Project Title	**Customer Satisfaction Prediction**
language	Machine learning, python, SQL, Excel
Tools	VS code, Jupyter notebook
Domain	Data Science
Project Difficulties level	Advance

Dataset : Dataset is available in the given link. You can download it at your convenience.

Click here to download data set

About Dataset

The Customer Support Ticket Dataset is a dataset that includes customer support tickets for various tech products. It consists of customer inquiries related to hardware issues, software bugs, network problems, account access, data loss, and other support topics. The dataset provides information about the customer, the product purchased, the ticket type, the ticket channel, the ticket status, and other relevant details.

The dataset can be used for various analysis and modelling tasks in the customer service domain.

Features Description:

- Ticket ID: A unique identifier for each ticket.
- Customer Name: The name of the customer who raised the ticket.
- Customer Email: The email address of the customer (Domain name - @example.com is intentional for user data privacy concern).
- Customer Age: The age of the customer.
- Customer Gender: The gender of the customer.
- Product Purchased: The tech product purchased by the customer.
- Date of Purchase: The date when the product was purchased.
- Ticket Type: The type of ticket (e.g., technical issue, billing inquiry, product inquiry).
- Ticket Subject: The subject/topic of the ticket.
- Ticket Description: The description of the customer's issue or inquiry.
- Ticket Status: The status of the ticket (e.g., open, closed, pending customer response).
- Resolution: The resolution or solution provided for closed tickets.
- Ticket Priority: The priority level assigned to the ticket (e.g., low, medium, high, critical).
- Ticket Channel: The channel through which the ticket was raised (e.g., email, phone, chat, social media).
- First Response Time: The time taken to provide the first response to the customer.
- Time to Resolution: The time taken to resolve the ticket.
- Customer Satisfaction Rating: The customer's satisfaction rating for closed tickets (on a scale of 1 to 5).

Use Cases of such dataset:

- Customer Support Analysis: The dataset can be used to analyze customer support ticket trends, identify common issues, and improve support processes.
- Natural Language Processing (NLP): The ticket descriptions can be used for training NLP models to automate ticket categorization or sentiment analysis.
- Customer Satisfaction Prediction: The dataset can be used to train models to predict customer satisfaction based on ticket information.
- Ticket Resolution Time Prediction: The dataset can be used to build models for predicting the time it takes to resolve a ticket based on various factors.
- Customer Segmentation: The dataset can be used to segment customers based on their ticket types, issues, or satisfaction levels.
- Recommender Systems: The dataset can be used to build recommendation systems for suggesting relevant solutions or products based on customer inquiries.

<u>Example: You can get the basic idea how you can create a project from here</u>

Customer Satisfaction Prediction Machine Learning Project

Project Overview

The goal of this project is to predict customer satisfaction using historical data. This involves using machine learning algorithms to analyze factors that influence customer satisfaction and build a predictive model.

Dataset

A commonly used dataset for this type of project is the "Customer Satisfaction Survey" dataset, which includes features such as:

- **CustomerID**
- **Age**
- **Gender**
- **Income**
- **Education Level**
- **Product Purchased**
- **Purchase Frequency**
- **Customer Service Interactions**
- **Feedback Scores**
- **Overall Satisfaction**

This dataset can be found on platforms like Kaggle or UCI Machine Learning Repository.

Steps and Implementation

1. **Data Preprocessing**
2. **Exploratory Data Analysis (EDA)**
3. **Feature Engineering**

4. **Model Building**
5. **Model Evaluation**
6. **Visualization**

Implementation Code

Here is a sample implementation in Python:

```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Load the dataset
data = pd.read_csv('customer_satisfaction.csv')

# Display basic info about the dataset
print(data.info())

# Data Preprocessing
# Handling missing values
data = data.dropna()

# Encoding categorical variables
```

```
label_encoders = {}
for column in data.select_dtypes(include=['object']).columns:
    label_encoders[column] = LabelEncoder()
    data[column] = label_encoders[column].fit_transform(data[column])

# Define features and target variable
X = data.drop(['CustomerID', 'Overall Satisfaction'], axis=1)
y = data['Overall Satisfaction']

# Splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)

# Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Model Building
# Train a Random Forest Classifier
rfc = RandomForestClassifier(random_state=42)
rfc.fit(X_train, y_train)

# Predict on the test set
y_pred = rfc.predict(X_test)

# Model Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))

# Visualization of Results
# Feature Importance
feature_importances = pd.Series(rfc.feature_importances_, index=X.columns)
feature_importances.nlargest(10).plot(kind='barh')
plt.title('Top 10 Feature Importances')
plt.show()
```

Example: You can get the basic idea how you can create a project from here

Explanation of Code

1. **Data Preprocessing:**
   - Load the dataset and display basic information.
   - Handle missing values by dropping rows with NA values.
   - Encode categorical variables using `LabelEncoder`.
2. **Exploratory Data Analysis (EDA):**
   - Although not shown in the code snippet, EDA typically involves visualizing data distributions, correlations, and patterns using libraries like `matplotlib` and `seaborn`.
3. **Feature Engineering:**
   - Define the feature set `X` and the target variable `y`.
   - Split the data into training and testing sets using `train_test_split`.
4. **Feature Scaling:**
   - Standardize the features using `StandardScaler` to ensure all features contribute equally to the model.
5. **Model Building:**
   - Train a `RandomForestClassifier` on the training data.

   - Predict customer satisfaction on the test data.
6. **Model Evaluation:**
   - Evaluate the model using metrics like accuracy, classification report, and confusion matrix.
   - Visualize the top 10 feature importances to understand which factors contribute most to customer satisfaction.

Additional Resources

- [Customer Satisfaction Survey Data on Kaggle]
- Random Forest Classifier Documentation
- Handling Missing Data in Pandas
- Feature Scaling with StandardScaler

This implementation provides a framework for predicting customer satisfaction using machine learning. You can extend it by experimenting with different algorithms, fine-tuning hyperparameters, and incorporating additional features to improve the model's performance.

Sample code with output

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.cluster import KMeans

# Load the dataset
data =
pd.read_csv("/kaggle/input/customer-support-ticket-dataset/cust
omer_support_tickets.csv")

# Display the first few rows of the dataset
print(data.head())

# Perform initial exploratory data analysis (EDA)
print(data.info())
print(data.describe())
```

```
  Ticket ID        Customer Name              Customer Email
Customer Age  \
0          1        Marisa Obrien  carrollallison@example.com
32
1          2          Jessica Rios    clarkeashley@example.com
42
2          3  Christopher Robbins   gonzalestracy@example.com
48
```

```
3          4     Christina Dillon    bradleyolson@example.org
27
4          5    Alexander Carroll     bradleymark@example.com
67

  Customer Gender Product Purchased Date of Purchase
Ticket Type  \
0           Other        GoPro Hero       2021-03-22  Technical
issue
1          Female       LG Smart TV       2021-05-22  Technical
issue
2           Other          Dell XPS       2020-07-14  Technical
issue
3          Female  Microsoft Office       2020-11-13  Billing
inquiry
4          Female  Autodesk AutoCAD       2020-02-04  Billing
inquiry

             Ticket Subject  \
0             Product setup
1  Peripheral compatibility
2           Network problem
3            Account access
4                 Data loss
```

```
                                  Ticket Description  \
0  I'm having an issue with the {product_purchase...
1  I'm having an issue with the {product_purchase...
2  I'm facing a problem with my {product_purchase...
3  I'm having an issue with the {product_purchase...
4  I'm having an issue with the {product_purchase...

               Ticket Status
Resolution  \
0  Pending Customer Response
NaN
1  Pending Customer Response
NaN
2                     Closed   Case maybe show recently my
computer follow.
3                     Closed  Try capital clearly never color
toward story.
4                     Closed                    West decision
evidence bit.

