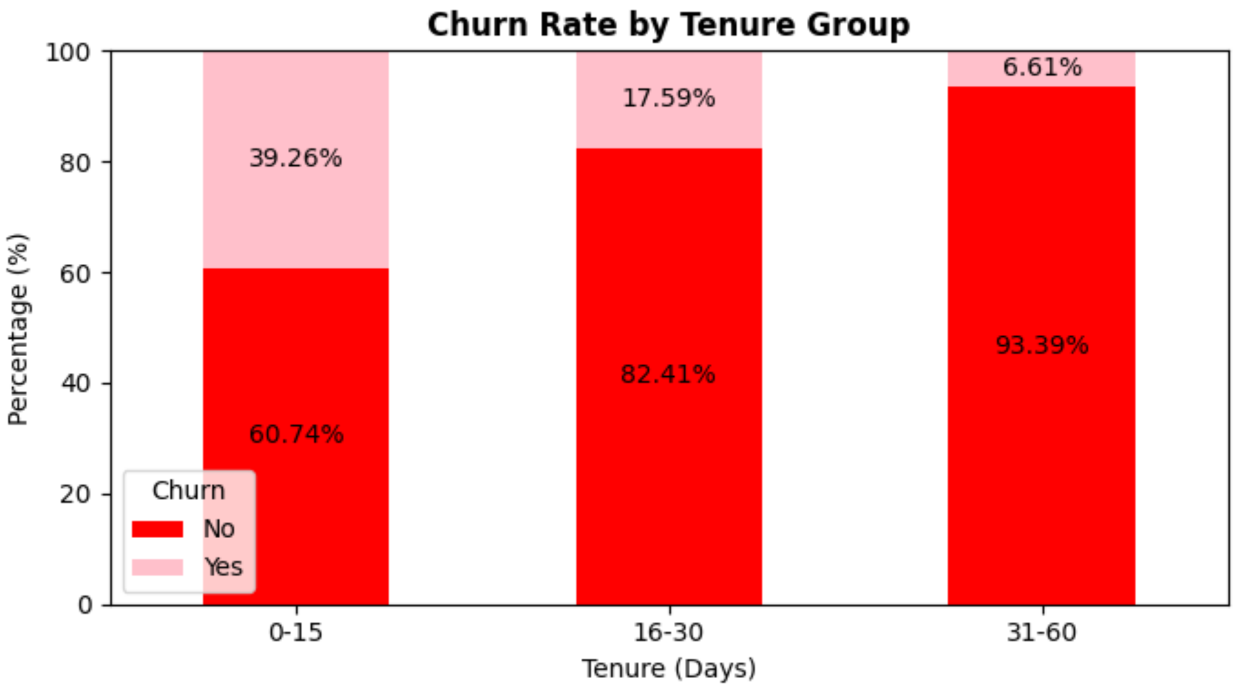
- Target **customers without dependents** with loyalty programs or value-added services to improve retention.
- Consider **personalized engagement** (exclusive offers, product bundles) for this high-risk group.

5.Churn Rate by tenure

In [57]:

```
bins=[0,30,60,90,120]
labels=['0-15','16-30','31-60','61-90']

df['TenureGroup'] = pd.cut(df['tenure'], bins=bins, labels=labels, right=

tenure_churn = pd.crosstab(df['TenureGroup'], df['Churn'], normalize='ind
tenure_churn = tenure_churn.round(2)
print(tenure_churn)

tc = tenure_churn.plot(
    kind='bar',
    stacked=True,
    color=['red', 'pink'],
    figsize=(7, 4)
)

plt.title('Churn Rate by Tenure Group', fontsize=12, weight='bold')
plt.ylabel('Percentage (%)')
plt.xlabel('Tenure (Days)')
plt.xticks(rotation=0)
plt.ylim(0, 100)
plt.legend(title='Churn')

for container in tc.containers:
    tc.bar_label(container, fmt='%.2f%%', label_type='center')

plt.tight_layout()
plt.show()
```

```
Churn            No    Yes
TenureGroup
0-15          60.74  39.26
16-30         82.41  17.59
31-60         93.39   6.61
```



Insights:

- Very high churn (39.26%) occurs within the first 15 days.
- Churn significantly drops to 17.59% between 16–30 days.
- Lowest churn (6.61%) seen after 30 days indicating long-term retention.

