Customer Satisfaction Prediction

Project Overview

To develop a predictive model that accurately estimates customer satisfaction levels using historical customer data. The goal is to identify key drivers of satisfaction and proactively address areas of concern to improve customer experience and retention.

Tools Used

Programming Languages : Python, Machine learning

Database: SQL

Spreadsheet Software: Excel

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.

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

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_importan
ces_, 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
```

```
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 Carrollbradleymark@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       CriticalChat 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             LowEmail 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 CountDtype
--- ------                           -------------------
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
```

```
          [2]:
# Print column names
print(data.columns)
```

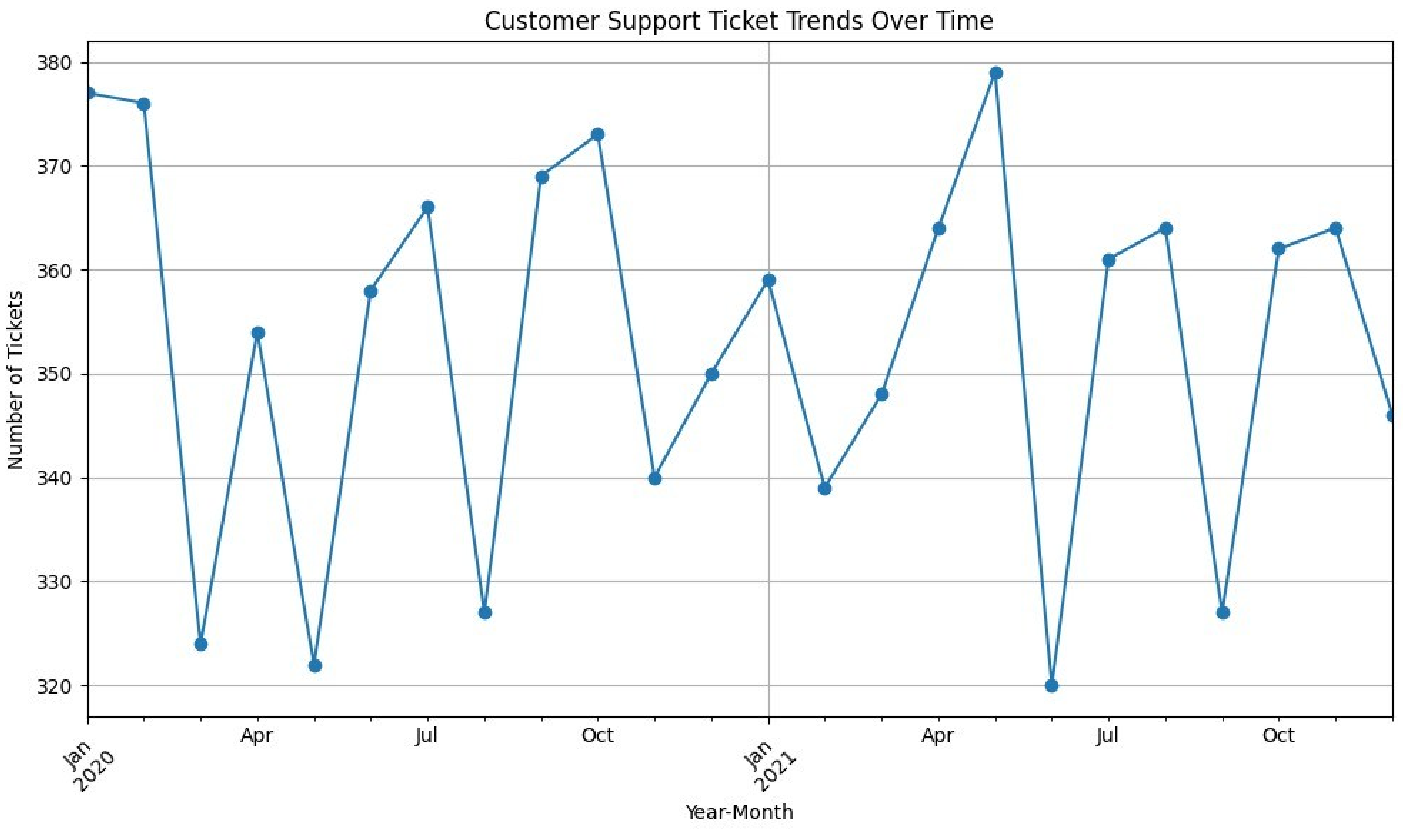
```
Index(['Ticket ID', 'Customer Name', 'Customer Email',
'Customer Age',
       'Customer Gender', 'Product Purchased', 'Date of
Purchase',
       'Ticket Type', 'Ticket Subject', 'Ticket Description',
'Ticket Status',
       'Resolution', 'Ticket Priority', 'Ticket Channel',
       'First Response 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
```



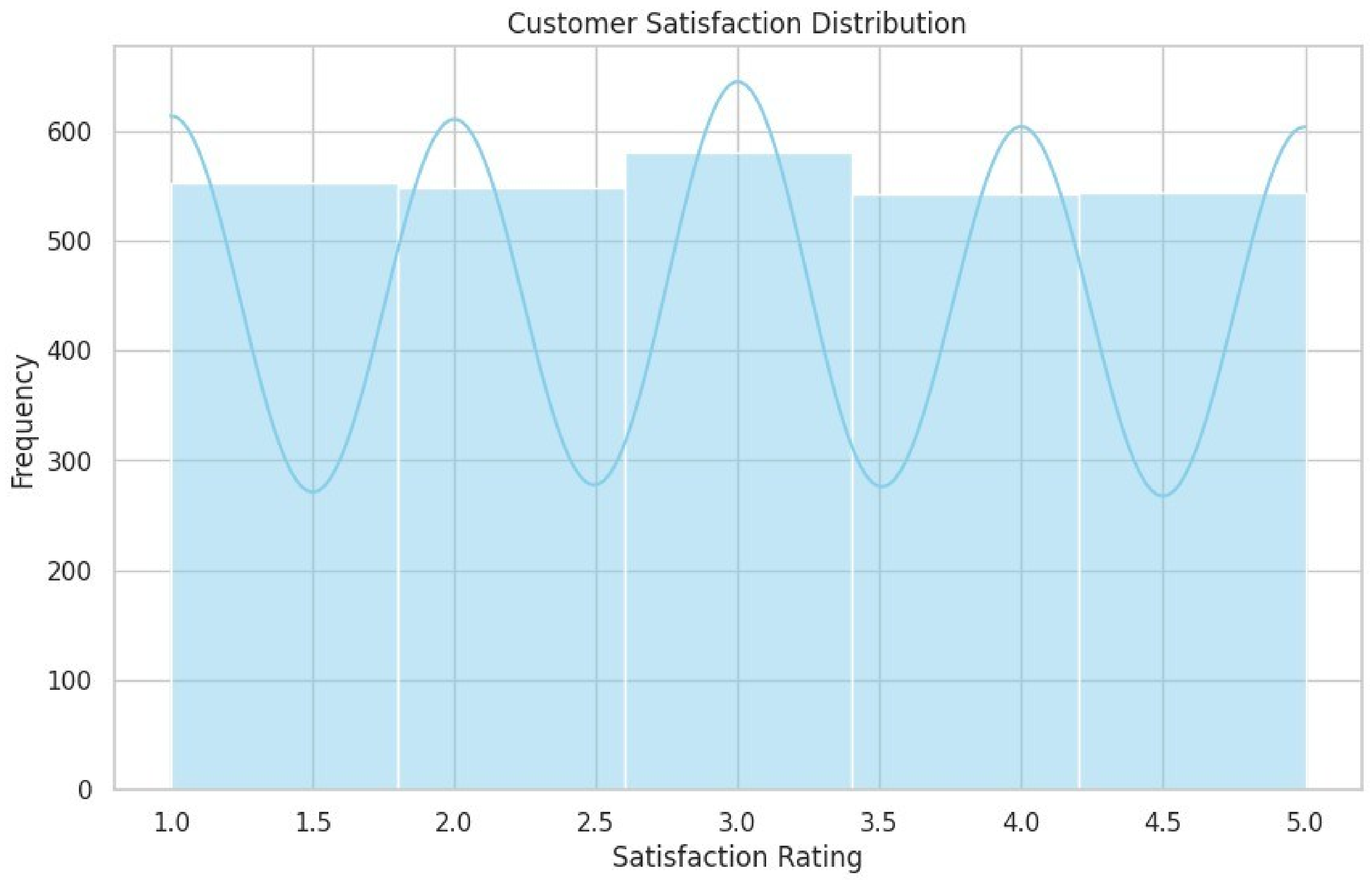
```
In [4]:
# Segment customers
# Segment based on ticket types
ticket_type_segmentation = data.groupby('Ticket Type').size()
print("\nSegmentation based on Ticket Types:")
print(ticket_type_segmentation)
```

