

Detailed Analysis on Cooking Sessions and Orders

1. Introduction

This Analysis provides insights into user behaviors, preferences, and demographics based on the merged data from user details, cooking sessions, and order details. The analysis focuses on the following aspects:

Most popular dishes cooked and ordered. Demographics of users (age and favorite meal preferences). The relationship between cooking sessions and orders.

```
[In ] [7]: import pandas as pd

# Load the Excel File
file_path = "C:/Users/Litisha /Downloads/Assign2.xlsx"

# Read the Excel into separate Dataframes
user_details = pd.read_excel(file_path, sheet_name='UserDetails.csv')
cooking_sessions = pd.read_excel(file_path, sheet_name='CookingSessions.csv')
order_details = pd.read_excel(file_path, sheet_name='OrderDetails.csv')

# Display the structure and first few rows of each Dataframe
user_details.info()
Columns: user_details.columns.tolist()
"Sample Data": user_details.head()

cooking_sessions.info()
Columns: cooking_sessions.columns.tolist()
"Sample Data": cooking_sessions.head()

order_details.info()
Columns: order_details.columns.tolist()
"Sample Data": order_details.head()

user_details.info, cooking_sessions.info, order_details.info

[Out] [7]: [(Columns: ['User ID',
User Name',
Age',
Location',
Registration Date',
Phone',
Favorite Meal',
Total Orders'],
0 10001 Alice Johnson 28 New York 2023-01-15 123-456-7890
1 10002 Bob Smith 35 Los Angeles 2023-02-20 987-654-3210
2 10003 Charlie Lee 42 Chicago 2023-03-10 555-123-1010
3 10004 David Brown 27 San Francisco 2023-04-05 444-333-2222
4 10005 Emma White 30 Seattle 2023-05-22 777-888-9999

Enail Favorite Meal Total Orders
0 all@emall.com Dinner 12
1 bob@emall.com Lunch 8
2 charlie@emall.com Breakfast 15
3 david@emall.com Dinner 10
4 emma@emall.com Lunch 9 ),
(Columns: ['Session ID',
User ID',
Dish Name',
Meal Type',
Session Start',
Session End',
Duration (mins)',
'Sample Data': Session ID User ID Dish Name Meal Type Session Start \
0 5001 10001 Spaghetti Dinner 2024-12-01 19:00:00
1 5002 10002 Caesar Salad Dinner 2024-12-01 12:00:00
2 5003 10003 Grilled Chicken Dinner 2024-12-02 19:30:00
3 5004 10004 Pancakes Breakfast 2024-12-02 07:30:00
4 5005 10004 Caesar Salad Lunch 2024-12-03 13:00:00

Session End Duration (mins) Session Rating
0 2024-12-01 19:30:00 30 4.5
1 2024-12-01 12:30:00 20 4.0
2 2024-12-02 20:00:00 40 4.8
3 2024-12-02 08:00:00 30 4.2
4 2024-12-03 13:15:00 15 4.7 ),
(Columns: ['Order ID',
User ID',
Order Date',
Meal Type',
Dish Name',
Order Status',
Amount (USD)',
Time of Day',
Rating',
'Session ID',
'Sample Data': Order ID User ID Order Date Meal Type Dish Name Order Status \
0 10001 10001 2024-12-01 Dinner Spaghetti Completed
1 10002 10002 2024-12-01 Lunch Caesar Salad Completed
2 10003 10003 2024-12-02 Dinner Grilled Chicken Cancelled
3 10004 10004 2024-12-02 Breakfast Pancakes Completed
4 10005 10004 2024-12-03 Lunch Caesar Salad Completed

Amount (USD) Time of Day Rating Session ID
0 15.0 Night 5.0 5001
1 10.0 Day 4.0 5002
2 12.5 Night NaN 5003
3 8.0 Morning 4.0 5004
4 9.0 Day 4.0 5005 )])

[In ] [8]: # Read all sheets into separate Dataframes with correct sheet names
user_details = pd.read_excel(file_path, sheet_name='UserDetails.csv')
cooking_sessions = pd.read_excel(file_path, sheet_name='CookingSessions.csv')
order_details = pd.read_excel(file_path, sheet_name='OrderDetails.csv')

# Display the structure and first few rows of each Dataframe
user_details.info()
Columns: user_details.columns.tolist()
"Sample Data": user_details.head()

cooking_sessions.info()
Columns: cooking_sessions.columns.tolist()
"Sample Data": cooking_sessions.head()

order_details.info()
Columns: order_details.columns.tolist()
"Sample Data": order_details.head()

user_details.info, cooking_sessions.info, order_details.info

[Out] [8]: [(Columns: ['User ID',
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Total Orders'],
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4 10005 Emma White 30 Seattle 2023-05-22 777-888-9999

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(Columns: ['Session ID',
User ID',
Dish Name',