  Ticket Priority Ticket Channel  First Response Time   Time to
Resolution  \
0        Critical   Social media  2023-06-01 12:15:36
NaN
1        Critical           Chat  2023-06-01 16:45:38
```

```
NaN
2            Low   Social media  2023-06-01 11:14:38
2023-06-01 18:05:38
3            Low   Social media  2023-06-01 07:29:40
2023-06-01 01:57:40
4            Low          Email  2023-06-01 00:12:42
2023-06-01 19:53:42

   Customer Satisfaction Rating
0                           NaN
1                           NaN
2                           3.0
3                           3.0
4                           1.0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8469 entries, 0 to 8468
Data columns (total 17 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   Ticket ID                     8469 non-null   int64
 1   Customer Name                 8469 non-null   object
 2   Customer Email                8469 non-null   object
 3   Customer Age                  8469 non-null   int64
 4   Customer Gender               8469 non-null   object
 5   Product Purchased             8469 non-null   object
```

```
 6   Date of Purchase               8469 non-null   object
 7   Ticket Type                    8469 non-null   object
 8   Ticket Subject                 8469 non-null   object
 9   Ticket Description             8469 non-null   object
 10  Ticket Status                  8469 non-null   object
 11  Resolution                     2769 non-null   object
 12  Ticket Priority                8469 non-null   object
 13  Ticket Channel                 8469 non-null   object
 14  First Response Time            5650 non-null   object
 15  Time to Resolution             2769 non-null   object
 16  Customer Satisfaction Rating  2769 non-null   float64
dtypes: float64(1), int64(2), object(14)
memory usage: 1.1+ MB
None
         Ticket ID  Customer Age  Customer Satisfaction Rating
count  8469.000000   8469.000000                   2769.000000
mean   4235.000000     44.026804                      2.991333
std    2444.934048     15.296112                      1.407016
min       1.000000     18.000000                      1.000000
25%    2118.000000     31.000000                      2.000000
50%    4235.000000     44.000000                      3.000000
75%    6352.000000     57.000000                      4.000000
max    8469.000000     70.000000                      5.000000
```

In [2]:

```
# Print column names
print(data.columns)
```

```
Index(['Ticket ID', 'Customer Name', 'Customer Email',
'Customer Age',
       'Customer Gender', 'Product Purchased', 'Date of
Purchase',
       'Ticket Type', 'Ticket Subject', 'Ticket Description',
'Ticket Status',
       'Resolution', 'Ticket Priority', 'Ticket Channel',
       'First Response Time', 'Time to Resolution',
       'Customer Satisfaction Rating'],
      dtype='object')
```

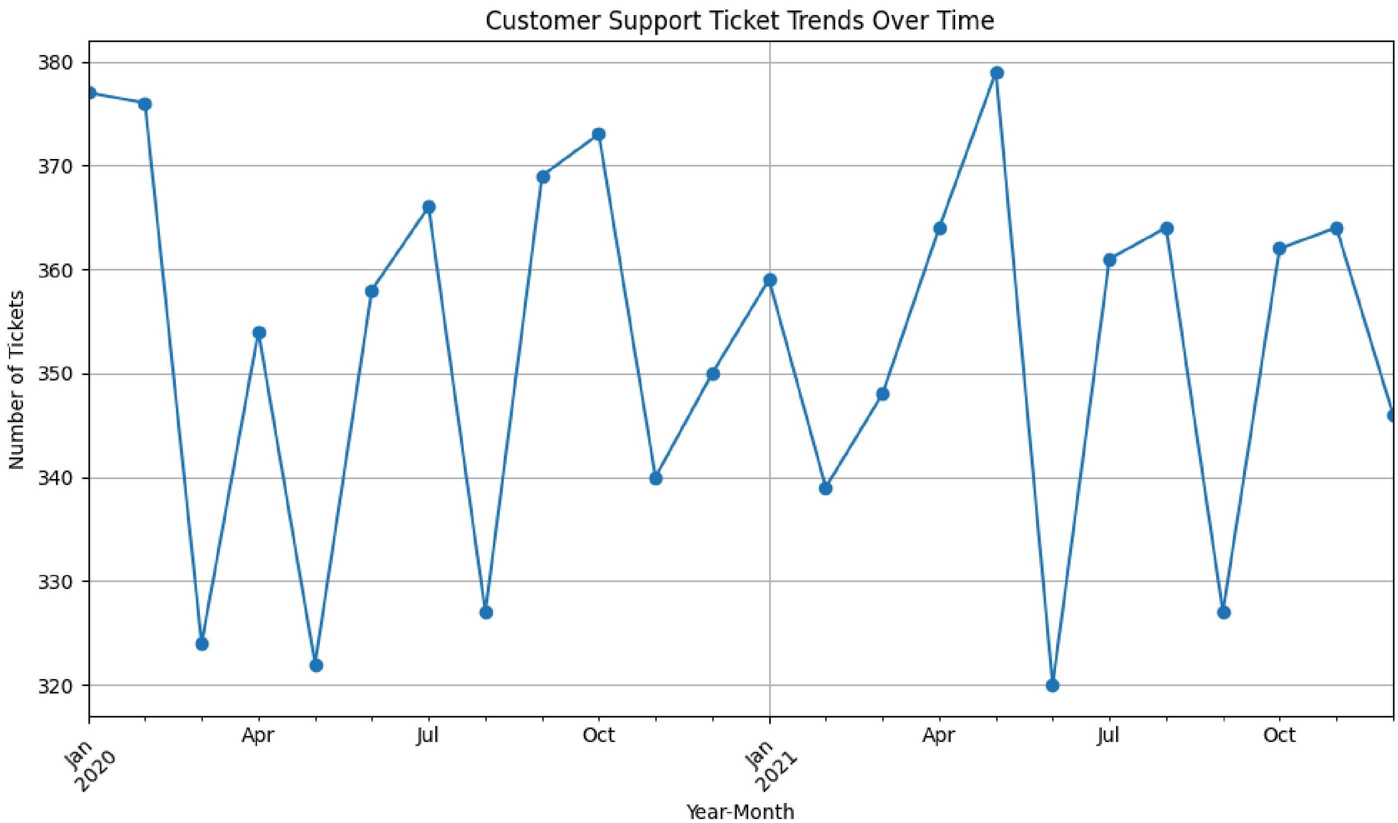
In [3]:

```
#Analyze customer support ticket trends
# Identify common issues
common_issues = data['Ticket Subject'].value_counts().head(10)
print("Top 10 Common Issues:")
print(common_issues)

# Plotting ticket trends over time
```

```
data['Date of Purchase'] = pd.to_datetime(data['Date of
Purchase'])
data['YearMonth'] = data['Date of Purchase'].dt.to_period('M')
ticket_trends = data.groupby('YearMonth').size()

plt.figure(figsize=(10, 6))
ticket_trends.plot(kind='line', marker='o')
plt.title('Customer Support Ticket Trends Over Time')
plt.xlabel('Year-Month')
plt.ylabel('Number of Tickets')
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
Top 10 Common Issues:
Ticket Subject
Refund request            576
Software bug              574
Product compatibility     567
Delivery problem          561
Hardware issue            547
Battery life              542
Network problem           539
```

```
Installation support     530
Product setup            529
Payment issue            526
Name: count, dtype: int64
```



In [4]:

```python
# Segment customers
# Segment based on ticket types
ticket_type_segmentation = data.groupby('Ticket Type').size()
print("\nSegmentation based on Ticket Types:")
print(ticket_type_segmentation)
```

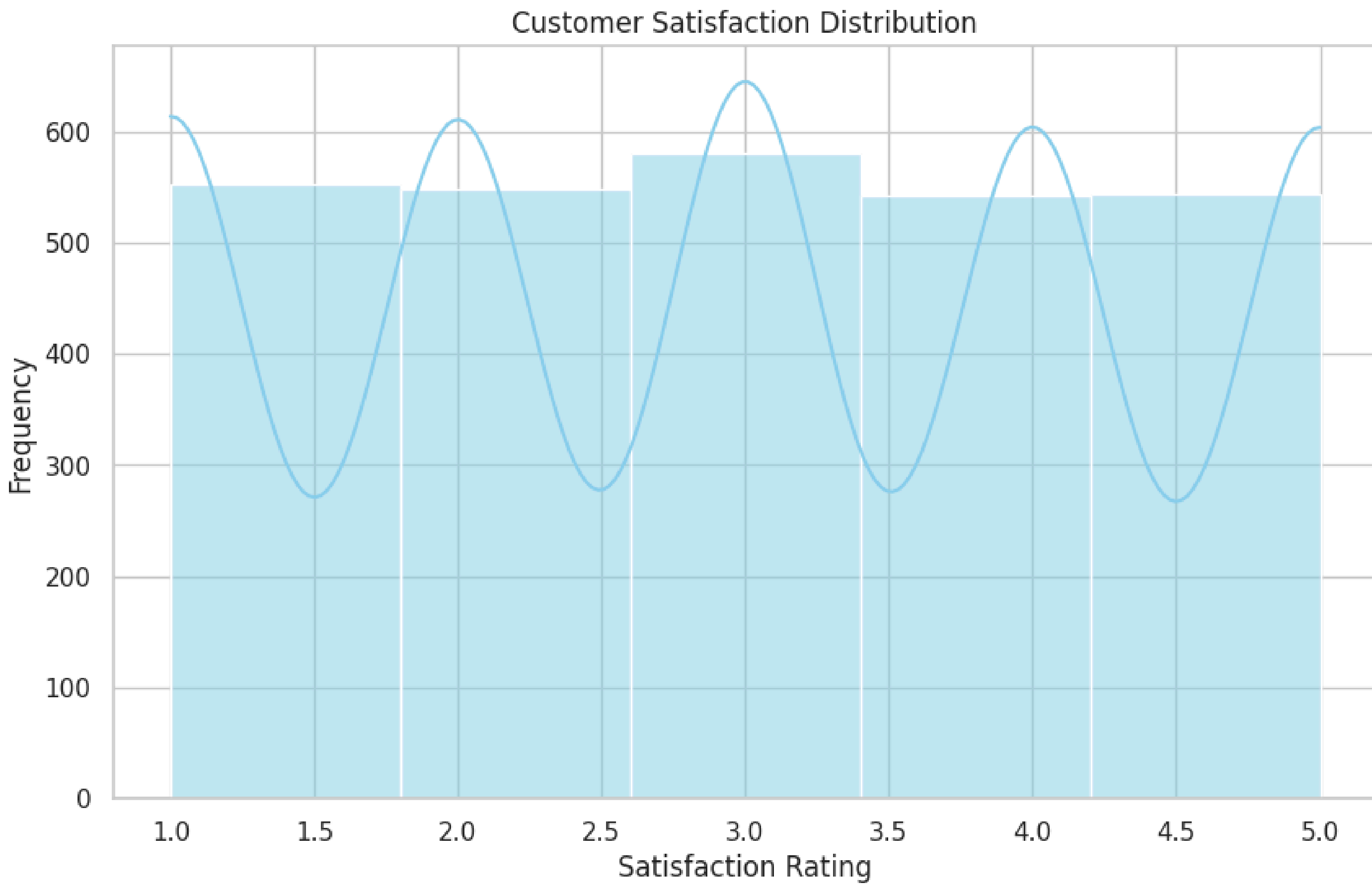
```python
# Segment based on satisfaction levels
satisfaction_segmentation = data.groupby('Customer Satisfaction Rating').size()
print("\nSegmentation based on Customer Satisfaction Levels:")
print(satisfaction_segmentation)
```

```
Segmentation based on Ticket Types:
Ticket Type
Billing inquiry         1634
Cancellation request    1695
Product inquiry         1641
Refund request          1752
Technical issue         1747
dtype: int64

Segmentation based on Customer Satisfaction Levels:
Customer Satisfaction Rating
1.0    553
2.0    549
3.0    580
4.0    543
5.0    544
dtype: int64
```

In [5]:

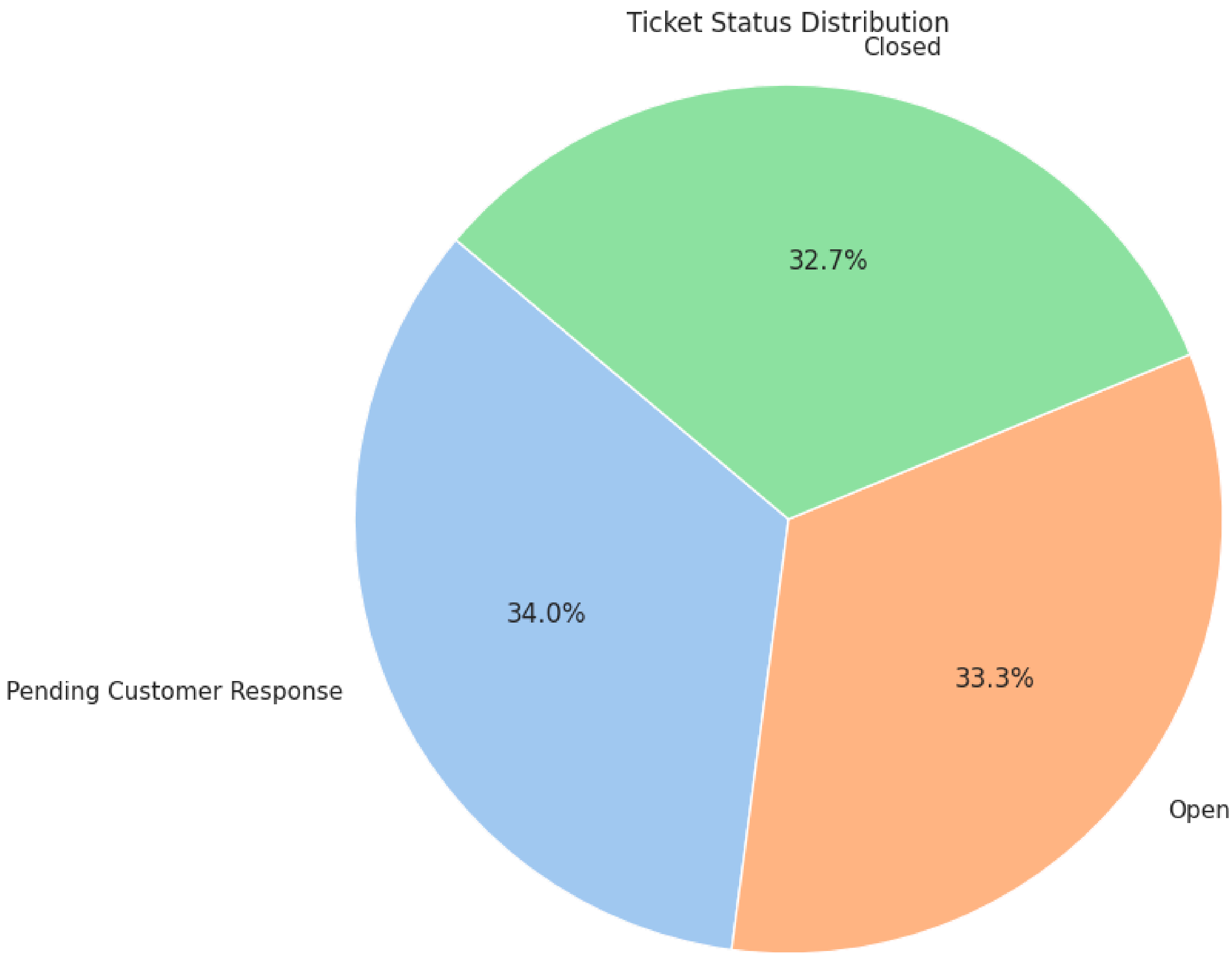
```python
# Set up the plotting aesthetics
sns.set(style="whitegrid")