```
# Segment based on satisfaction levels

satisfaction_segmentation = data.groupby('Customer

Satisfaction Rating').size() print("\nSegmentation based on

Customer Satisfaction Levels:")

print(satisfaction_segmentation)
```

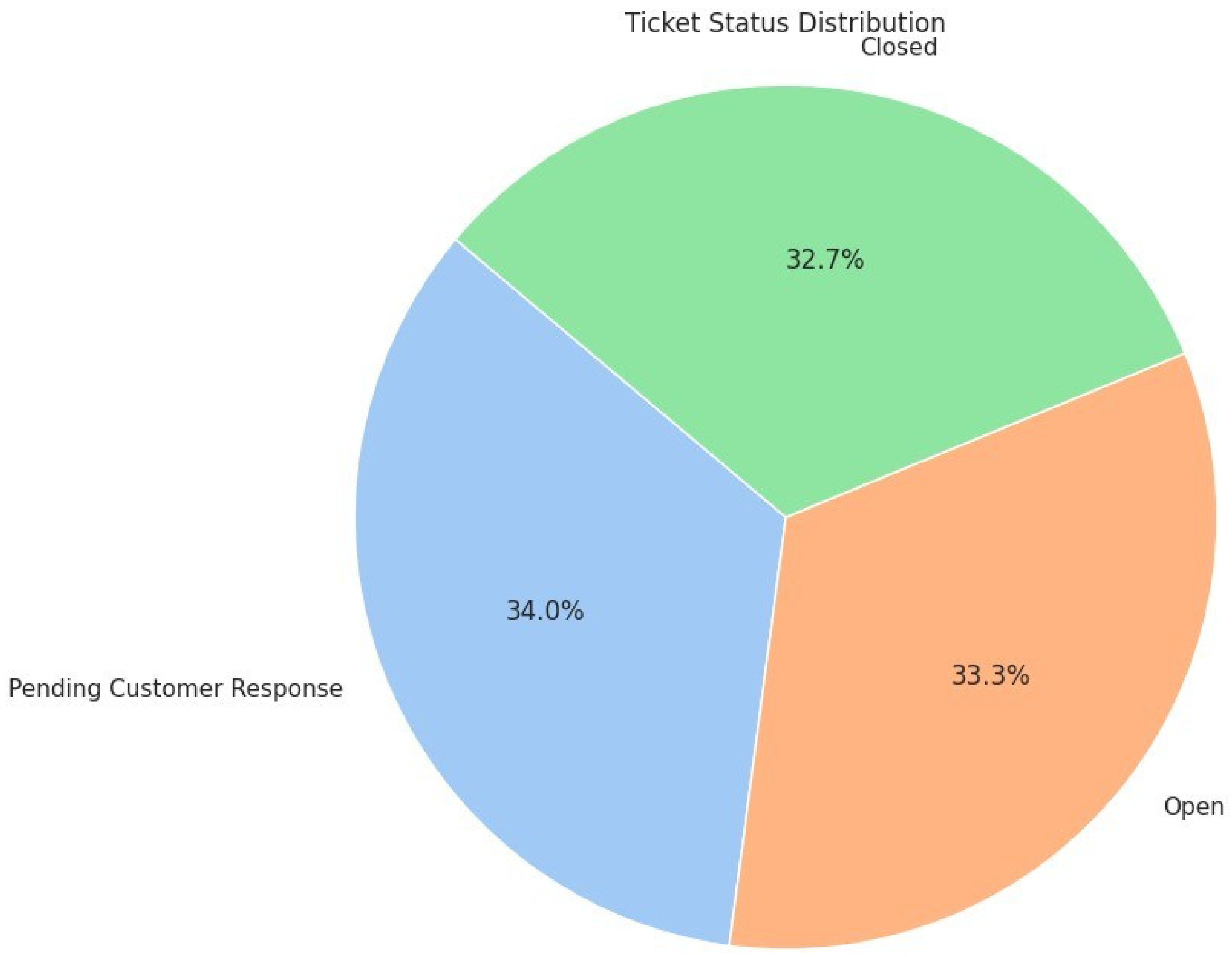
```
Segmentation based on Ticket Types:

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]:
# 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):
```



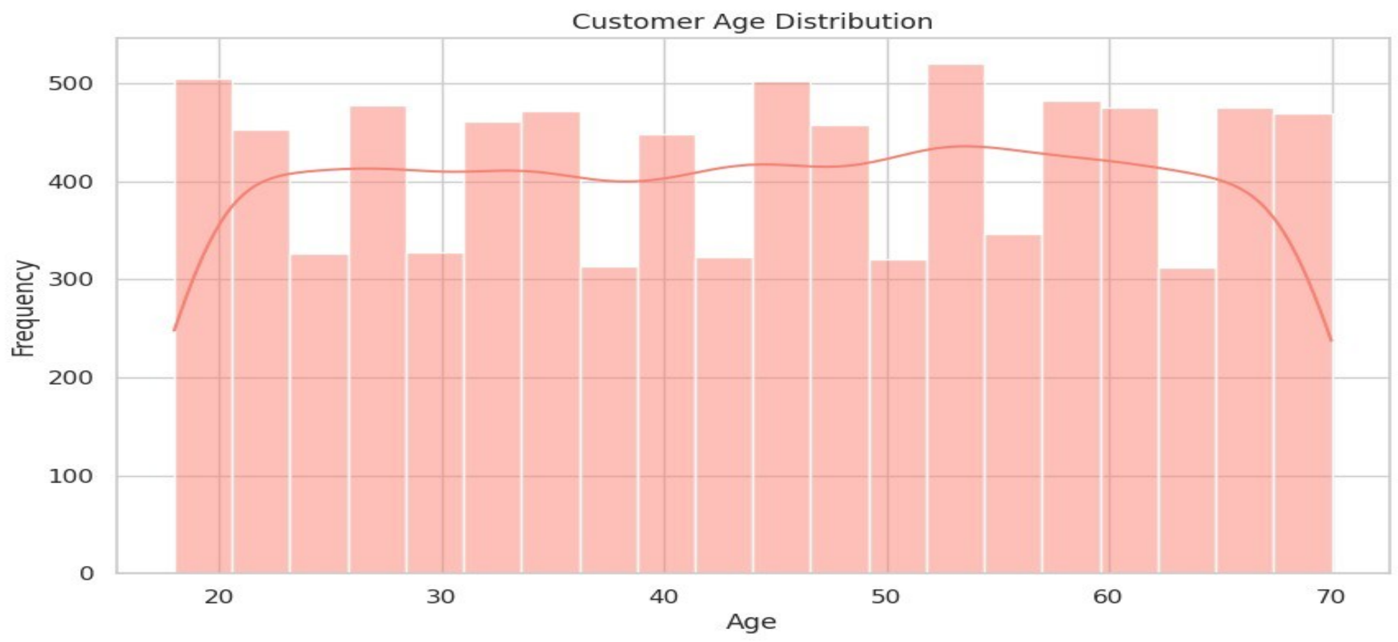
```
In [6]:
#Ticket Status Distribution
ticket_status_distribution = data['Ticket
Status'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(ticket_status_distribution,
labels=ticket_status_distribution.index, autopct='%1.1f%%',
colors=sns.color_palette('pastel'), startangle=140)
plt.title('Ticket Status Distribution')
plt.axis('equal')
plt.show()
```



In [7]:

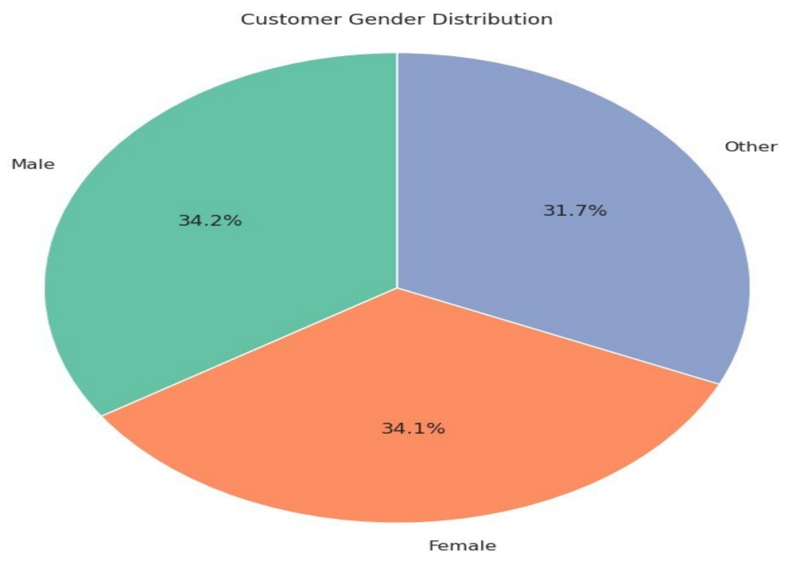
```
#Customer Age Distribution

