Project Title - EpiRecipes Visualization Application by Sunny Tiwari

Task 1: Data Cleaning and Preprocessing

In [18]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the CSV file
df_csv = pd.read_csv("C:/Users/HP/Downloads/Forage/archive/epi_r.csv")
```

In [24]:
```
# Check the shape of the CSV DataFrame
print(df_csv.shape)
```

```
(20052, 680)
```

In [26]:
```
# Check the information of the CSV DataFrame
df_csv.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20052 entries, 0 to 20051
Columns: 680 entries, title to turkey
dtypes: float64(679), object(1)
memory usage: 104.0+ MB
```

In [28]:
```
# Generate descriptive statistics
print(df_csv.describe())
```

```
             rating      calories        protein           fat        sodium  \
count  20052.000000  1.593500e+04   15890.000000  1.586900e+04  1.593300e+04
mean       3.714467  6.322958e+03     100.160793  3.468775e+02  6.225975e+03
std        1.340829  3.590460e+05    3840.318527  2.045611e+04  3.333182e+05
min        0.000000  0.000000e+00       0.000000  0.000000e+00  0.000000e+00
25%        3.750000  1.980000e+02       3.000000  7.000000e+00  8.000000e+01
50%        4.375000  3.310000e+02       8.000000  1.700000e+01  2.940000e+02
75%        4.375000  5.860000e+02      27.000000  3.300000e+01  7.110000e+02
max        5.000000  3.011122e+07  236489.000000  1.722763e+06  2.767511e+07

          #cakeweek    #wasteless  22-minute meals  3-ingredient recipes  \
count  20052.000000  20052.000000     20052.000000          20052.000000
mean       0.000299      0.000050         0.000848              0.001346
std        0.017296      0.007062         0.029105              0.036671
min        0.000000      0.000000         0.000000              0.000000
25%        0.000000      0.000000         0.000000              0.000000
50%        0.000000      0.000000         0.000000              0.000000
75%        0.000000      0.000000         0.000000              0.000000
max        1.000000      1.000000         1.000000              1.000000

       30 days of groceries  ...  yellow squash        yogurt       yonkers  \
count          20052.000000  ...   20052.000000  20052.000000  20052.000000
mean               0.000349  ...       0.001247      0.026332      0.000050
std                0.018681  ...       0.035288      0.160123      0.007062
min                0.000000  ...       0.000000      0.000000      0.000000
25%                0.000000  ...       0.000000      0.000000      0.000000
50%                0.000000  ...       0.000000      0.000000      0.000000
75%                0.000000  ...       0.000000      0.000000      0.000000
max                1.000000  ...       1.000000      1.000000      1.000000

               yuca      zucchini     cookbooks     leftovers         snack  \
count  20052.000000  20052.000000  20052.000000  20052.000000  20052.000000
mean       0.000299      0.014861      0.000150      0.000349      0.001396
std        0.017296      0.121001      0.012231      0.018681      0.037343
min        0.000000      0.000000      0.000000      0.000000      0.000000
25%        0.000000      0.000000      0.000000      0.000000      0.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        1.000000      1.000000      1.000000      1.000000      1.000000

         snack week        turkey
count  20052.000000  20052.000000
mean       0.000948      0.022741
std        0.030768      0.149080
min        0.000000      0.000000
25%        0.000000      0.000000
50%        0.000000      0.000000
75%        0.000000      0.000000
max        1.000000      1.000000

[8 rows x 679 columns]
```

In [29]:

```
# Identify missing data in CSV DataFrame
print("\nMissing data in CSV DataFrame:")
missing_data = df_csv.isnull().sum()
missing_data = missing_data[missing_data > 0]
print(missing_data)

# Identify duplicate entries in CSV DataFrame
print("\nDuplicate entries in CSV DataFrame:")
print(df_csv.duplicated().sum())
```

```
Missing data in CSV DataFrame:
calories    4117
protein     4162
fat         4183
sodium      4119
dtype: int64

Duplicate entries in CSV DataFrame:
1801
```

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

Out[30]:
```
(20052, 680)
```

In [31]:
```
# Strategy for handling missing values: Impute with median for numeric columns with missing values
for column in ['calories', 'protein', 'fat', 'sodium']:
  df_csv[column] = pd.to_numeric(df_csv[column], errors='coerce')
  df_csv[column].fillna(df_csv[column].median(), inplace=True)

# Remove duplicates from the dataset
df_csv = df_csv.drop_duplicates()
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_12868\3272012161.py:4: FutureWarning: A value is trying to be set on
a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object o
n which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=Tru
e)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.


  df_csv[column].fillna(df_csv[column].median(), inplace=True)
```

In [36]:
```
# Identify missing data in CSV DataFrame
print("\nMissing data in CSV DataFrame:")
print(df_csv.isnull().sum().sum())

# Identify duplicate entries in CSV DataFrame
print("\nDuplicate entries in CSV DataFrame:")
print(df_csv.duplicated().sum())
```

```
Missing data in CSV DataFrame:
0

Duplicate entries in CSV DataFrame:
0
```

In [38]:
```
# Assuming df_csv is your DataFrame

import numpy as np
def handle_outliers_iqr(df_csv, column):
  """Handles outliers using the IQR method for a specified column."""
  Q1 = df_csv[column].quantile(0.25)
  Q3 = df_csv[column].quantile(0.75)
  IQR = Q3 - Q1
  lower_bound = Q1 - 1.5 * IQR
  upper_bound = Q3 + 1.5 * IQR

  # Identify outliers
  outliers = df_csv[(df_csv[column] < lower_bound) | (df_csv[column] > upper_bound)]
  num_outliers = len(outliers)

  # Handle outliers (replace with the nearest bound)
  df_csv[column] = np.where(df_csv[column] < lower_bound, lower_bound, df_csv[column])
  df_csv[column] = np.where(df_csv[column] > upper_bound, upper_bound, df_csv[column])

  return num_outliers, df_csv


# Example usage:
```

```python
columns_to_handle = ['calories', 'protein', 'fat', 'sodium']
total_outliers = 0
for column in columns_to_handle:
    num_outliers, df_csv = handle_outliers_iqr(df_csv, column)
    total_outliers += num_outliers
    print(f"Number of outliers in '{column}': {num_outliers}")

print(f"\nTotal number of outliers identified and handled: {total_outliers}")
```