#Customer Satisfaction Distribution
plt.figure(figsize=(10, 6))
sns.histplot(data['Customer Satisfaction Rating'], bins=5,
kde=True, color='skyblue')
plt.title('Customer Satisfaction Distribution')
plt.xlabel('Satisfaction Rating')
plt.ylabel('Frequency')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will
be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [6]:

```
#Ticket Status Distribution
ticket_status_distribution = data['Ticket
Status'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(ticket_status_distribution,
labels=ticket_status_distribution.index, autopct='%1.1f%%',
colors=sns.color_palette('pastel'), startangle=140)
plt.title('Ticket Status Distribution')
plt.axis('equal')
plt.show()
```

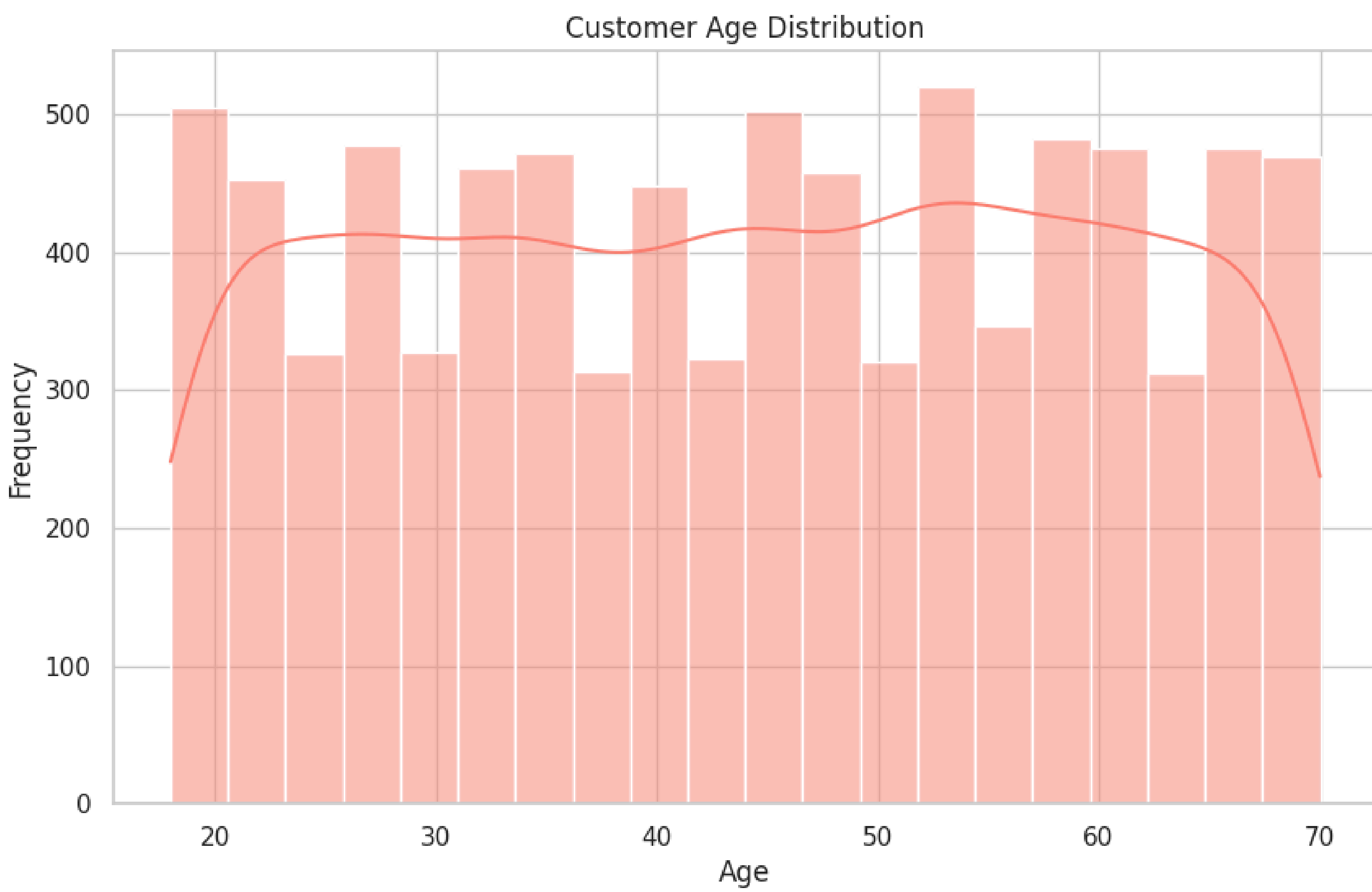


In [7]:

```
#Customer Age Distribution
plt.figure(figsize=(10, 6))
sns.histplot(data['Customer Age'], bins=20, kde=True,
color='salmon')
plt.title('Customer Age Distribution')
plt.xlabel('Age')
```

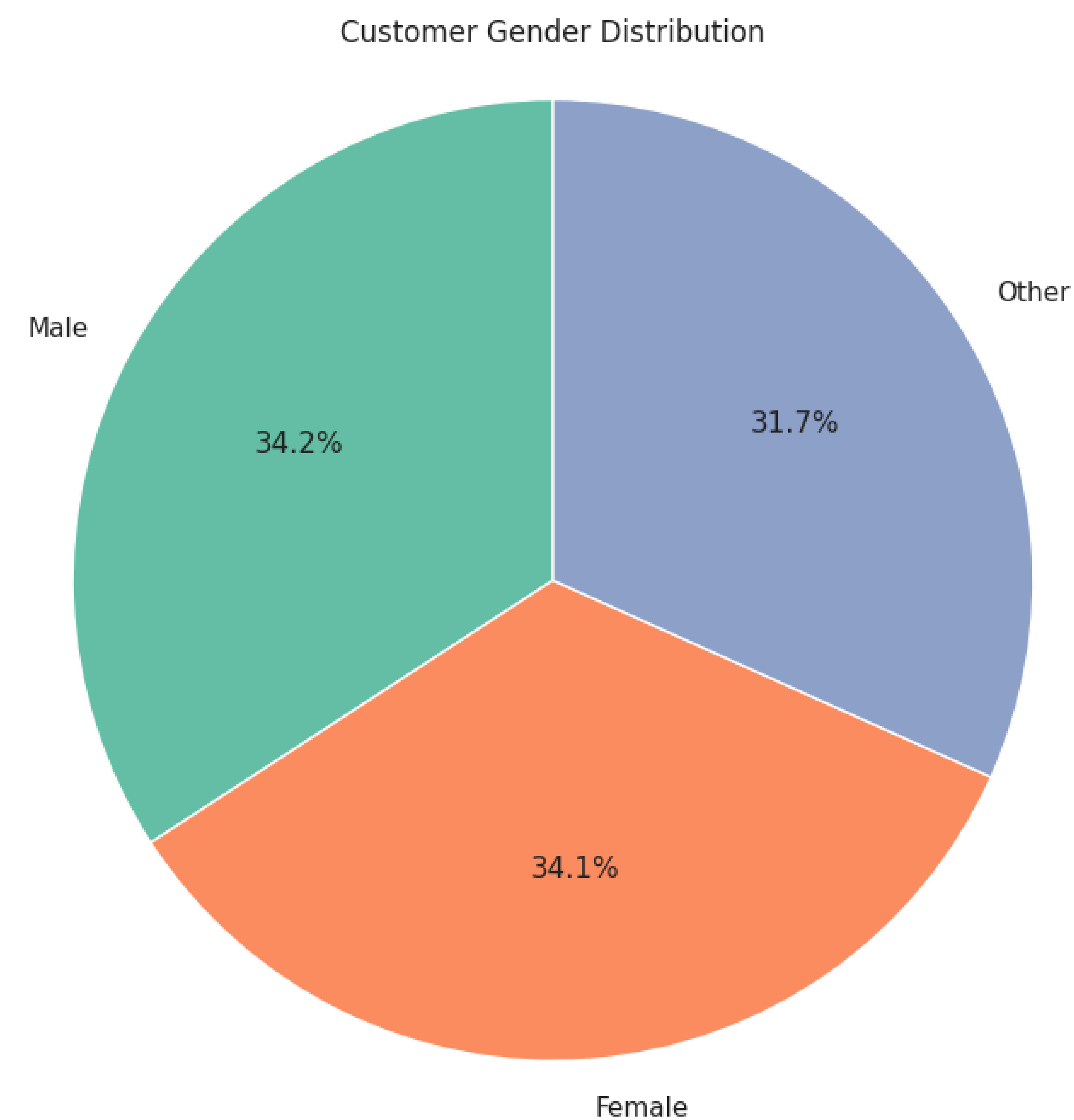
```
plt.ylabel('Frequency')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```