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: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):
```

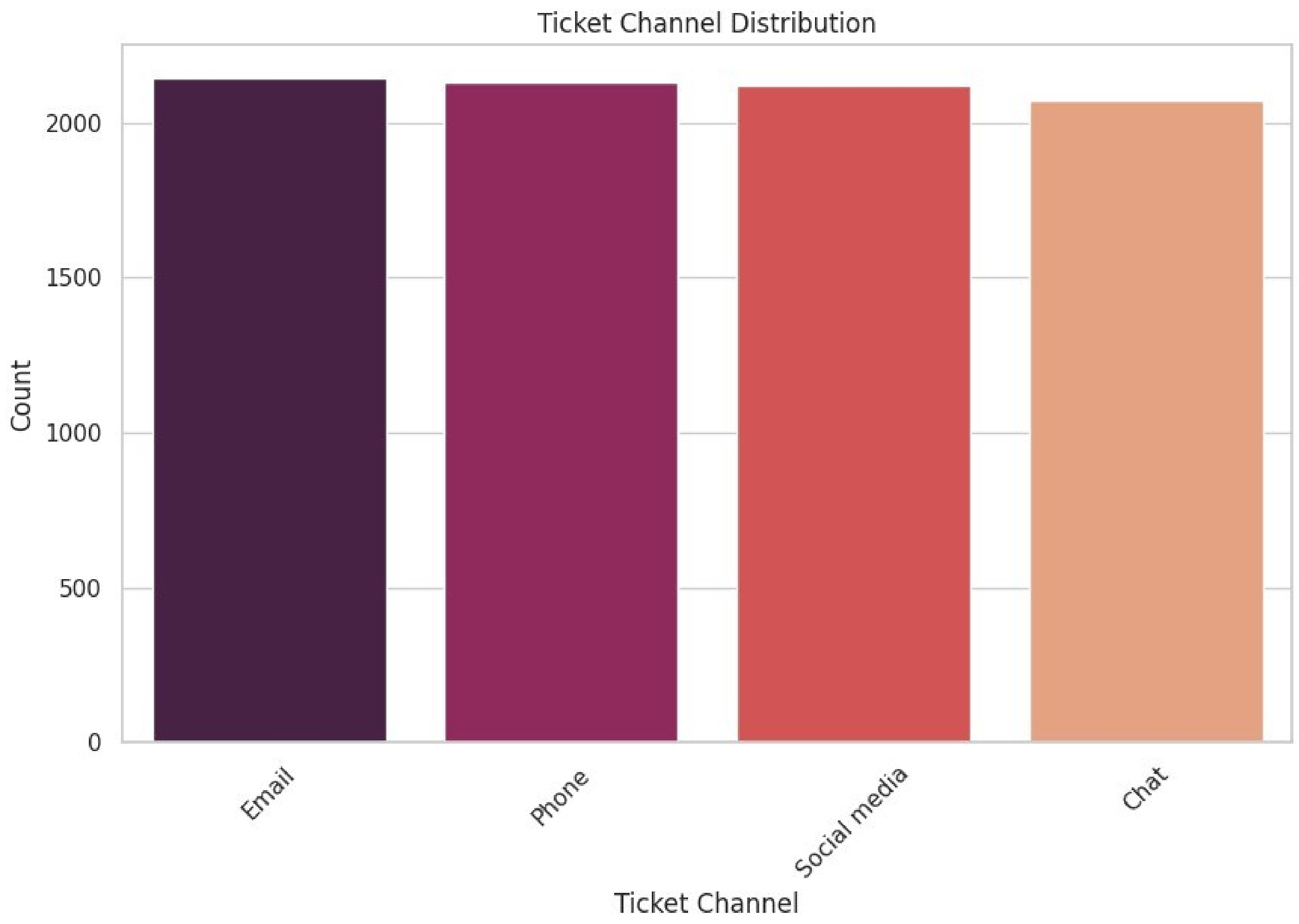