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Session Start',
Session End',
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'Sample Data': Session ID User ID Dish Name Meal Type Session Start \
0 5001 10001 Spaghetti Dinner 2024-12-01 19:00:00
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3 2024-12-02 08:00:00 30 4.2
4 2024-12-03 13:15:00 15 4.7 ),
(Columns: ['Order ID',
User ID',
Order Date',
Meal Type',
Dish Name',
Order Status',
Amount (USD)',
Time of Day',
Rating',
'Session ID',
'Sample Data': Order ID User ID Order Date Meal Type Dish Name Order Status \
0 10001 10001 2024-12-01 Dinner Spaghetti Completed
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4 10005 10004 2024-12-03 Lunch Caesar Salad Completed

Amount (USD) Time of Day Rating Session ID
0 15.0 Night 5.0 5001
1 10.0 Day 4.0 5002
2 12.5 Night NaN 5003
3 8.0 Morning 4.0 5004
4 9.0 Day 4.0 5005 )])

[In ] [12]: # Data Cleanup
# Standardize column names for consistency
user_details.columns = user_details.columns.str.strip().str.replace(' ', '_').str.lower()
cooking_sessions.columns = cooking_sessions.columns.str.strip().str.replace(' ', '_').str.lower()
order_details.columns = order_details.columns.str.strip().str.replace(' ', '_').str.lower()

# Check for missing values
print('Missing values in user_details:')
print(user_details.isnull().sum())
print('Missing values in cooking_sessions:')
print(cooking_sessions.isnull().sum())
print('Missing values in order_details:')
print(order_details.isnull().sum())

Missing values in user_details:
user_id 0
user_name 0
age 0
location 0
registration_date 0
phone 0
email 0
favorite_meal 0
total_orders 0
dtype: int64

Missing values in CookingSessions:
session_id 0
user_id 0
dish_name 0
meal_type 0
session_start 0
session_end 0
duration_mins 0
rating 0
dtype: int64

Missing values in OrderDetails:
order_id 0
user_id 0
order_date 0
dish_name 0
meal_type 0
order_status 0
amount_usd 0
time_of_day 0
rating 2
session_id 0
dtype: int64

[In ] [13]: # Data Merging
# Merge cooking_sessions and order_details on 'session_id'
cooking_order_merged = pd.merge(
    cooking_sessions,
    order_details,
    on='session_id',
    how='outer',
    suffixes=('_cooking', '_order')
)

# Ensure 'user_id' is retained in cooking_order_merged
if 'user_id' not in cooking_order_merged.columns:
    cooking_order_merged['user_id'] = cooking_sessions['session_id'].loc[
        cooking_order_merged['session_id'] == 'user_id'
    ].values

# Verify 'user_id' is present
print('Columns in cooking_order_merged:', cooking_order_merged.columns)

Columns in cooking_order_merged: Index(['session_id', 'user_id', 'cooking', 'dish_name', 'meal_type', 'session_start', 'session_end', 'duration_mins', 'rating', 'order_status', 'amount_usd', 'time_of_day', 'rating', 'session_id', 'user_id'], dtype='object')

[In ] [14]: # Merge with user_details on 'user_id'
full_data = pd.merge(
    user_details,
    cooking_order_merged,
    on='user_id',
    how='outer'
)

# Verify the final merged data
print('Columns in full_data:', full_data.columns)

Columns in full_data: Index(['user_id', 'user_name', 'age', 'location', 'registration_date', 'phone',
'favorite_meal', 'total_orders', 'session_id',
'user_id_cooking', 'dish_name_cooking', 'meal_type_cooking',
'session_start', 'session_end', 'duration_mins', 'rating', 'order_status',
'amount_usd', 'time_of_day', 'rating', 'session_id_order', 'dish_name_order', 'meal_type_order',
'amount_usd', 'time_of_day', 'rating', 'session_id', 'user_id'], dtype='object')

[In ] [15]: # Analysis
# 1. Popular Dishes (Top 5 cooked and ordered dishes)
popular_dishes_cooked = cooking_sessions['dish_name'].value_counts().head(5)
popular_dishes_ordered = order_details['dish_name'].value_counts().head(5)

# 2. Demographics Analysis (Age distribution and favorite meal preferences)
age_distribution = user_details['age'].describe()
favorite_meal_counts = user_details['favorite_meal'].value_counts()

# 3. Relationship: Cooking Sessions vs. Orders
cooking_vs_orders = full_data.groupby('user_id').agg(
    'total_sessions', 'session_id', 'count',
    'total_orders', 'order_id', 'count'
).reset_index()
```