```
In [8]:
```

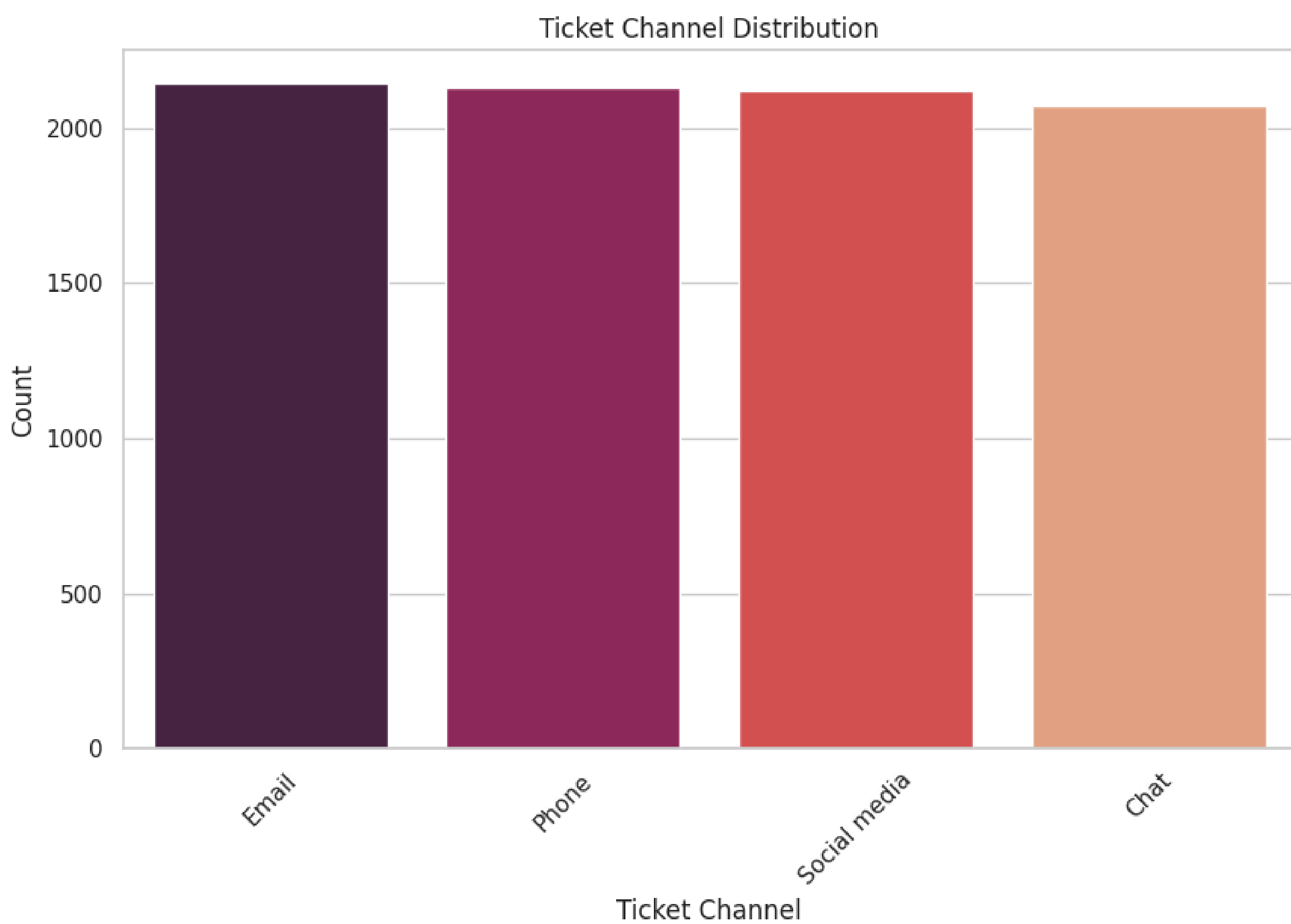
```
#Customer Gender Distribution
customer_gender_distribution = data['Customer
Gender'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(customer_gender_distribution,
labels=customer_gender_distribution.index, autopct='%1.1f%%',
colors=sns.color_palette('Set2'), startangle=90)
plt.title('Customer Gender Distribution')
plt.axis('equal')
plt.show()
```



In [9]:

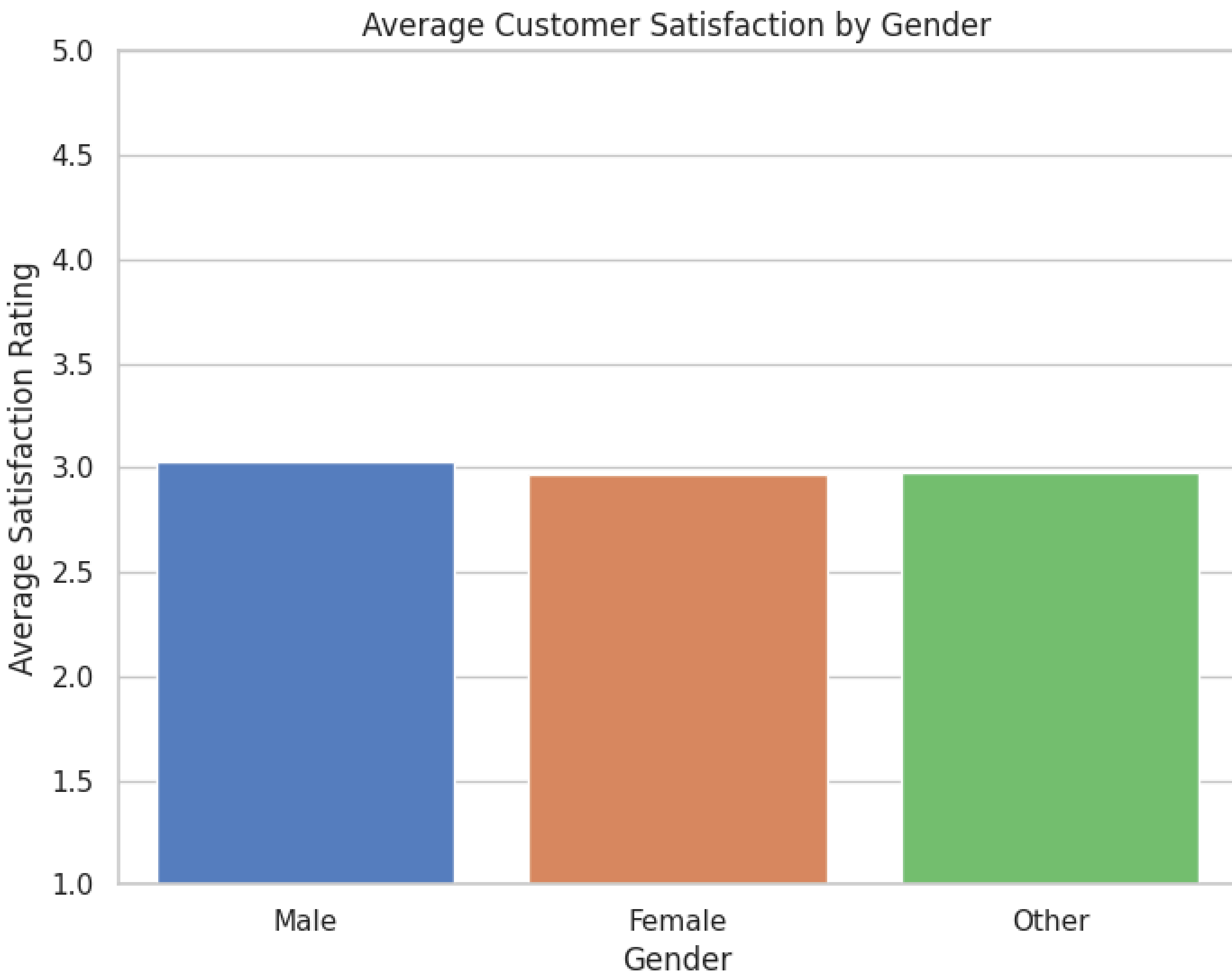
```
#Ticket Channel Distribution
plt.figure(figsize=(10, 6))
ticket_channel_distribution = data['Ticket
Channel'].value_counts()
sns.barplot(x=ticket_channel_distribution.index,
```