```
In [8]:
```

```
#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()
```

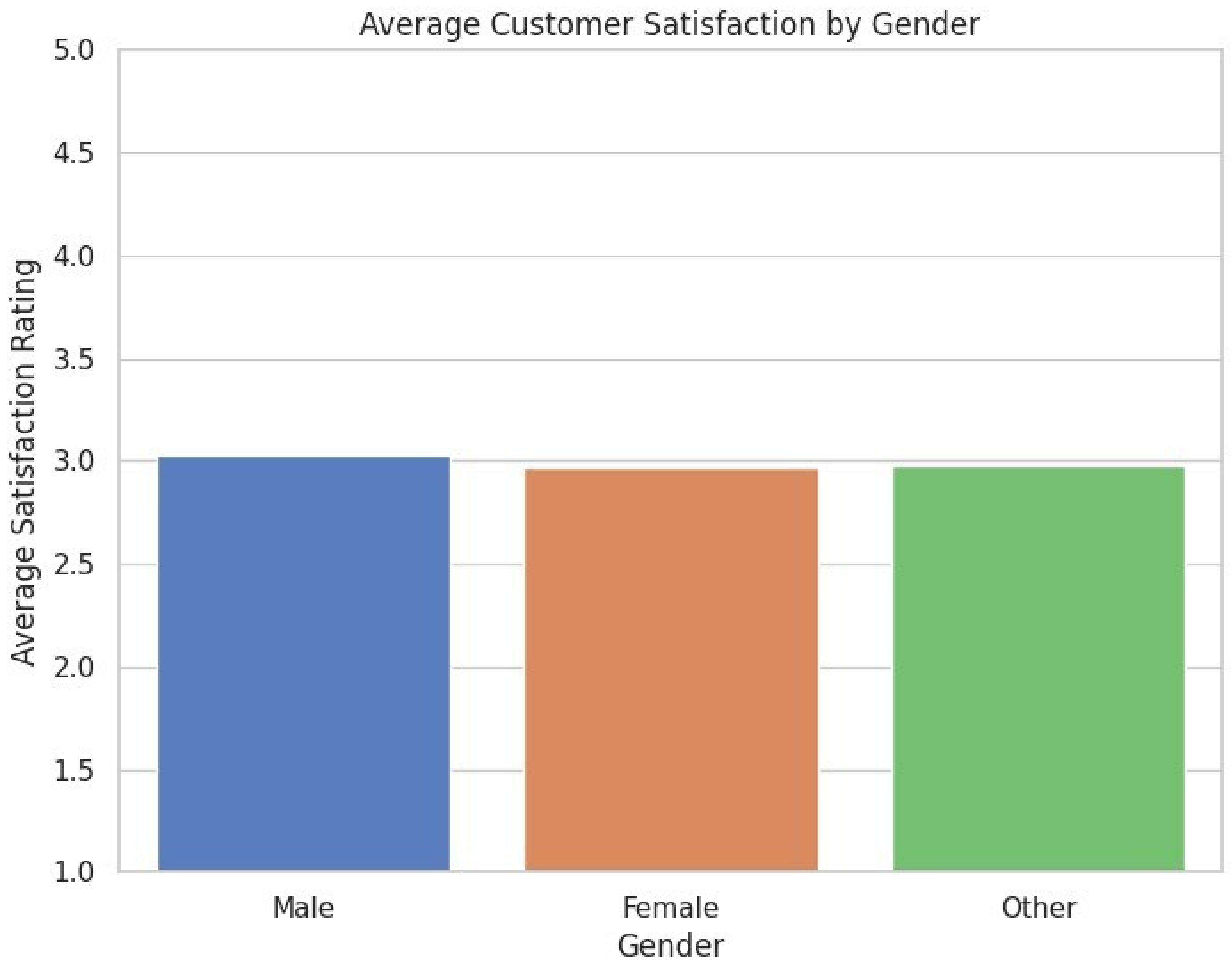


```
In [9]:
#Ticket Channel Distribution
plt.figure(figsize=(10, 6))
ticket_channel_distribution = data['Ticket
Channel'].value_counts()
sns.barplot(x=ticket_channel_distribution.index,
y=ticket_channel_distribution, palette='rocket')
plt.title('Ticket Channel Distribution')
plt.xlabel('Ticket Channel')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```

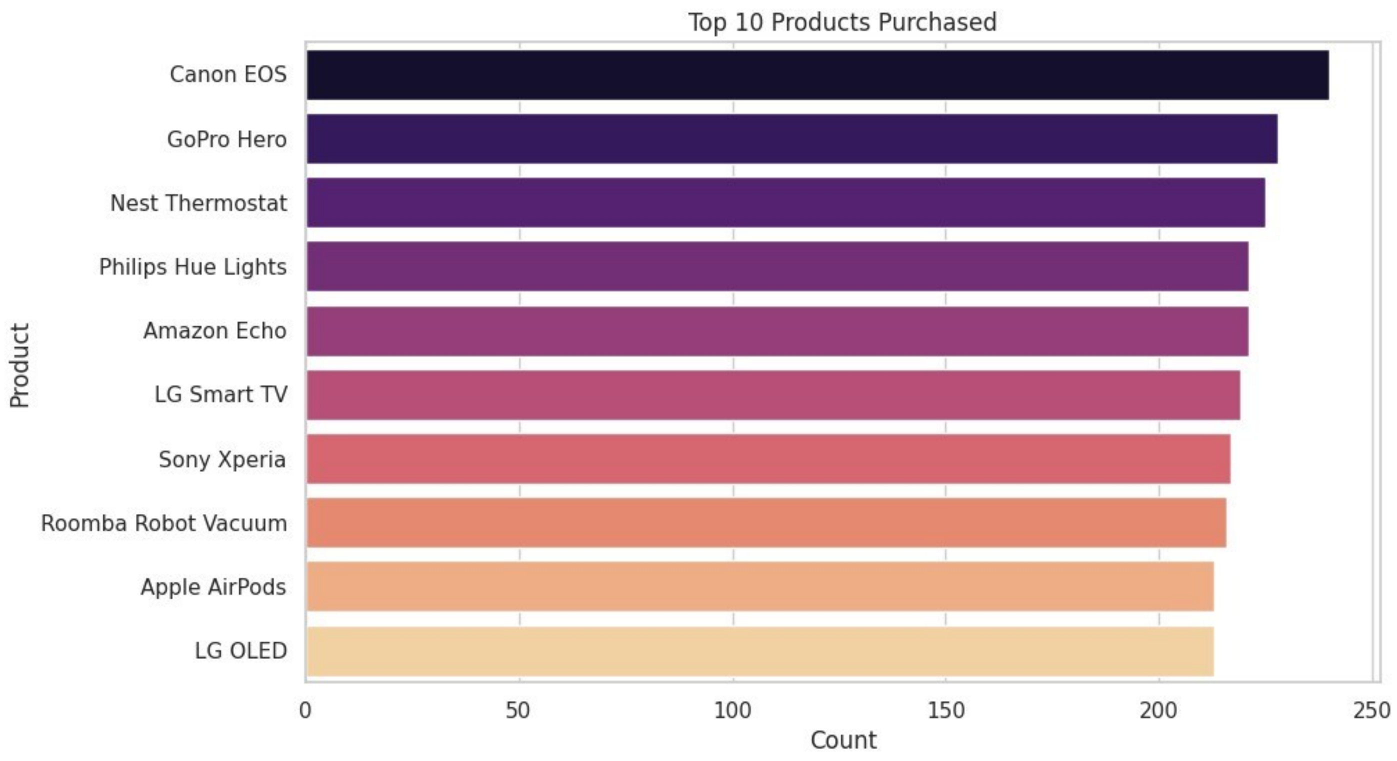


```
In [10]:
# Chart 1: Average Customer Satisfaction by Gender (Bar Plot)
```