Recommendations:

- Improve onboarding and first-touch experience to reduce 0–15 day churn.
- Introduce **retention offers** (e.g., discount, support) during the first month.
- Monitor early user activity to flag high-risk churn candidates quickly.

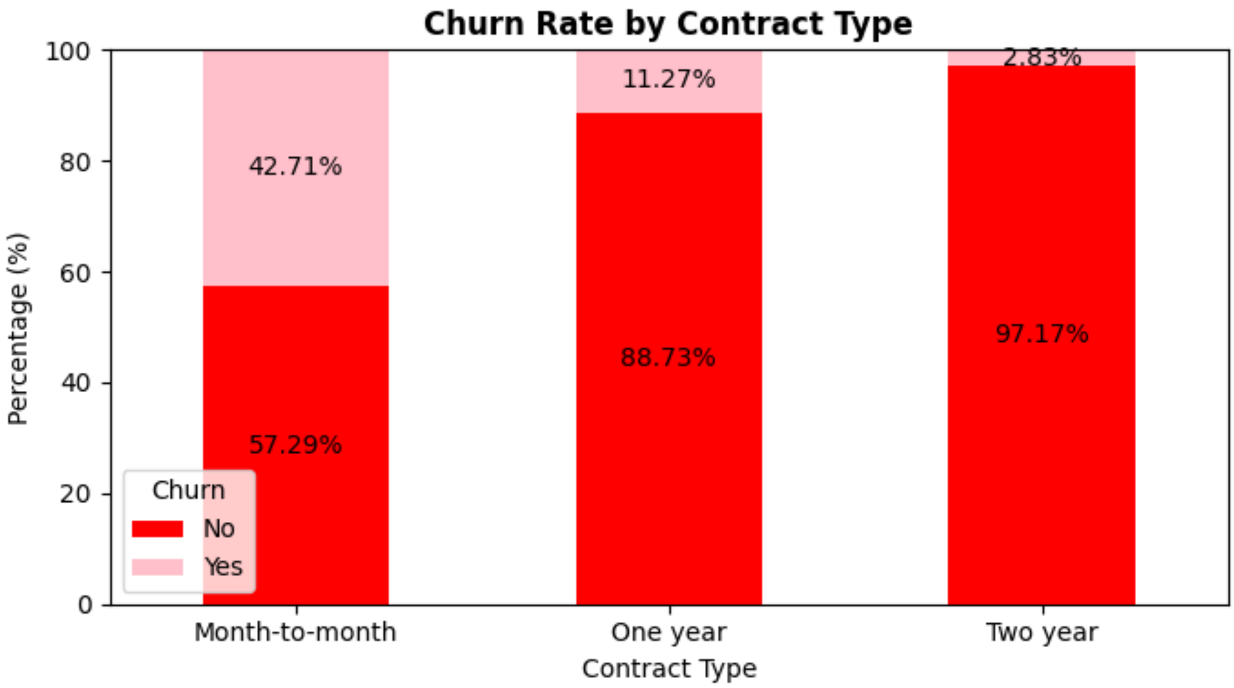
6.Churn Rate by contract

In [ ]:

```
contract_churn = pd.crosstab(df['Contract'], df['Churn'], normalize='inde
contract_churn = contract_churn.round(2)
print(contract_churn)

cc = contract_churn.plot(
    kind='bar',
    stacked=True,
    figsize=(7, 4),
    color=['red', 'pink']
)

plt.title('Churn Rate by Contract Type', fontsize=12, weight='bold')
plt.xlabel('Contract Type')
plt.ylabel('Percentage (%)')
plt.xticks(rotation=0)
plt.ylim(0, 100)
plt.legend(title='Churn')
```

```python
for container in cc.containers:
    cc.bar_label(container, fmt='%.2f%%', label_type='center')

plt.tight_layout()
plt.show()
```

```
Churn              No    Yes
Contract
Month-to-month  57.29  42.71
One year        88.73  11.27
Two year        97.17   2.83
```



Interpretation:

- **Month-to-month contracts** have the highest churn (42.71%), indicating a lack of long-term commitment and possible dissatisfaction.
- **One-year contracts** show significantly lower churn (11.27%), suggesting better retention through longer commitment.
- **Two-year contracts** have the lowest churn (2.83%), reflecting high loyalty, satisfaction, or switching barriers.