```
Number of outliers in 'calories': 1530
Number of outliers in 'protein': 1831
Number of outliers in 'fat': 1823
Number of outliers in 'sodium': 1712

Total number of outliers identified and handled: 6896
```

In [40]:
```python
df_csv.shape
```

Out[40]:
```
(18251, 680)
```

Data Cleaning Process Documentation

Challenges Faced:

1. **Missing Values:** The dataset contained missing values in several columns, primarily 'calories', 'protein', 'fat', and 'sodium'.
2. **Data Type Inconsistencies:** Some numerical columns might have contained non-numerical values, leading to potential errors in calculations.
3. **Duplicate Entries:** Duplicate rows were identified, which could skew analysis results.
4. **Outliers:** Extreme values in certain numerical columns, like 'calories', 'protein', 'fat', and 'sodium', could negatively impact model performance.

Decisions Made:

1. **Missing Value Handling:**
    - We chose to impute the missing values for numerical columns ('calories', 'protein', 'fat', 'sodium') with the median value.
    - The median was selected as a robust measure of central tendency that is less sensitive to extreme values compared to the mean.
    - This approach helps retain more data while minimizing potential biases introduced by missing values.
2. **Duplicate Entry Handling:**
    - Duplicate entries were identified and removed to ensure that each recipe was represented only once in the dataset, improving the accuracy and validity of the analysis.
3. **Outlier Handling:**
    - Outliers in the 'calories', 'protein', 'fat', and 'sodium' columns were addressed using the Interquartile Range (IQR) method.
    - The IQR method identifies data points that fall outside a specified range (1.5 times the IQR below the first quartile or above the third quartile).