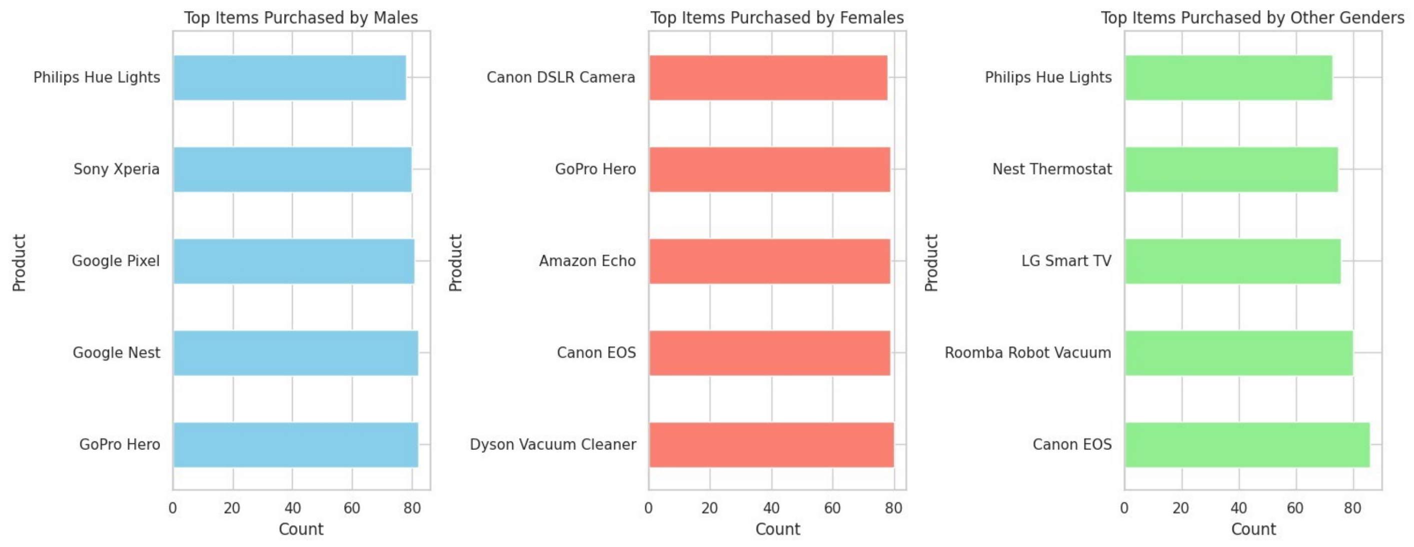
```
average_satisfaction = data.groupby('Customer
Gender')['Customer Satisfaction Rating'].mean().reset_index()


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()
```