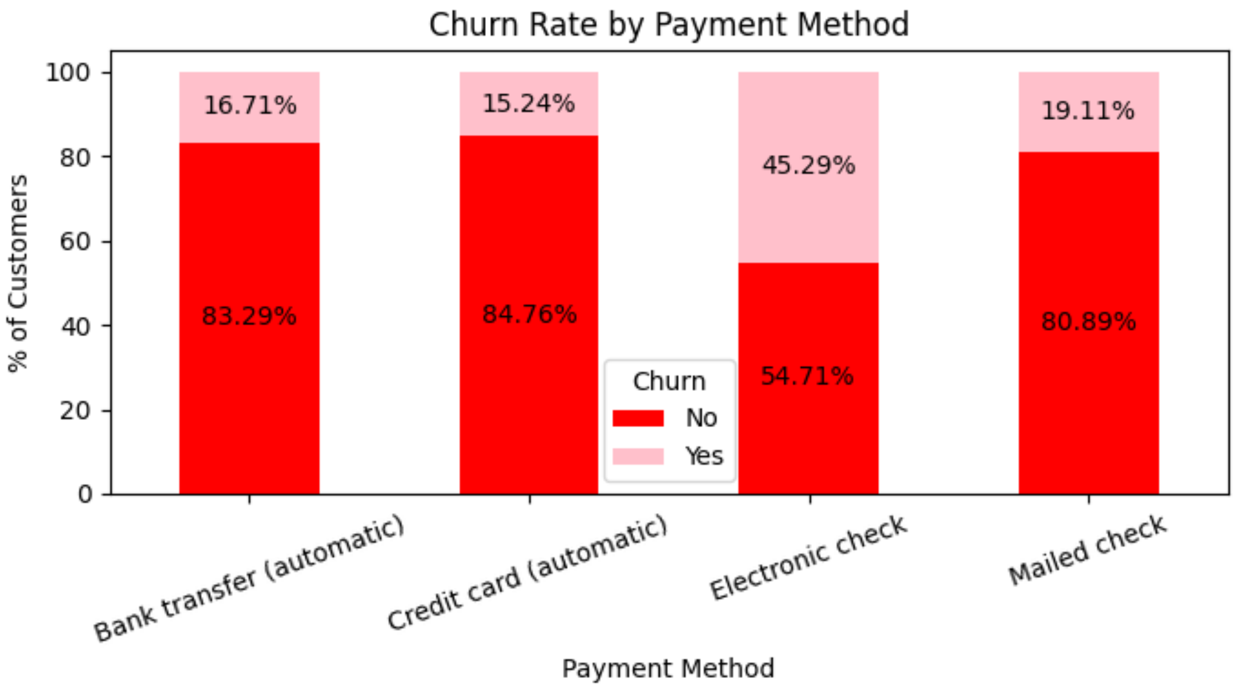
Recommendations:

- Offer discounts or benefits for customers who switch from monthly to 1 or 2-year plans.
- Focus customer success and **marketing efforts** on month-to-month users.
- Engage them with onboarding support, **incentives**, or loyalty programs to prevent early churn.
- Monitor month-to-month users as a high-risk group and **track feedback**, complaints, and inactivity patterns.