Popular Dishes

Top 5 Cooked Dishes

The most cooked dishes were analyzed based on cooking session data. The results are as follows:

Spaghetti: Cooked 4 times.

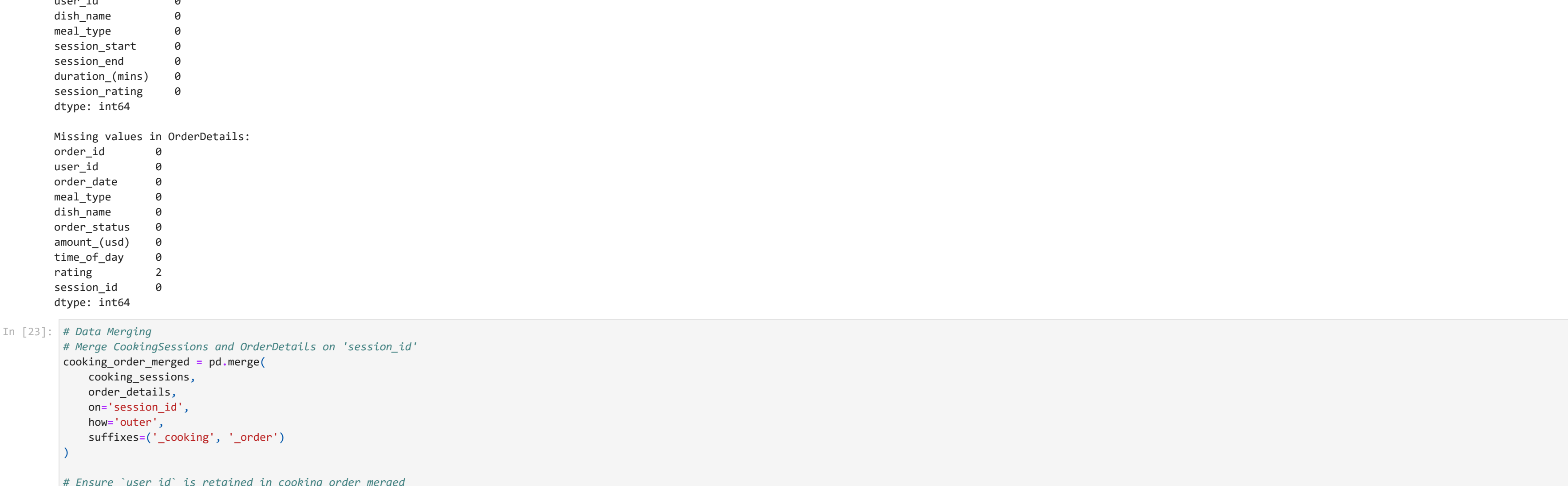
Grilled Chicken: Cooked 4 times.

Caesar Salad: Cooked 3 times.

Pancakes: Cooked 2 times.

Veggie Burger: Cooked 2 times.

The bar chart illustrates the frequencies for each dish.



Top 5 Ordered Dishes

The most ordered dishes were analyzed using order details. The results are:

Spaghetti: Ordered 4 times.