```
y=ticket_channel_distribution, palette='rocket')
plt.title('Ticket Channel Distribution')
plt.xlabel('Ticket Channel')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```




```
In [10]:
# Chart 1: Average Customer Satisfaction by Gender (Bar Plot)
```

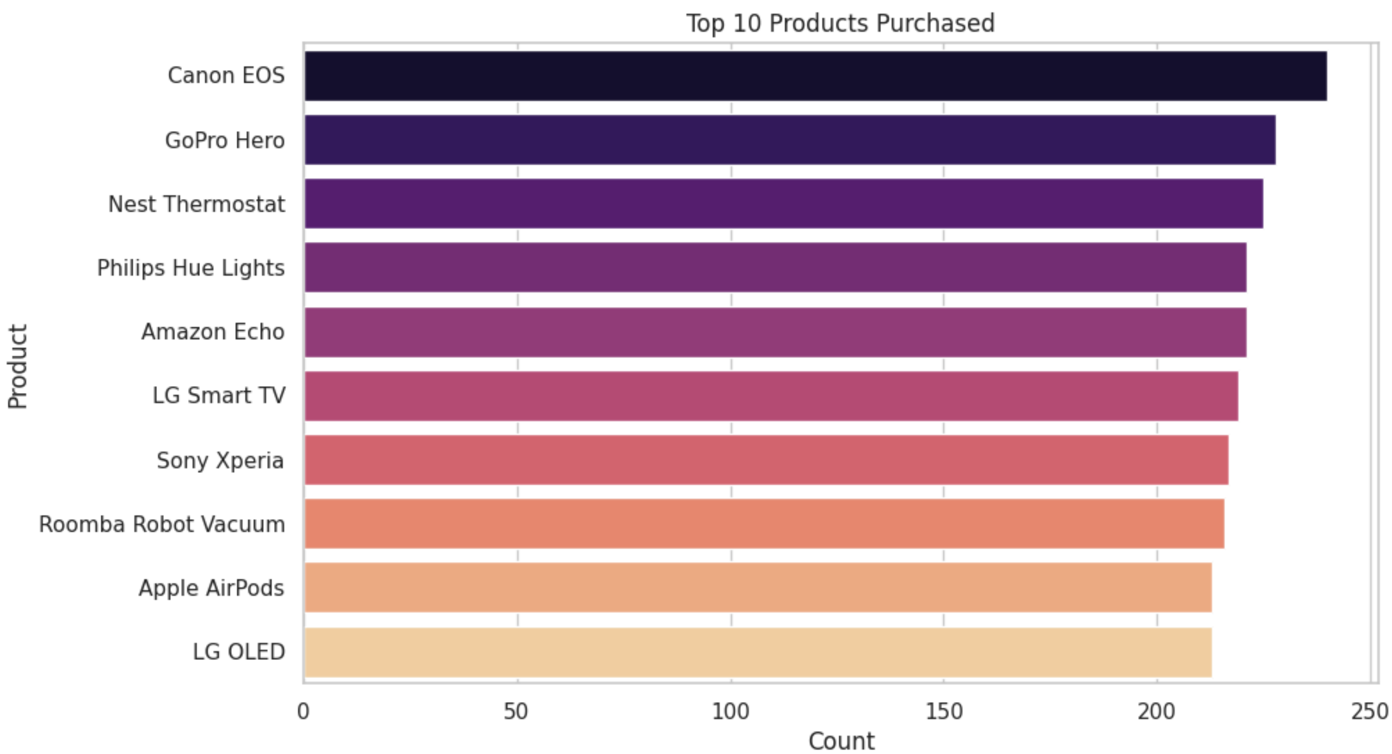
```
average_satisfaction = data.groupby('Customer
Gender')['Customer Satisfaction Rating'].mean().reset_index()


plt.figure(figsize=(8, 6))
sns.barplot(x='Customer Gender', y='Customer Satisfaction
Rating', data=average_satisfaction, palette='muted',
order=['Male', 'Female', 'Other'])
plt.title('Average Customer Satisfaction by Gender')
plt.xlabel('Gender')
plt.ylabel('Average Satisfaction Rating')
plt.ylim(1, 5)  # Adjust y-axis limit if needed
plt.show()
```



In [11]:

```
#Product Purchased Distribution
plt.figure(figsize=(10, 6))
product_purchased_distribution = data['Product
Purchased'].value_counts().head(10)
sns.barplot(y=product_purchased_distribution.index,
x=product_purchased_distribution, palette='magma')
plt.title('Top 10 Products Purchased')
plt.xlabel('Count')
```