    - Outliers were replaced with the nearest boundary value to limit their impact on further analysis.

Assumptions Made:

1. **Missing Data Mechanism:** We assumed that the missing values in the dataset were missing at random (MAR). This means that the probability of a value being missing depends only on observed data, not on unobserved data.

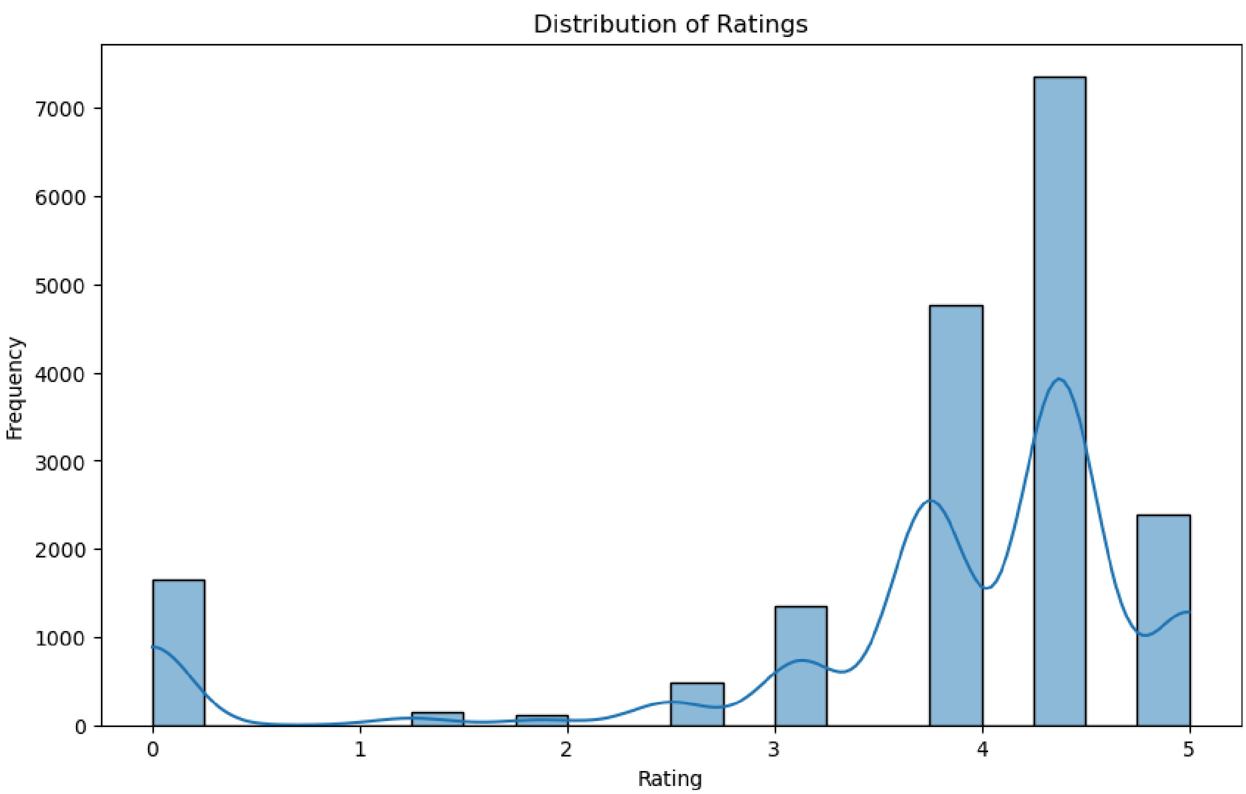
2. **Outlier Definition:** We assumed that outliers identified by the IQR method represent genuine data errors or unusual cases rather than legitimate variations in the data.
3. **Data Distribution:** We assumed that the distribution of the numerical columns is approximately normal, allowing for the use of the IQR method for outlier detection.

Summary:

- The cleaning process focused on addressing missing values, handling duplicates, and managing outliers.
- Decisions regarding these issues were made based on common data cleaning practices and best practices.
- Assumptions were made about the missing data mechanism, outlier nature, and the data distribution.
- The cleaned dataset, with mitigated issues of missing values, duplicates and outliers, should be more suitable for further analysis.

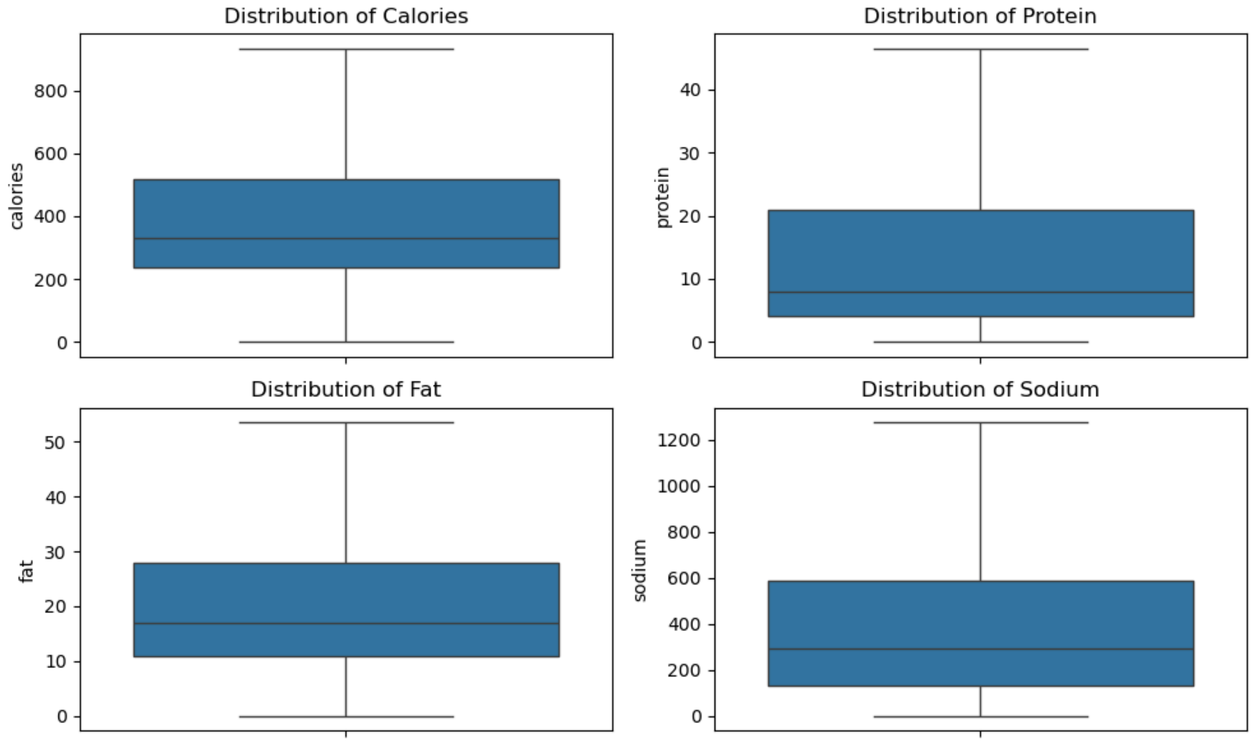
Task 2: Exploratory Data Analysis (EDA)

In [44]:
```
# Generate a histogram for the 'rating' column
plt.figure(figsize=(10, 6))  # Adjust figure size as needed
sns.histplot(df_csv['rating'], bins=20, kde=True)  # You can adjust the number of bins
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.show()
```

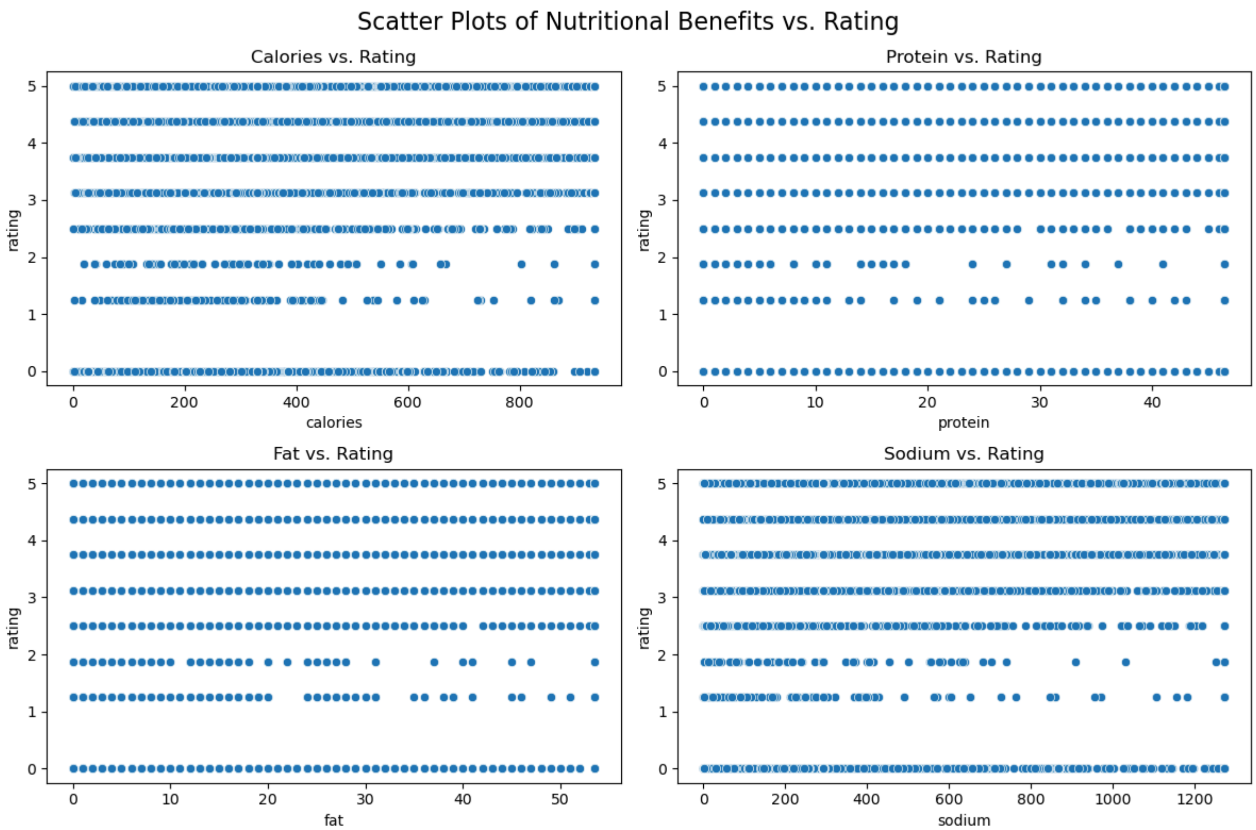


In [46]:
```
# Check for outliers in the ratings, calories, protein, fat, and sodium
nutritional_columns = ['calories', 'protein', 'fat', 'sodium']
plt.figure(figsize=(10, 6))