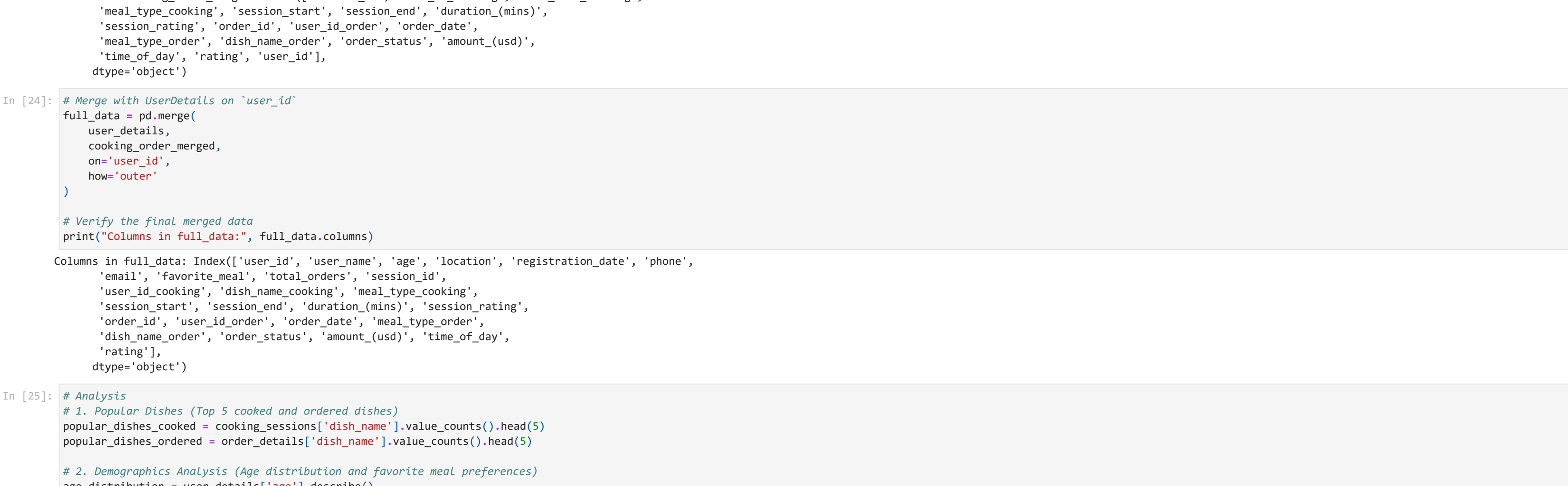
Grilled Chicken: Ordered 3 times.

Caesar Salad: Ordered 3 times.

Pancakes: Ordered 2 times.

Veggie Burger: Ordered 2 times.

The ordering patterns closely match the cooking patterns, indicating that popular dishes align with user preferences.