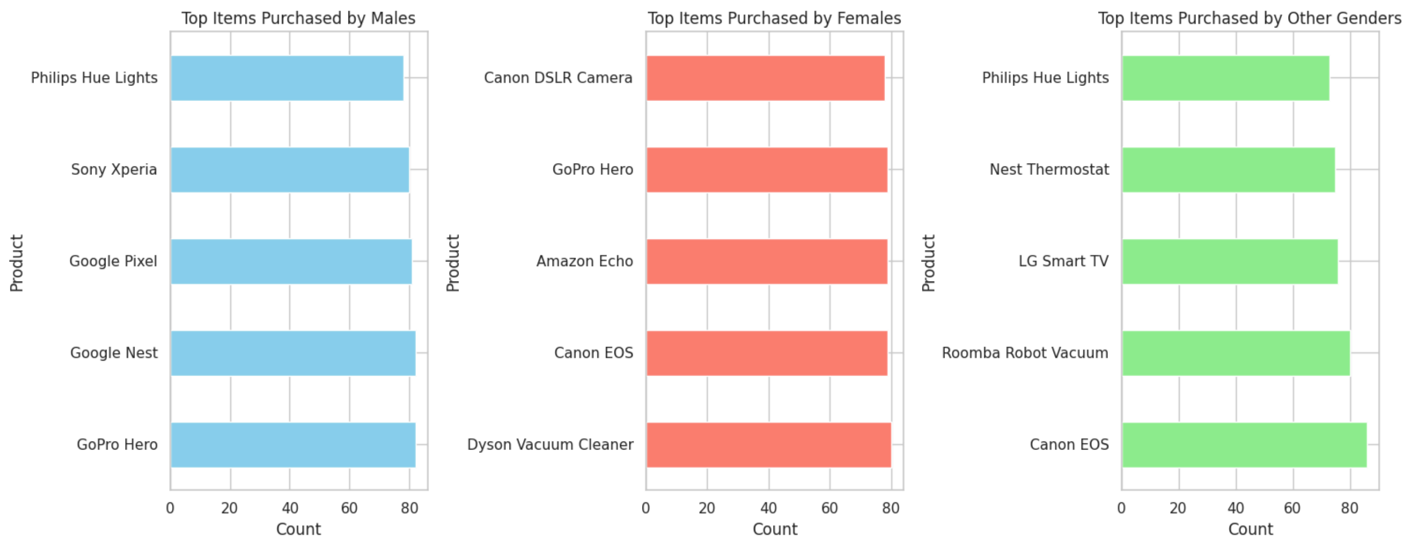
```
plt.ylabel('Product')
plt.show()
```



In [12]:

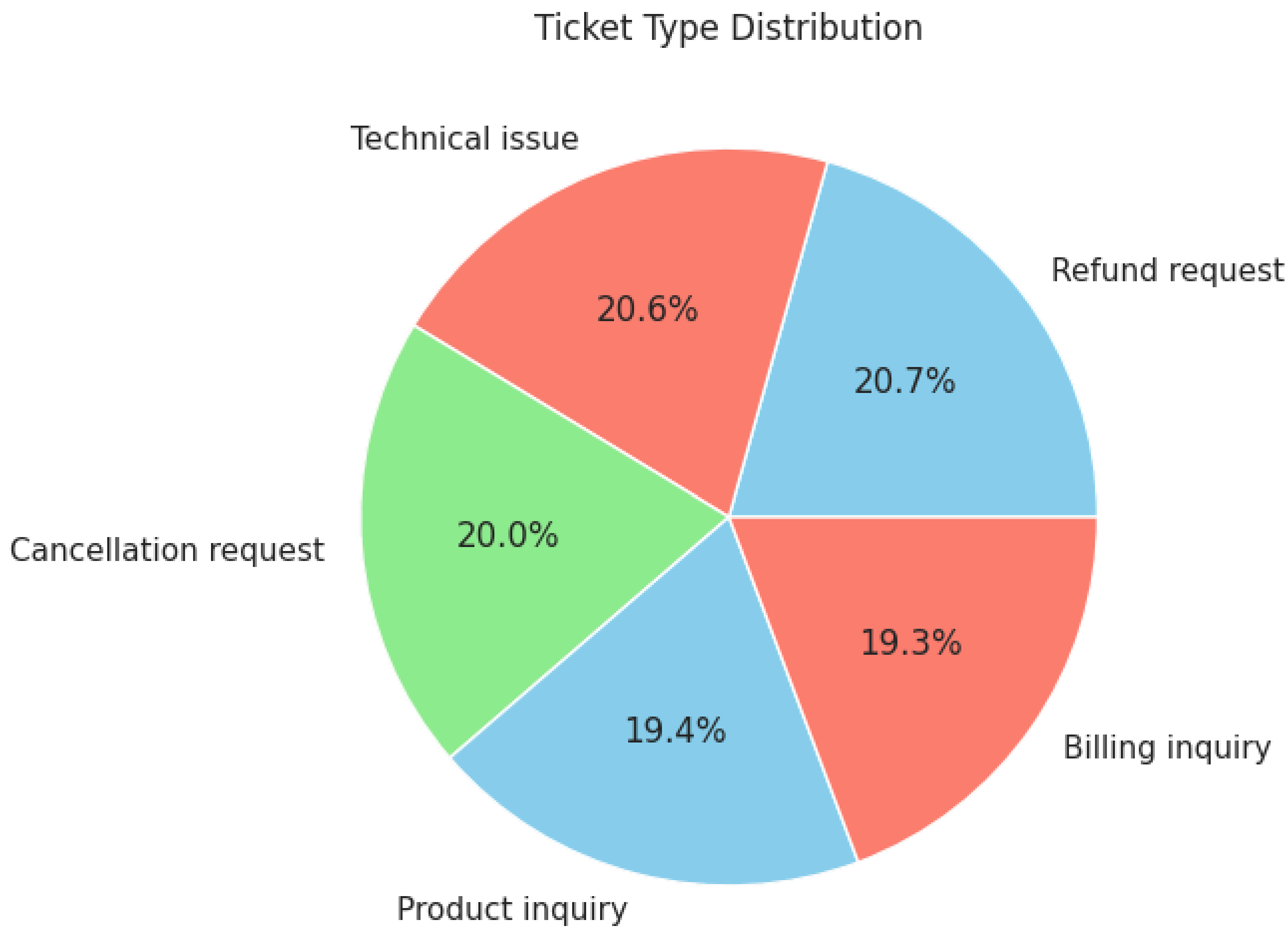
```
# Chart 2: Top Items Purchased by Gender (Horizontal Bar Chart)
plt.figure(figsize=(15, 6))

# Top Items Purchased by Males
plt.subplot(1, 3, 1)
top_items_male = data[data['Customer Gender'] ==
'Male']['Product Purchased'].value_counts().head(5)
top_items_male.plot(kind='barh', color='skyblue')
plt.title('Top Items Purchased by Males')
```

```
plt.xlabel('Count')
plt.ylabel('Product')

# Top Items Purchased by Females
plt.subplot(1, 3, 2)
top_items_female = data[data['Customer Gender'] ==
'Female']['Product Purchased'].value_counts().head(5)
top_items_female.plot(kind='barh', color='salmon')
plt.title('Top Items Purchased by Females')
plt.xlabel('Count')
plt.ylabel('Product')

# Top Items Purchased by Other Gender
plt.subplot(1, 3, 3)
top_items_other = data[data['Customer Gender'] ==
'Other']['Product Purchased'].value_counts().head(5)
top_items_other.plot(kind='barh', color='lightgreen')
plt.title('Top Items Purchased by Other Genders')
plt.xlabel('Count')
plt.ylabel('Product')

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



In [13]:

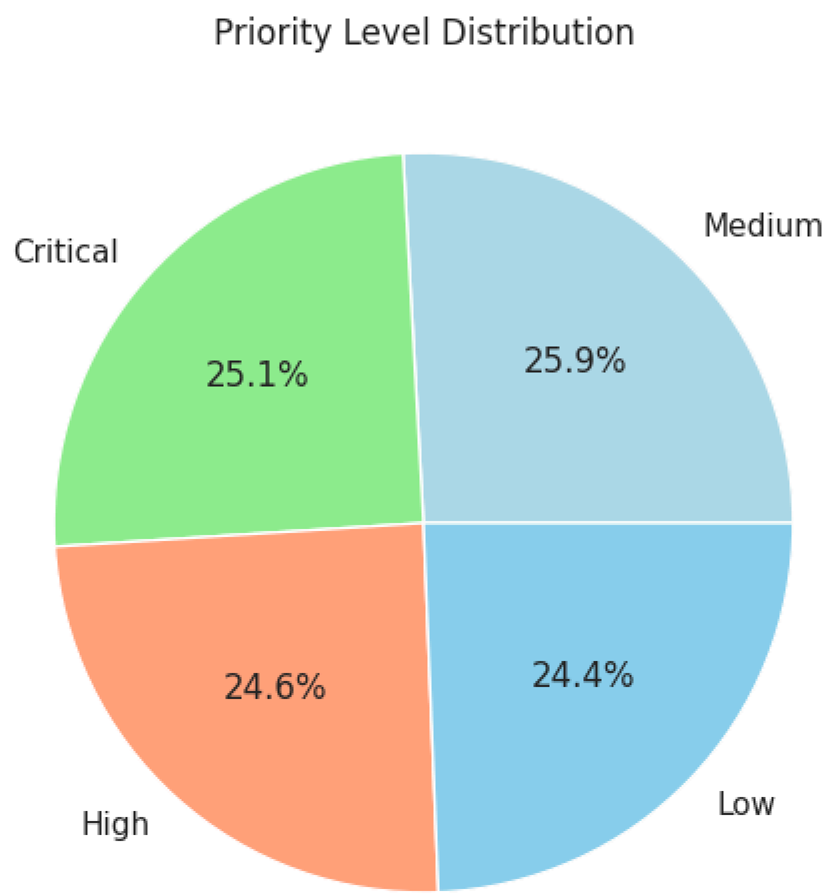
```
# Count ticket types
ticket_type_distribution = data['Ticket Type'].value_counts()