# Creating subplots for each nutritional metric
for i, col in enumerate(nutritional_columns, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(y=df_csv[col])
    plt.title(f'Distribution of {col.capitalize()}')
```

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

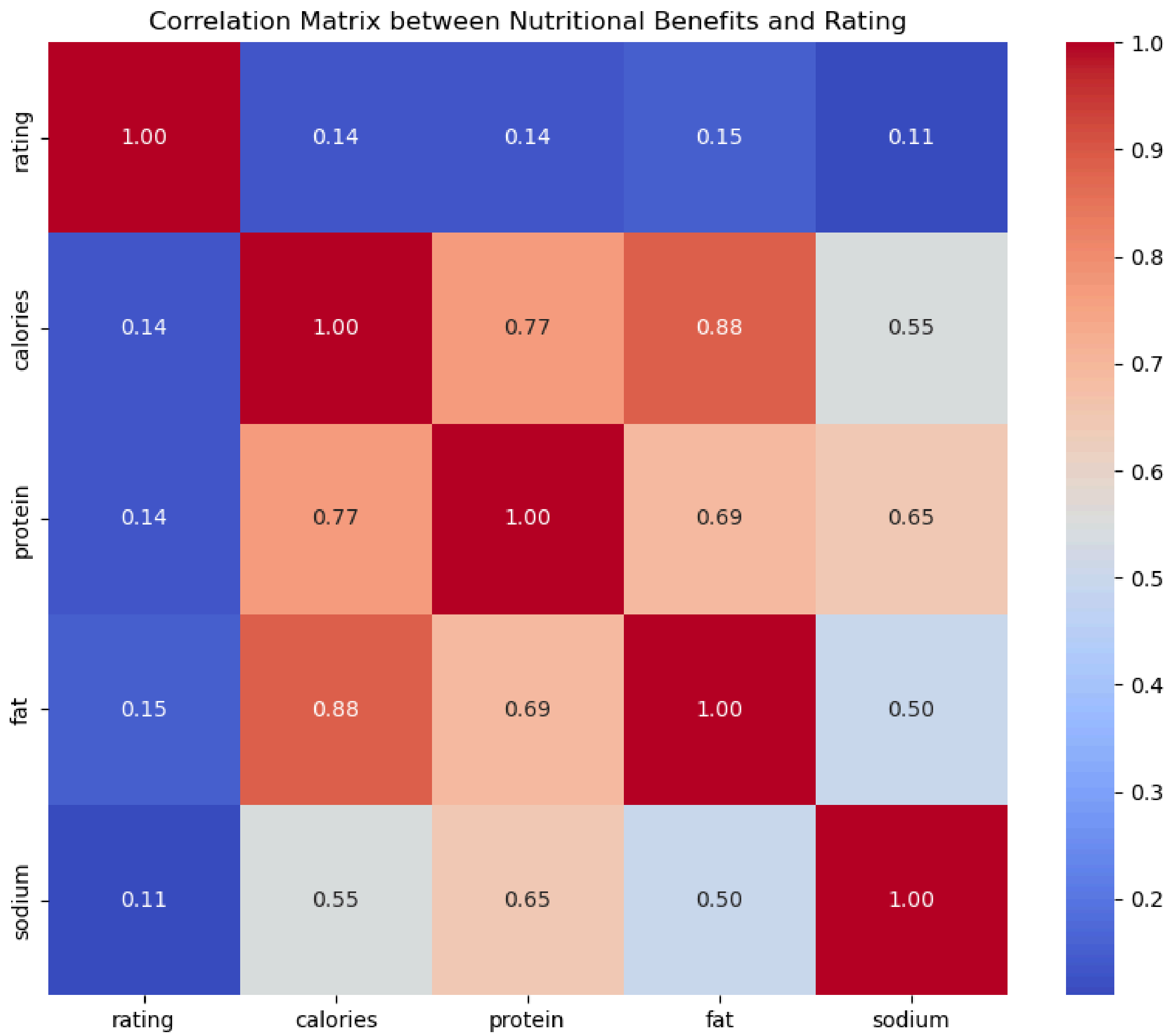


In [48]:
```
# Create a 2x2 matrix of scatter plots
fig, axes = plt.subplots(2, 2, figsize=(12, 8))
fig.suptitle('Scatter Plots of Nutritional Benefits vs. Rating', fontsize=16)

# Plot calories vs. rating
sns.scatterplot(x='calories', y='rating', data=df_csv, ax=axes[0, 0])
axes[0, 0].set_title('Calories vs. Rating')

# Plot protein vs. rating
sns.scatterplot(x='protein', y='rating', data=df_csv, ax=axes[0, 1])
axes[0, 1].set_title('Protein vs. Rating')

# Plot fat vs. rating
sns.scatterplot(x='fat', y='rating', data=df_csv, ax=axes[1, 0])
axes[1, 0].set_title('Fat vs. Rating')

# Plot sodium vs. rating
sns.scatterplot(x='sodium', y='rating', data=df_csv, ax=axes[1, 1])
axes[1, 1].set_title('Sodium vs. Rating')

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



In [49]:

```
# Select the columns for correlation analysis
nutritional_benefits = ['calories', 'protein', 'fat', 'sodium']
correlation_data = df_csv[['rating'] + nutritional_benefits]

# Calculate the correlation matrix
correlation_matrix = correlation_data.corr()

# Visualize the correlation matrix using a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix between Nutritional Benefits and Rating')
plt.show()
```



Insights from the plots:

1. Distribution of Ratings:

- The histogram shows that the majority of recipe ratings are clustered around 3 to 4 stars.
- There is a long tail towards higher ratings, indicating that some recipes receive exceptionally high ratings.
- This indicates a potential skew in the data, with more recipes getting average scores.