7. Churn Rate by Payment Method

In [58]:
```
churn_by_payment = pd.crosstab(df['PaymentMethod'], df['Churn'], normaliz
churn_by_payment = churn_by_payment.round(2)
print(churn_by_payment)

cp= churn_by_payment.plot(kind='bar', stacked=True, color=['red', 'pink']
plt.title('Churn Rate by Payment Method')
plt.ylabel('% of Customers')
plt.xlabel('Payment Method')
plt.legend(title='Churn')
plt.xticks(rotation=20)

for container in cp.containers:
    cp.bar_label(container, fmt='%.2f%%', label_type='center')

plt.tight_layout()
plt.show()
```

```
Churn                        No    Yes
PaymentMethod
Bank transfer (automatic)  83.29  16.71
Credit card (automatic)    84.76  15.24
Electronic check           54.71  45.29
Mailed check               80.89  19.11
```



Interpretation:

- **Electronic check** users have the highest churn rate (45.29%). This method may reflect less tech-savvy or lower-engagement customers.
- **Automatic payments** (bank transfer and credit card) show significantly lower churn rates (~15–17%), suggesting that auto-pay reduces the likelihood of cancellation.
- **Mailed check** users churn at a moderate rate (19.11%), slightly worse than

automatic methods but much better than electronic check users.

Recommendations:

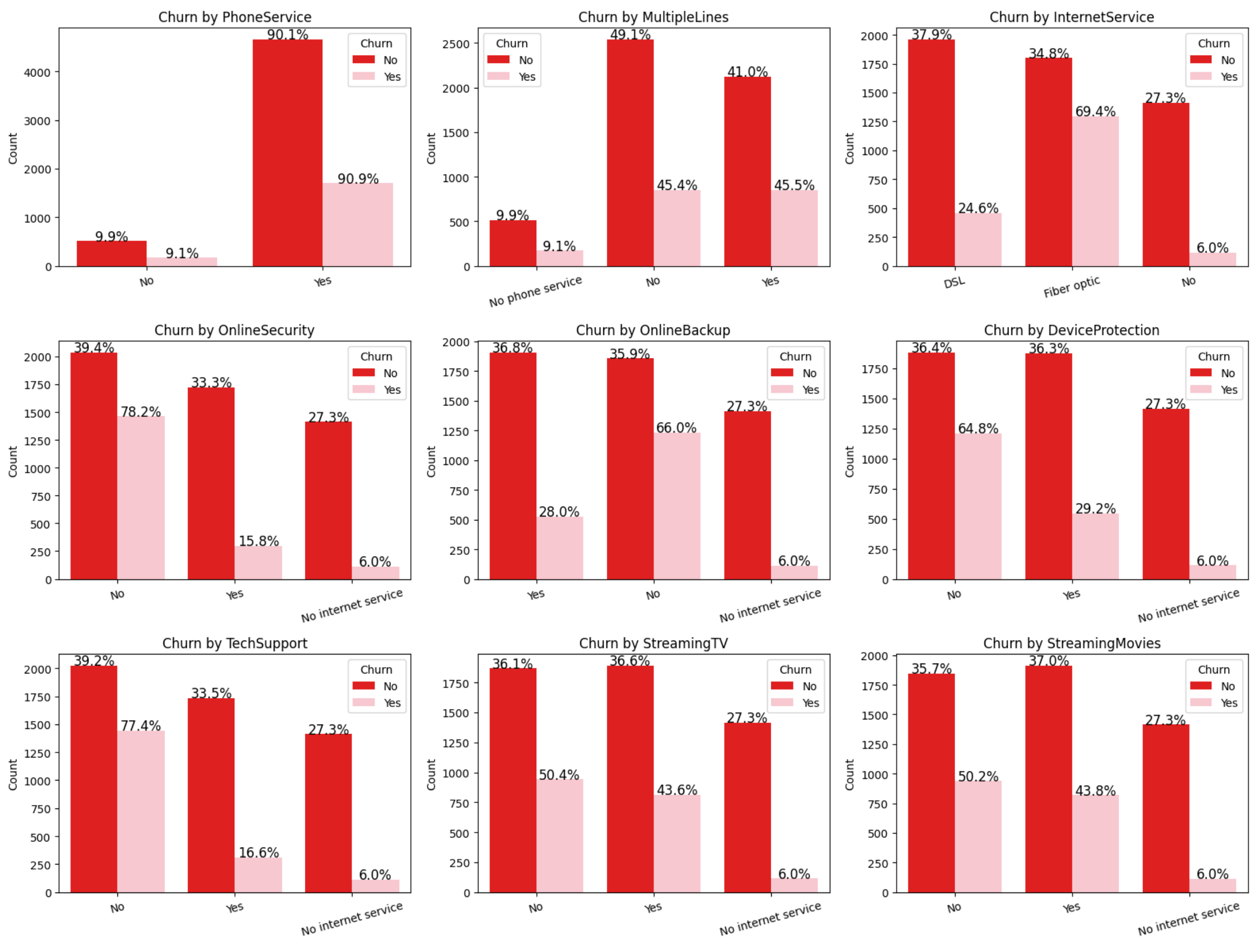
- Incentivize customers to switch to automatic payment methods (bank transfer or credit card) with small discounts or reward points.
- Monitor & Support Electronic Check Users, Consider proactive engagement like follow-up emails, loyalty rewards, or simplified onboarding.
- Make automatic payment the default method during sign-up, while still allowing changes this could passively improve retention.