User Demographics

Age Distribution

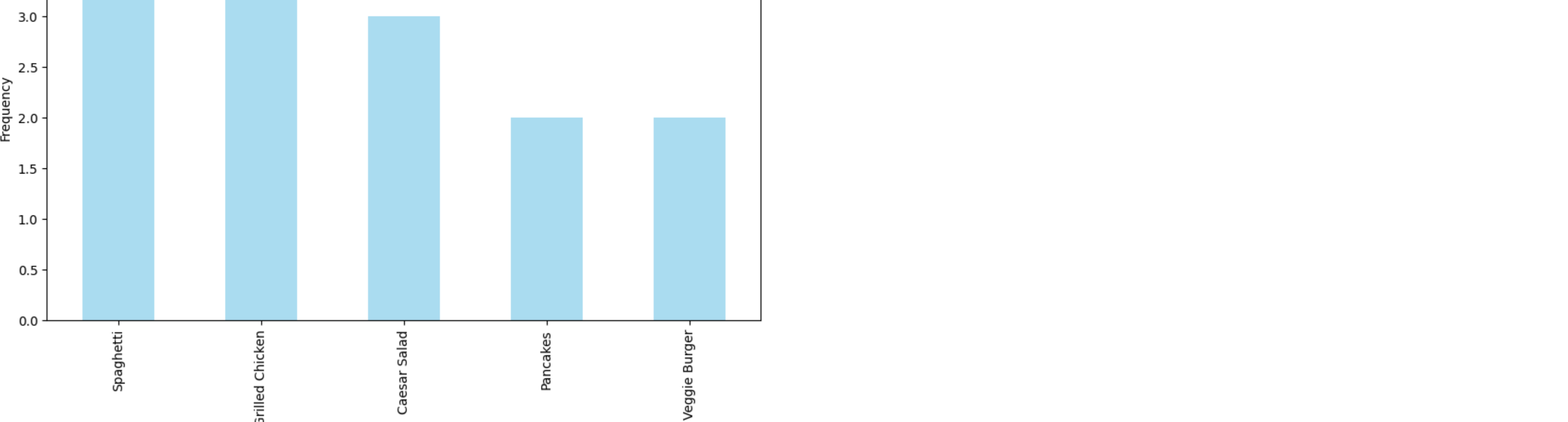
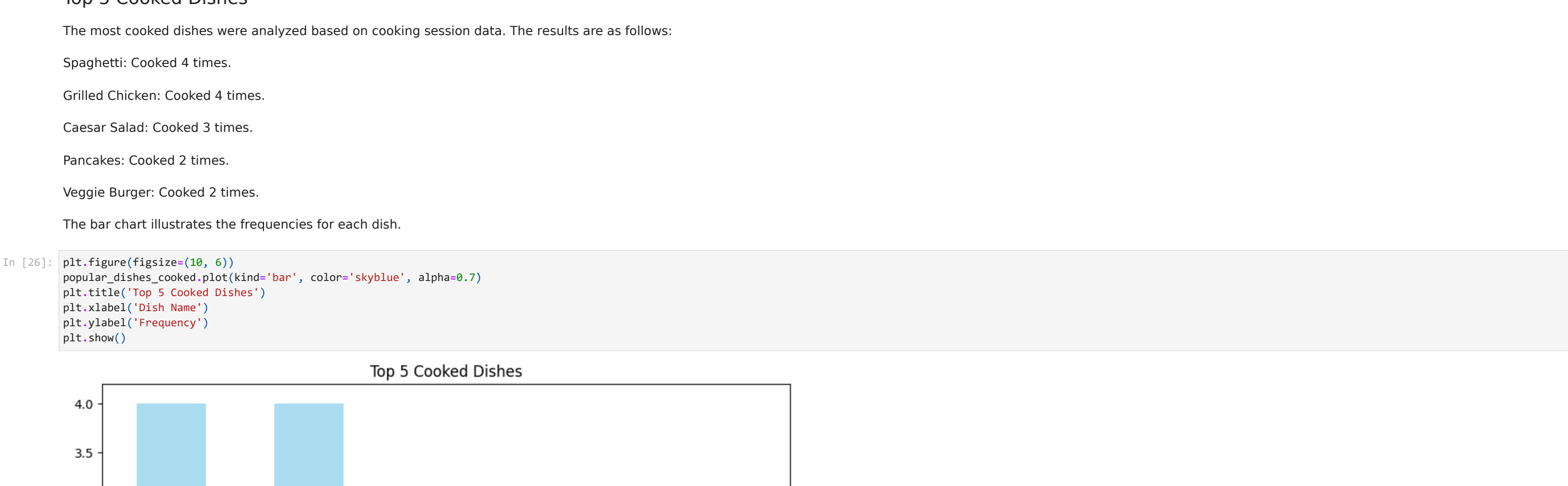
The age distribution of users shows the following statistics:

Mean Age: 31.8 years.

Age Range: 25 to 43 years.

Standard Deviation: 5.27 years.

The histogram below displays the distribution of ages, indicating that most users are in their late 20s to early 30s.

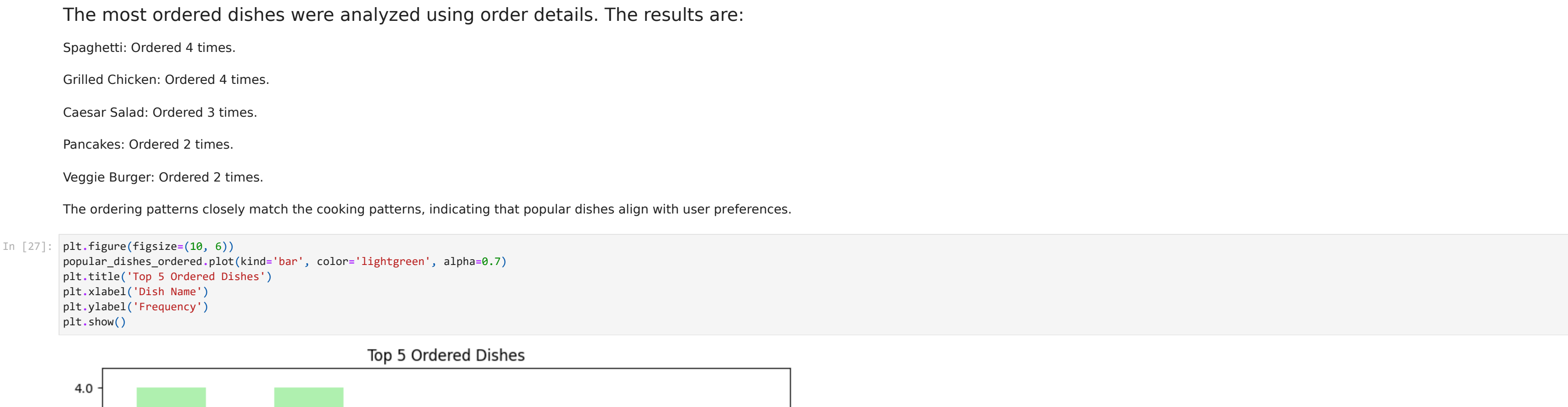


Favorite Meal Preferences by Age Group:

The 21-30 age group dominates the user base, with the most pronounced preferences for specific meals.