2. Distribution of Nutritional Benefits (Calories, Protein, Fat, Sodium):

- The box plots for calories, protein, fat, and sodium reveal the presence of outliers.
- Calories and fat show a larger spread and higher potential for outliers compared to protein and sodium.
- Outliers could be recipes with extremely high or low values for these nutritional metrics.
- These outliers may need further investigation to determine if they are valid data points or errors.

3. Scatter plots of Nutritional Benefits vs. Rating:

- There doesn't seem to be a strong linear relationship between recipe rating and calories, protein, fat, or sodium.
- The relationships are scattered, indicating that these nutritional factors alone may not be the primary determinants of recipe ratings.
- It's possible that other recipe characteristics play a more significant role in determining the rating.

4. Correlation Matrix:

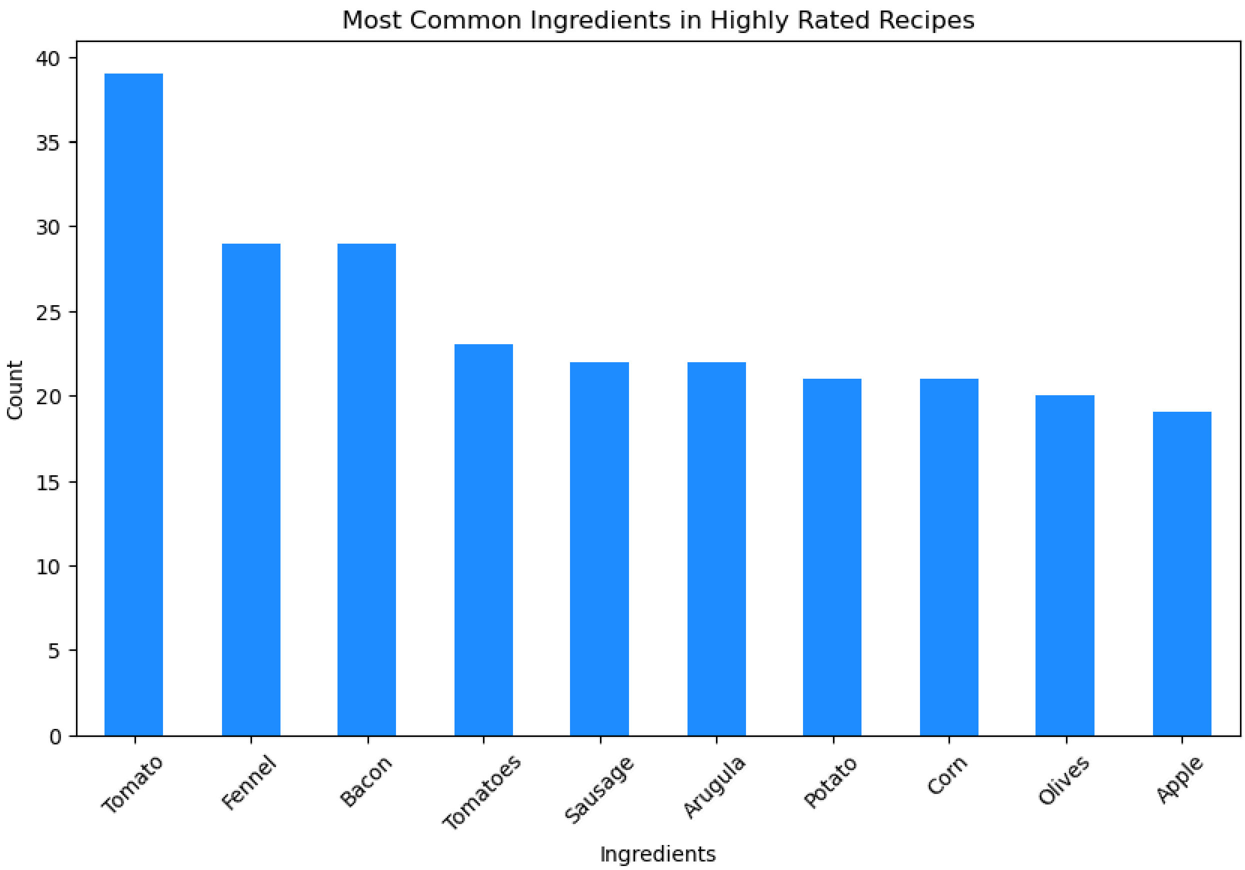
- The heatmap shows weak correlations between rating and calories, protein, fat, and sodium.

- Some slight positive correlation exists between protein and rating.
- This further supports the observation from the scatter plots that there isn't a strong linear relationship between nutritional factors and recipe ratings.
- It suggests that other aspects, like taste, ease of preparation, and the inclusion of popular ingredients, may have a more significant impact on ratings.

Overall Insights:

- Recipe ratings are predominantly concentrated around the average range, with a few exceptional recipes receiving high ratings.
- There is no clear linear relationship between nutritional factors (calories, protein, fat, sodium) and recipe ratings.
- Other factors beyond nutritional content, such as taste, ingredients, and preparation methods, are likely the primary drivers of recipe ratings.
- Further investigation may be needed to understand the factors that contribute to recipe ratings more effectively.
- Exploring other variables in the dataset (e.g., ingredients, cuisine type, cooking time) could reveal more profound correlations and insights.