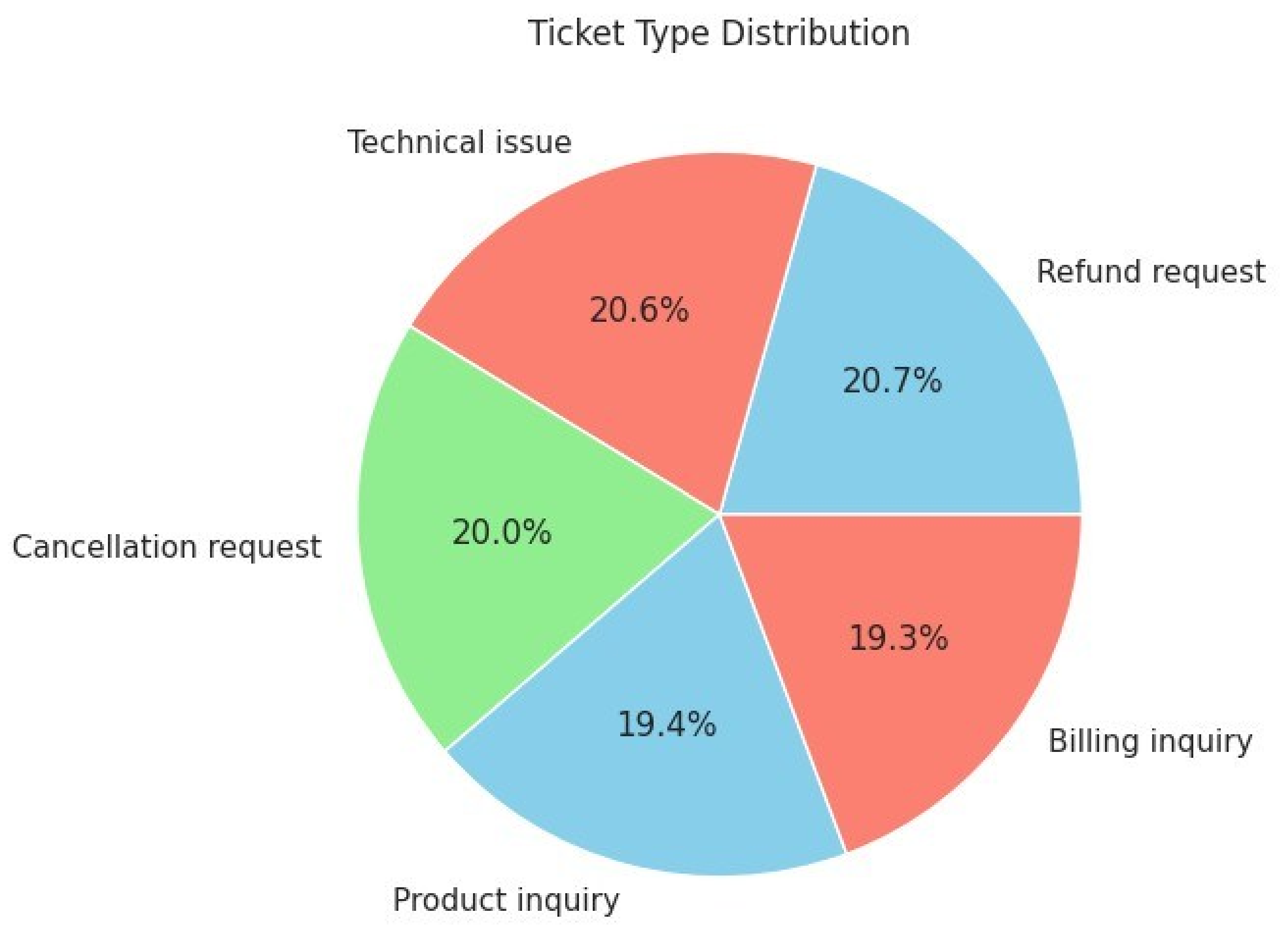
```
In [11]:
#Product Purchased Distribution
plt.figure(figsize=(10, 6))
product_purchased_distribution = data['Product
Purchased'].value_counts().head(10)
sns.barplot(y=product_purchased_distribution.index,
x=product_purchased_distribution, palette='magma')
plt.title('Top 10 Products Purchased')
plt.xlabel('Count')
plt.ylabel('Product')
plt.show()
```



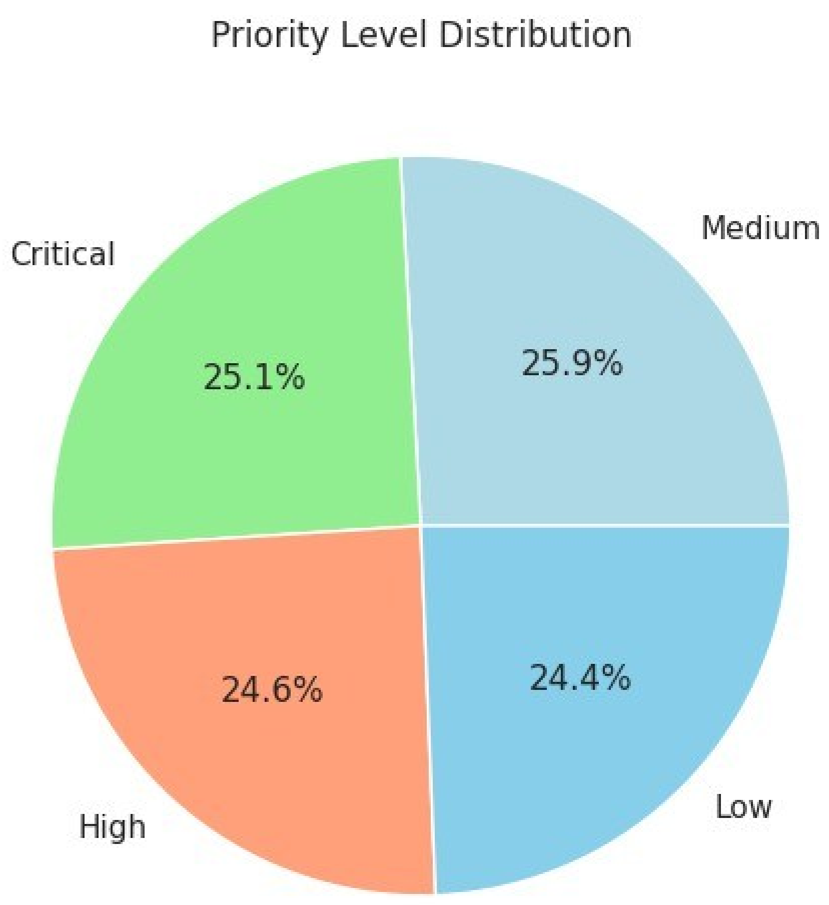
```
In [12]:
# Chart 2: Top Items Purchased by Gender (Horizontal Bar Chart)
plt.figure(figsize=(15, 6))

# 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()
```