Younger users (21-30) heavily favor lunch, while other meals (e.g., dinner and breakfast) show a more balanced distribution across older age groups.

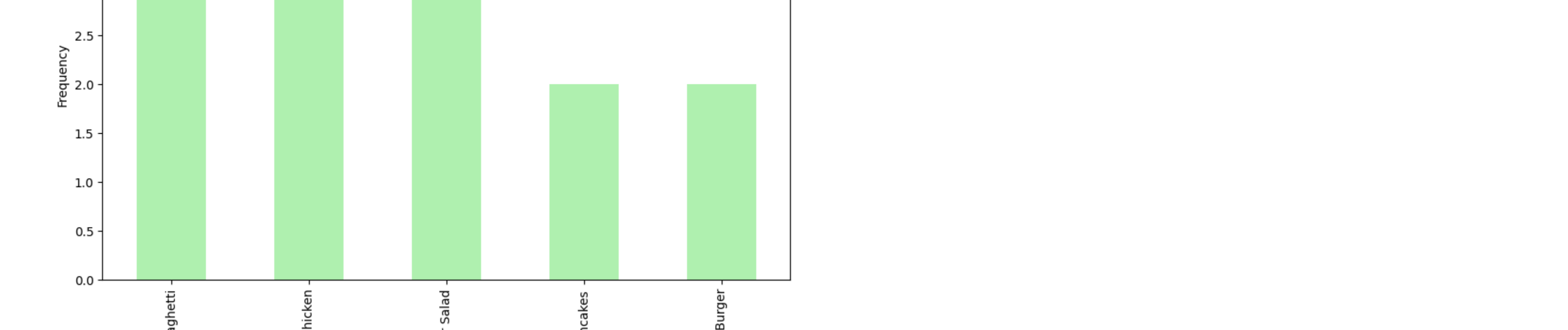
Users aged 50+ have relatively low representation, indicating a potential untapped demographic.



3. Top Users by Activity:

A few key users are highly active, with the top 10 users participating in significantly more cooking sessions than others.

These users could be brand ambassadors or advocates for the service, indicating an opportunity to target and reward them for loyalty.