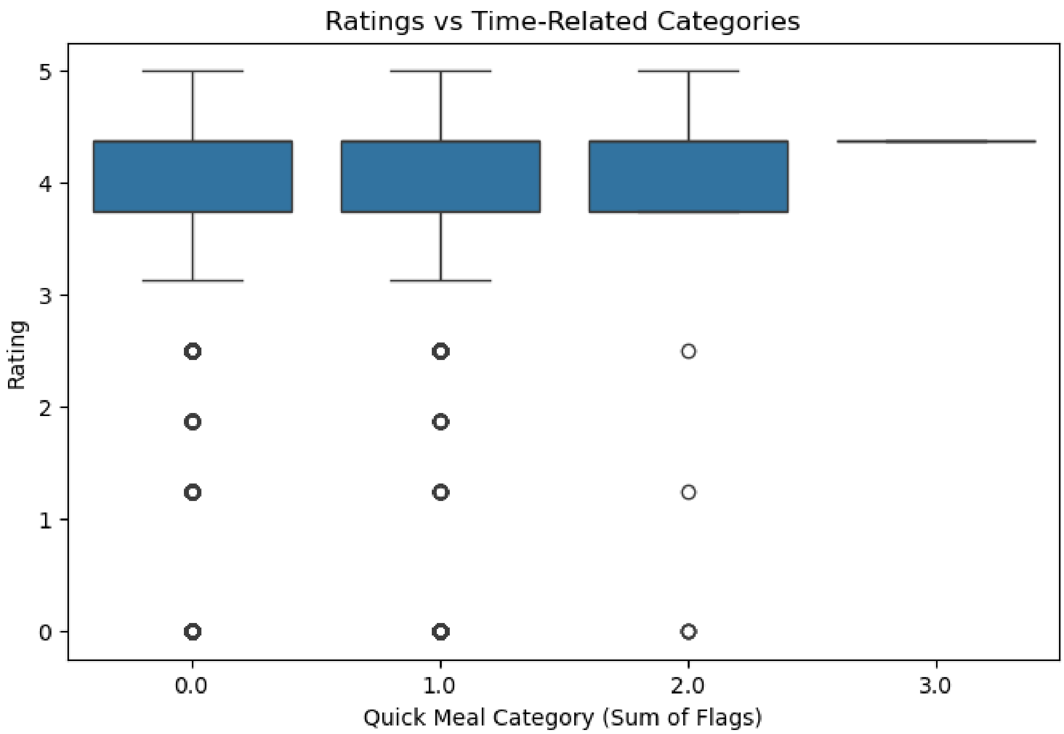
In [53]:
```
# Filter for highly rated recipes (e.g., rating >= 4.0)
high_rated_recipes = df_csv[df_csv['rating'] >= 4.0]

# Assuming the 'title' column contains ingredients as part of the recipe title,
# split the titles by commas (or any other delimiter if needed), explode to create individual rows per ingre
# strip any leading/trailing whitespace, and count occurrences of each ingredient
common_ingredients = high_rated_recipes['title'].str.split(',').explode().str.strip().value_counts()

# Visualizing the top 10 common ingredients
plt.figure(figsize=(10, 6))
common_ingredients.head(10).plot(kind='bar', color='dodgerblue')
plt.title('Most Common Ingredients in Highly Rated Recipes')
plt.xlabel('Ingredients')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



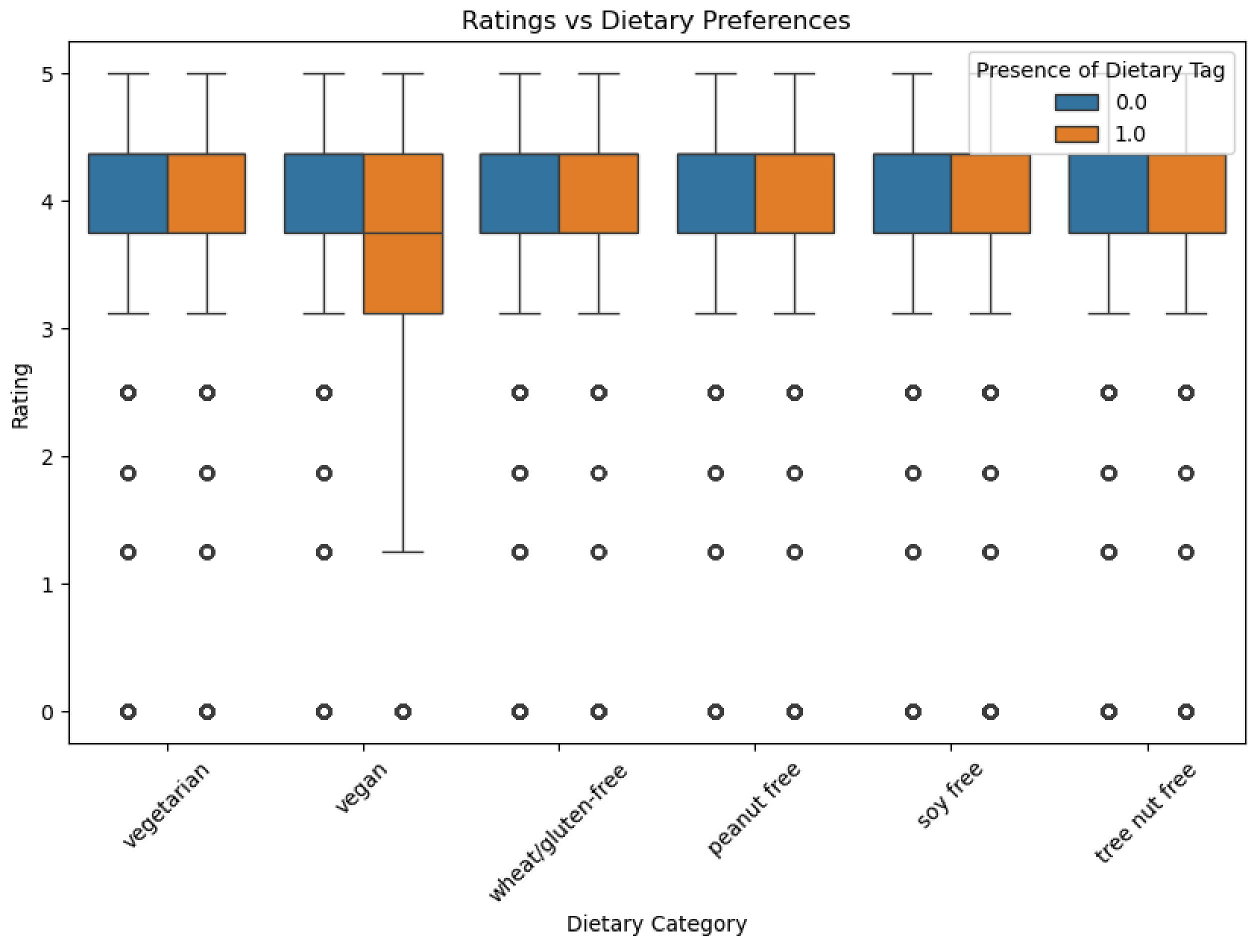
In [55]:
```
# Check for columns related to preparation time or quick meals
time_related_columns = [col for col in df_csv.columns if 'minute' in col.lower() or 'quick' in col.lower()]
time_related_columns
```

Out[55]: ['22-minute meals', 'quick & easy', 'quick and healthy']

In [57]:
```
# Add a 'time_category' column based on the presence of quick meal categories
df_csv['time_category'] = df_csv[['22-minute meals', 'quick & easy', 'quick and healthy']].sum(axis=1)