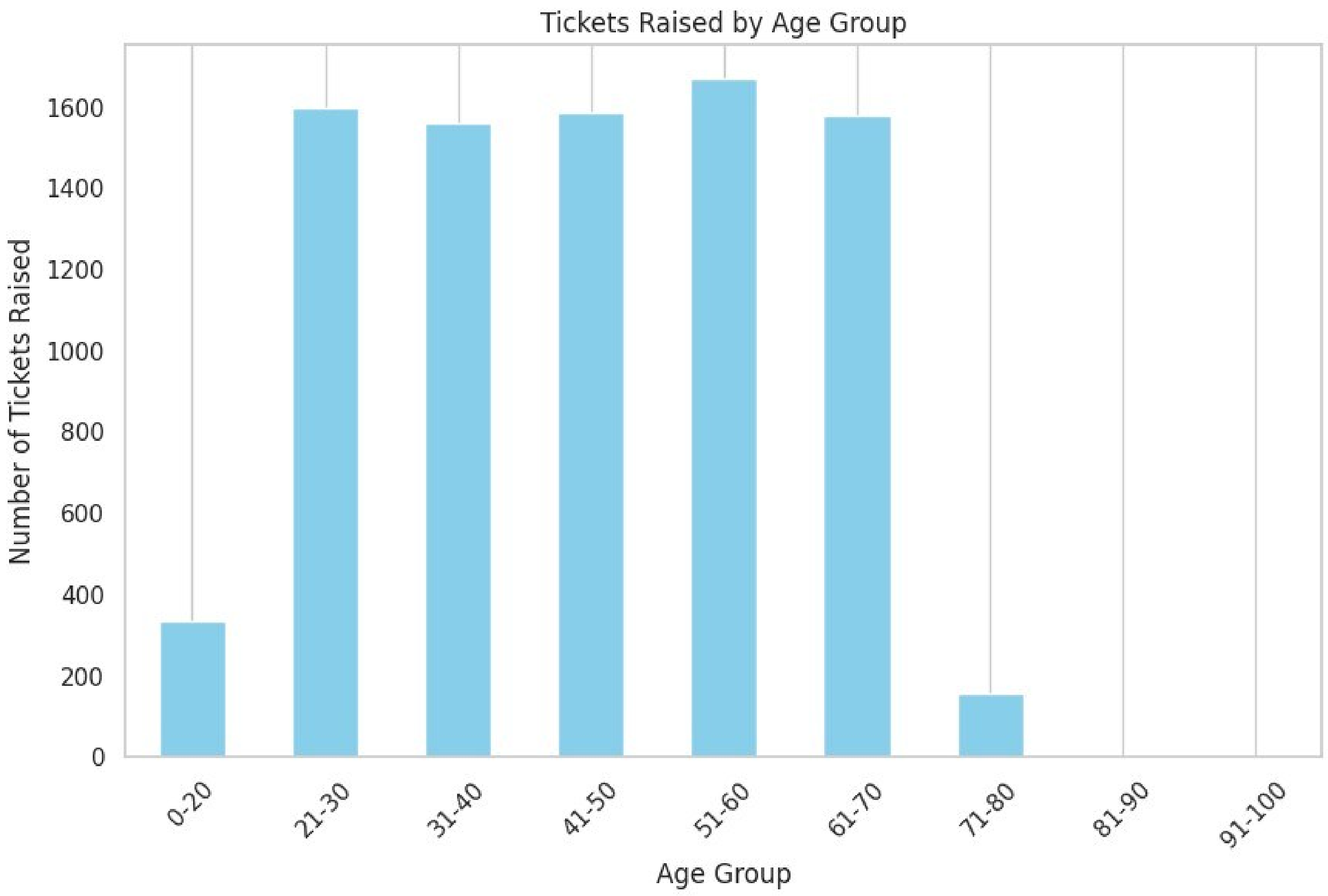
```
In [14]:
# Count ticket priorities
priority_distribution = data['Ticket Priority'].value_counts()


# 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('')
plt.show()
```



```
In [15]:
# 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
```

```
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
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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):
```

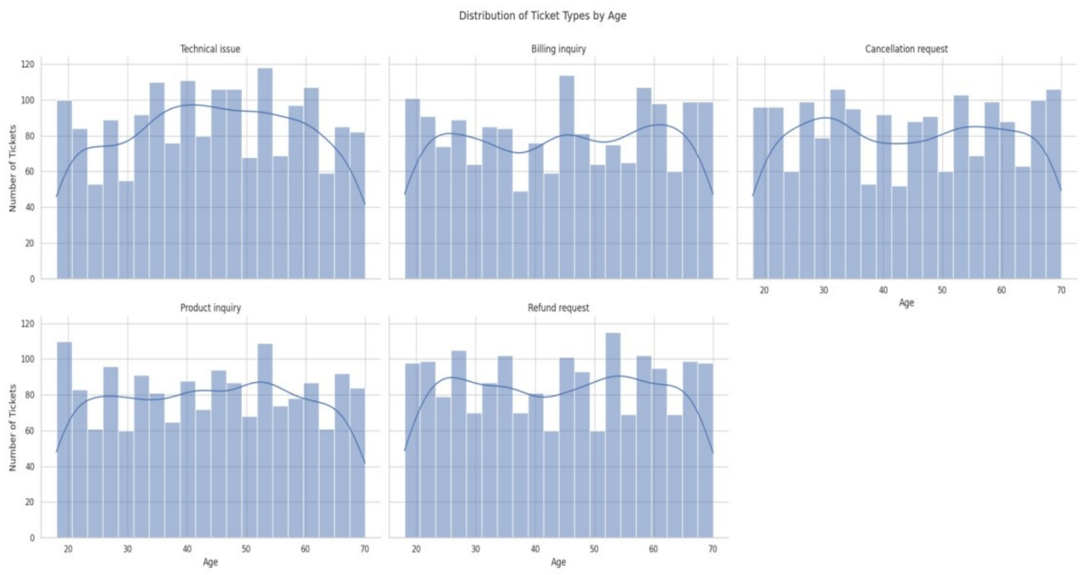
Distribution of Ticket Types by Age
Technical issue
Billing inquiry
Cancellation request
Product inquiry
Refund request
Number of Tickets
Age