# Plot
plt.figure(figsize=(8, 6))
ticket_type_distribution.plot(kind='pie', autopct='%1.1f%%',
colors=['skyblue', 'salmon', 'lightgreen'])
plt.title('Ticket Type Distribution')
plt.ylabel('')
plt.show()
```



In [14]:

```
# Count ticket priorities
priority_distribution = data['Ticket Priority'].value_counts()

# Plot
plt.figure(figsize=(8, 6))
priority_distribution.plot(kind='pie', autopct='%1.1f%%',
colors=['lightblue', 'lightgreen', 'lightsalmon', 'skyblue'])
plt.title('Priority Level Distribution')
plt.ylabel('')
```

```python
plt.show()
```

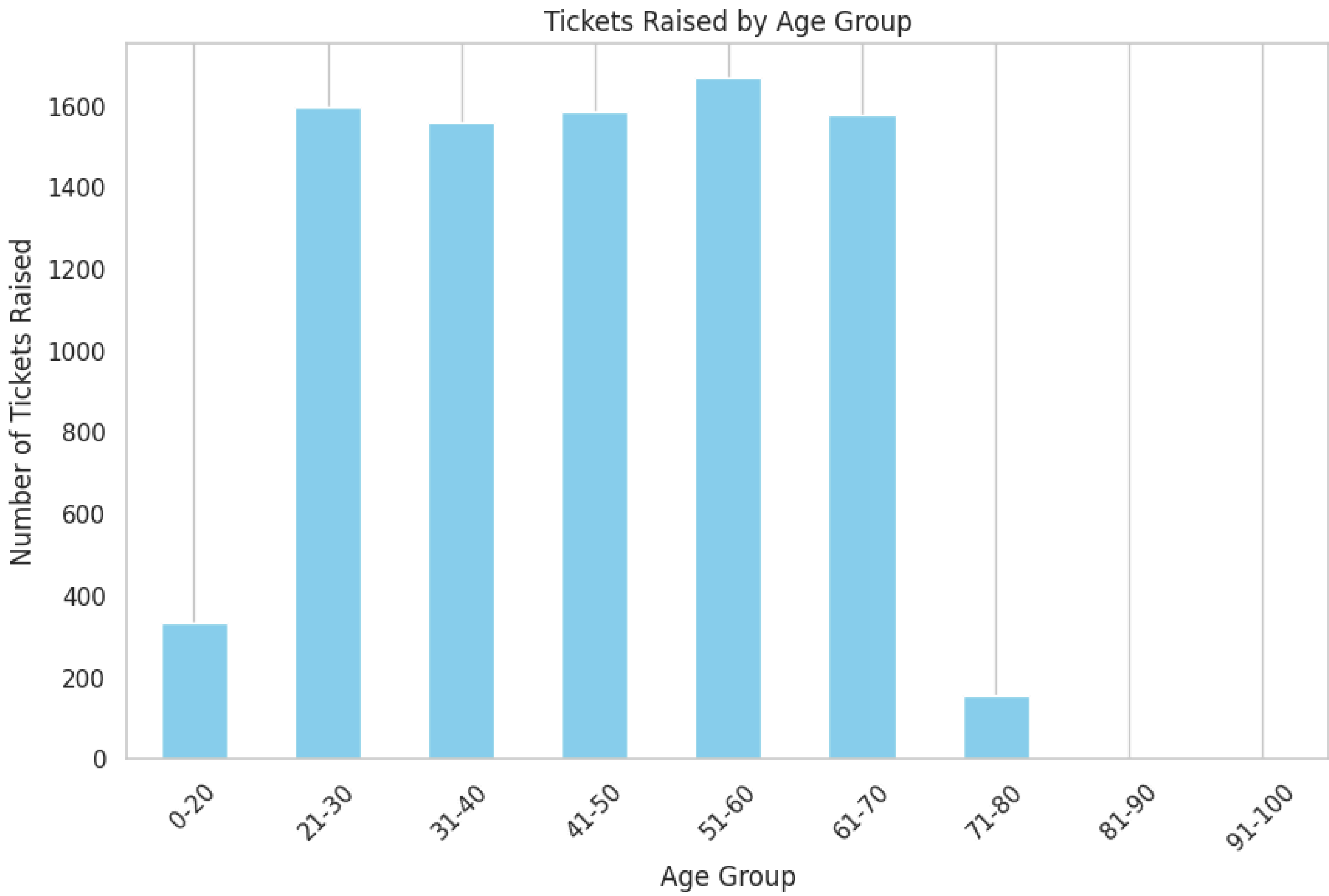


In [15]:

```python
# Define age groups
bins = [0, 20, 30, 40, 50, 60, 70, 80, 90, 100]
labels = ['0-20', '21-30', '31-40', '41-50', '51-60', '61-70',
'71-80', '81-90', '91-100']

# Categorize customers into age groups
```

```python
data['Age Group'] = pd.cut(data['Customer Age'], bins=bins,
labels=labels, right=False)

# Calculate number of tickets raised by each age group
tickets_by_age_group = data.groupby('Age Group').size()

# Plot
plt.figure(figsize=(10, 6))
tickets_by_age_group.plot(kind='bar', color='skyblue')
plt.title('Tickets Raised by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Number of Tickets Raised')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```

```
/tmp/ipykernel_18/91670186.py:9: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a
future version of pandas. Pass observed=False to retain current
behavior or observed=True to adopt the future default and
silence this warning.
  tickets_by_age_group = data.groupby('Age Group').size()
```



In [16]:

linkcode

```
# Replace inf values with NaN
data.replace([np.inf, -np.inf], np.nan, inplace=True)

# Create a facet grid for each ticket type
g = sns.FacetGrid(data, col='Ticket Type', col_wrap=3,
height=5, aspect=1.5)
g.map(sns.histplot, 'Customer Age', bins=20, kde=True)
```

```
# Set titles and labels
g.set_titles('{col_name}')
g.set_axis_labels('Age', 'Number of Tickets')

# Adjust layout
plt.subplots_adjust(top=0.9)
g.fig.suptitle('Distribution of Ticket Types by Age')

# Show plot
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will
be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will
be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will
be removed in a future version. Convert inf values to NaN
```

```
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will
be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:111
9: FutureWarning: use_inf_as_na option is deprecated and will
be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

[Reference link]