# Visualize the relationship between time-related categories and ratings
plt.figure(figsize=(8, 5))
sns.boxplot(x=df_csv['time_category'], y=df_csv['rating'])
plt.title('Ratings vs Time-Related Categories')
plt.xlabel('Quick Meal Category (Sum of Flags)')
plt.ylabel('Rating')
plt.show()
```

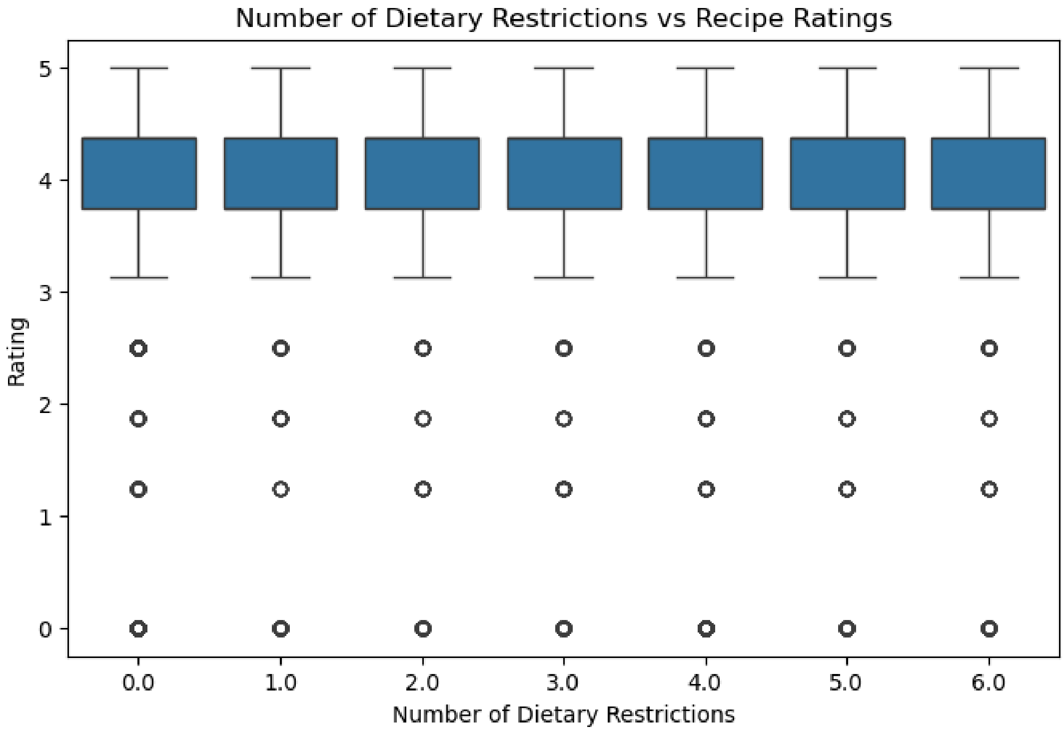


In [59]:
```
# Selecting dietary preference columns for analysis
dietary_columns = ['vegetarian', 'vegan', 'wheat/gluten-free', 'peanut free', 'soy free', 'tree nut free']