8.Factors with possibility of impact on churn rate

In [61]:

```
columns = ['PhoneService', 'MultipleLines','InternetService', 'OnlineSecu
           'OnlineBackup','DeviceProtection', 'TechSupport', 'StreamingTV

num_columns = len(columns)
n_cols = 3
n_rows = (num_columns + n_cols - 1) // n_cols

fig, axes = plt.subplots(n_rows, n_cols, figsize=(16, n_rows * 4))
axes = axes.flatten()

colors = ['red', 'pink']

for i, col in enumerate(columns):
    ax = axes[i]
    data = df.copy()

    plot = sns.countplot(data=data, x=col, hue='Churn', ax=ax, palette=co
    ax.set_title(f'Churn by {col}', fontsize=12)
    ax.set_ylabel('Count')
    ax.set_xlabel('')

    for container in ax.containers:
        total = sum([bar.get_height() for bar in container])
        for bar in container:
            height = bar.get_height()
            if height > 0:
                percentage = f'{100 * height / total:.1f}%'
                ax.text(bar.get_x() + bar.get_width() / 2, height + 5, pe
                        ha='center', fontsize=12, color='black')

    ax.tick_params(axis='x', rotation=15)

# Remove any unused subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
```

```
plt.show()
```



Insights

PhoneService

- Churn rate is nearly identical regardless of phone service (~9.1%).
- PhoneService does **not significantly** impact churn.

MultipleLines

- Churn rate remains similar for customers with or without multiple lines (~45%).
- MultipleLines has **minimal influence** on churn.

InternetService

- Fiber optic users have the highest churn rate (69.4%), DSL users lower (24.6%).
- Customers without internet service show the lowest churn (6.0%).
- Indicates fiber optic users may be dissatisfied.

OnlineSecurity

- Customers without OnlineSecurity churn at 78.2%, compared to 15.8% with it.
- Strong **negative correlation** with churn.

OnlineBackup

- 66.0% churn without backup, compared to 28.0% with it.
- OnlineBackup appears to significantly improve retention.

DeviceProtection

- Churn with DeviceProtection is 29.2%, without it is 64.8%.
- **Positive** retention impact from DeviceProtection.

TechSupport

- Customers with TechSupport churn only 16.6%, while those without churn at 77.4%.
- TechSupport is one of the **most effective** churn-reduction factors.

StreamingTV & StreamingMovies

- Churn differences are minimal (~43–50%) regardless of service usage.
- Limited impact on churn not a key retention factor.

Recommendations

Investigate High Churn Among Fiber Optic Users

- Analyze root causes (e.g., pricing, service quality).
- Offer support, promotions, or loyalty programs.

Promote Add-on Services That Reduce Churn

- Encourage subscription to OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport.
- Consider bundled packages,free trials, upgrade incentives

Deprioritize Low-Impact Services in Churn Strategy

- Services like StreamingTV and StreamingMovies show minimal influence.
- Use them to enhance bundles but not as standalone churn levers.

Use Customer Segmentation for Targeted Campaigns

- Identify customers without key retention services.
- Send targeted offers to improve retention in high-risk groups.

Collect Feedback from Churning Segment

- Focus on Fiber Optic users and those not using retention-related services.
- Use surveys and NPS scores to drive product/service improvements.

This project analyzed customer churn using various demographic, behavioral, and service-related features. Visualizations helped identify key drivers of churn such as contract type, payment method, tenure, and value-added services.