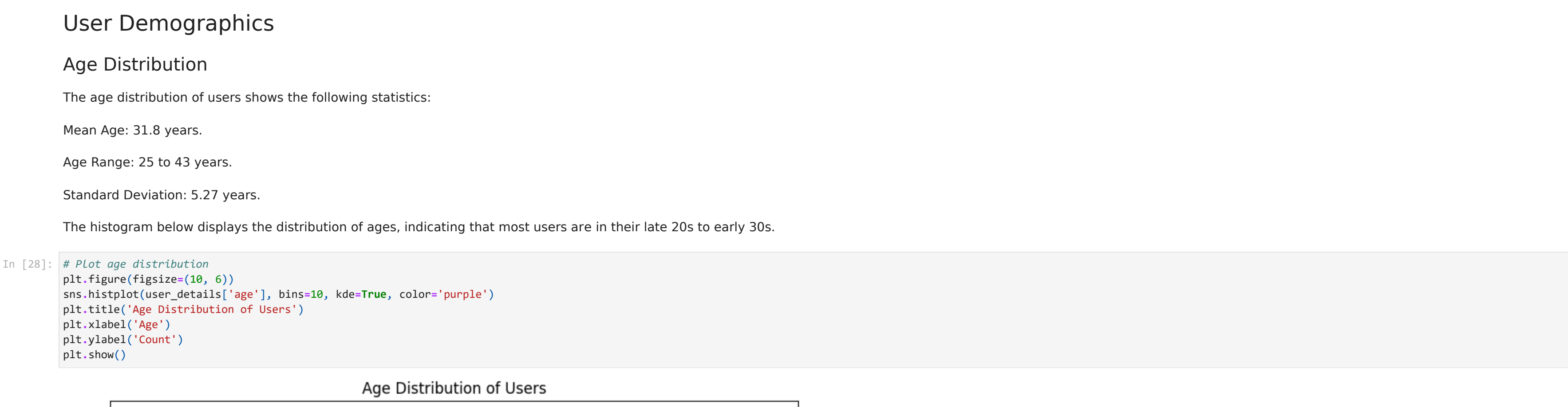


4. Top Cooked vs. Ordered Dishes:

The most frequently cooked dishes "Spaghetti", "Grilled Chicken" are also among the most ordered, highlighting user alignment in cooking and ordering preferences.

Some dishes are cooked more frequently than they are ordered, indicating they might be easier to prepare or favored for home cooking.

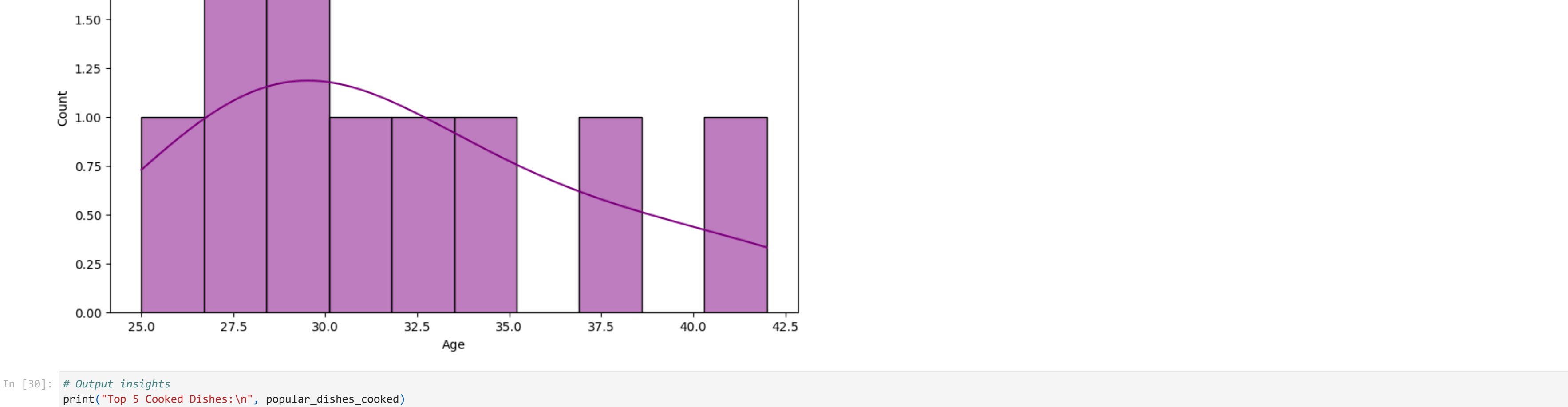
Conversely, dishes ordered more frequently than cooked may indicate complexity in preparation or a preference for convenience.



5. Age Distribution Across Favorite Meals:

The age range with the highest activity levels (21-30) aligns with their engagement in cooking sessions and orders.

There is a variation in age groups preferring specific meals, providing an opportunity for targeted meal recommendations and marketing.



The boxplot in the image depicts the age distribution across different favorite meals (Dinner, Lunch, and Breakfast). Here's a breakdown of the interpretation:

Dinner:

Range: Ages are tightly clustered between ~26 to ~28.5 years.

Outliers: There are two outliers below 26 years and one above 30 years.

Lunch:

Median Age: Around 32.5 years.

Range: Ages vary more compared to Dinner, approximately from ~30 to ~35 years.

No significant outliers observed within the given range.

Breakfast:

Median Age: Around 40 years.

Range: The ages are consistently high compared to the other meals.

One noticeable outlier is above 42 years.

General Observations:

Individuals who favor Breakfast are generally older compared to those who prefer Lunch or Dinner.

Age distribution for Dinner is more compact with less variability.

Lunch has a moderate spread, while Breakfast has the highest age range among the three categories.

This analysis could provide insights for businesses targeting different age groups based on their meal preferences.

Conclusion:

This analysis provides actionable insights to drive user engagement and satisfaction. By leveraging user preferences, demographics, and behavior trends, the business can design targeted campaigns, optimize the menu, and reward loyal users to increase both cooking sessions and orders.