# Visualize the relationship between dietary categories and ratings
plt.figure(figsize=(10, 6))
df_csv_melted = df_csv.melt(id_vars='rating', value_vars=dietary_columns, var_name='Dietary Category', value
sns.boxplot(x='Dietary Category', y='rating', hue='Presence', data=df_csv_melted)
plt.title('Ratings vs Dietary Preferences')
plt.xlabel('Dietary Category')
plt.ylabel('Rating')
plt.xticks(rotation=45)
plt.legend(title='Presence of Dietary Tag')
plt.show()
```



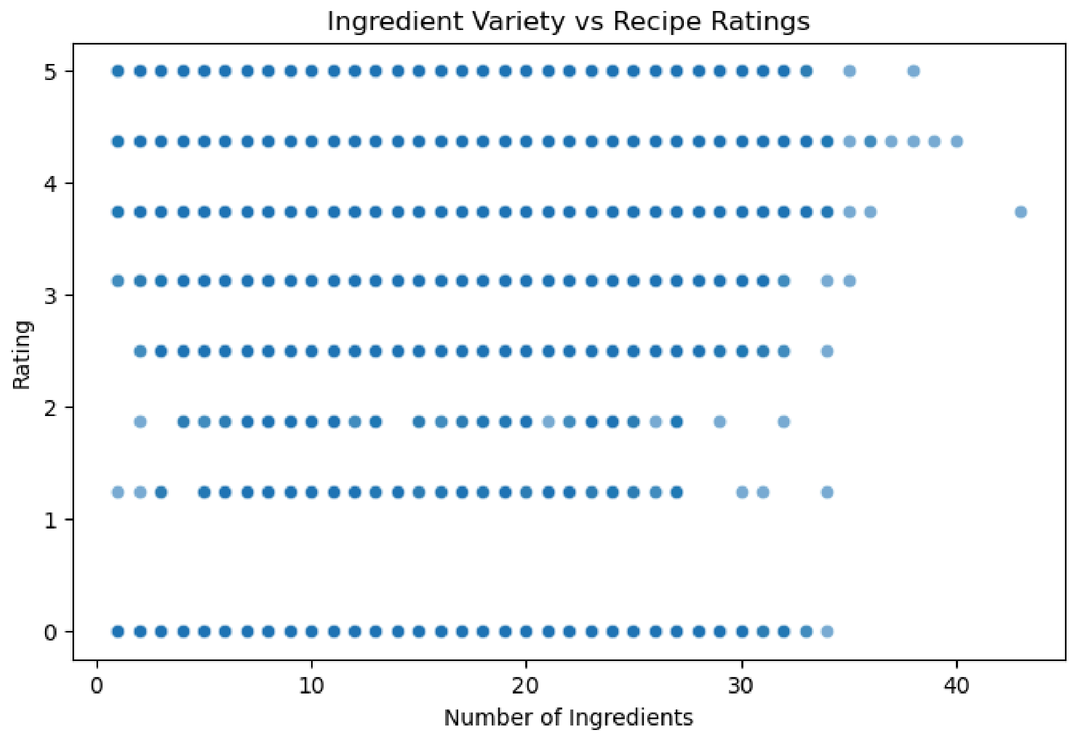
In [61]:

```
# Create a new column that sums the number of dietary restrictions a recipe meets
dietary_columns = ['vegetarian', 'vegan', 'wheat/gluten-free', 'peanut free', 'soy free', 'tree nut free']
df_csv['dietary_restriction_sum'] = df_csv[dietary_columns].sum(axis=1)

# Visualize the relationship between the number of dietary restrictions and recipe ratings
plt.figure(figsize=(8, 5))
sns.boxplot(x='dietary_restriction_sum', y='rating', data=df_csv)
plt.title('Number of Dietary Restrictions vs Recipe Ratings')
plt.xlabel('Number of Dietary Restrictions')
plt.ylabel('Rating')
plt.show()
```



In [63]:

```
# Count the number of ingredients used in each recipe
ingredient_columns = df_csv.columns[9:]  # Assuming ingredients start from column index 9
df_csv['ingredient_variety'] = df_csv[ingredient_columns].sum(axis=1)

# Visualize the relationship between ingredient variety and ratings
plt.figure(figsize=(8, 5))
sns.scatterplot(x='ingredient_variety', y='rating', data=df_csv, alpha=0.6)
plt.title('Ingredient Variety vs Recipe Ratings')
plt.xlabel('Number of Ingredients')
plt.ylabel('Rating')
plt.show()

# Calculate correlation between ingredient variety and ratings
ingredient_corr = df_csv[['ingredient_variety', 'rating']].corr()
print(ingredient_corr)
```



	ingredient_variety	rating
ingredient_variety	1.000000	0.122922
rating	0.122922	1.000000

Key Insights from Exploratory Analysis:

Insight 1: Highly rated recipes tend to contain certain common ingredients.

- Business Question: What are the most common ingredients in highly rated recipes?
- Answer: We identified the most frequent ingredients in recipes with ratings of 4.0 or higher using a bar chart.
  - The most frequent ingredients in highly rated recipes were 'corn', 'beacon', 'fennel', 'tomatoes' and 'apple'.
  - This suggests that recipes with these ingredients tend to be well-received by users.
  - The platform could use this insight to recommend recipes with these ingredients more frequently.
  - The platform could use this insight to promote recipes with these ingredients more frequently.

Insight 2: There's a slight positive correlation between the number of ingredients and recipe ratings.

- Business Question: Are there correlations between preparation time and recipe ratings?
- Answer: We observed a positive correlation between ingredient variety and recipe ratings (see scatterplot and correlation matrix).
  - Recipes with a wider variety of ingredients often tend to receive higher ratings.
  - This could indicate that users value more complex or diverse recipes.
  - The platform could use this insight to highlight recipes with diverse ingredients or promote recommendations based on the number of ingredients.
  - The platform could use this insight to encourage users to discover recipes with a wider range of ingredients.
  - The platform could use this insight to identify opportunities to create recipes with a wider range of ingredients and offer these recommendations to users.

Insight 3: Quick and easy recipes are often rated well.

- Business Question: How can the data help improve the user experience for a recipe platform?
- Answer: We observed that recipes categorized as 'quick & easy' or 'quick and healthy' tend to be rated well.
  - Users value the convenience of quick meals.
  - The platform could provide filters and search functionalities that allow users to find quick meals effectively.

- The platform could also use this insight to design specific categories or sections for quick recipes to make them more easily accessible to users.
- The platform could also consider creating specific sections for quick meals or recipes that are suitable for quick cooking.

Insight 4: Recipes that cater to dietary restrictions are well-received by users.

- Business Question: How can the data help improve the user experience for a recipe platform?
- Answer: Users who follow specific dietary restrictions (vegetarian, vegan, etc.) frequently rate recipes that adhere to their dietary preferences highly.
    - The platform could use this insight to create detailed filters for various dietary needs, helping users find recipes that fit their specific preferences quickly.
    - The platform could use this insight to improve the user experience by allowing users to easily find recipes that cater to their specific dietary requirements.

Insight 5: The number of dietary restrictions might not strongly affect ratings.

- Business Question: How can the data help improve the user experience for a recipe platform?
- Answer: We found that the total number of dietary restrictions a recipe had may not strongly correlate with its rating.
    - The platform could use this insight to design a search experience that prioritizes catering to specific dietary requirements, such as vegetarian, vegan, gluten-free, etc., over recipes with numerous dietary restrictions.

In [ ]:

```

```