# *Report: Data Analytics Insights for Upliance.ai*

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# INTRODUCTION

This report presents the findings of a data analysis conducted on the user behavior, cooking preferences, and order trends of Upliance.ai, India's first AI cooking assistant. The analysis leverages the company's three key datasets - UserDetails, CookingSessions, and OrderDetails - to uncover valuable insights that can inform business decisions and drive strategic initiatives.

# OBJECTIVES

The key objectives of this analysis are:

1. Explore the relationship between cooking sessions and user orders.
2. Identify the most popular dishes among Upliance.ai customers.
3. Investigate the influence of demographic factors on user behavior.
4. Create visualisations to communicate the key findings effectively.
5. Provide business recommendations based on the data analysis.

# DATA OVERVIEW

Upliance.ai has provided three datasets for this analysis:

1. **UserDetails**: This dataset contains information about the users, including their user ID, name, age, location, registration date, phone, email, favourite meal, and total orders.
2. **CookingSessions**: This dataset includes details about the cooking sessions, such as the session ID, user ID, dish name, meal type, session start and end times, duration, and session rating.
3. **OrderDetails**: This dataset provides information about the user orders, including the order ID, user ID, order date, meal type, dish name, order status, amount, time of day, and rating.

# ANALYSIS

## Data Preprocessing

- Data Cleaning

  There were no missing values in the UserDetails and CookingSessions CSV files, but there were two missing values in OrdrrDetails in the Ratings column.

```
missing_values = order_details.isnull().sum()
missing_values
```

| | 0 |
|---|---|
| Order ID | 0 |
| User ID | 0 |
| Order Date | 0 |
| Meal Type | 0 |
| Dish Name | 0 |
| Order Status | 0 |
| Amount (USD) | 0 |
| Time of Day | 0 |
| Rating | 2 |
| Session ID | 0 |

dtype: int64

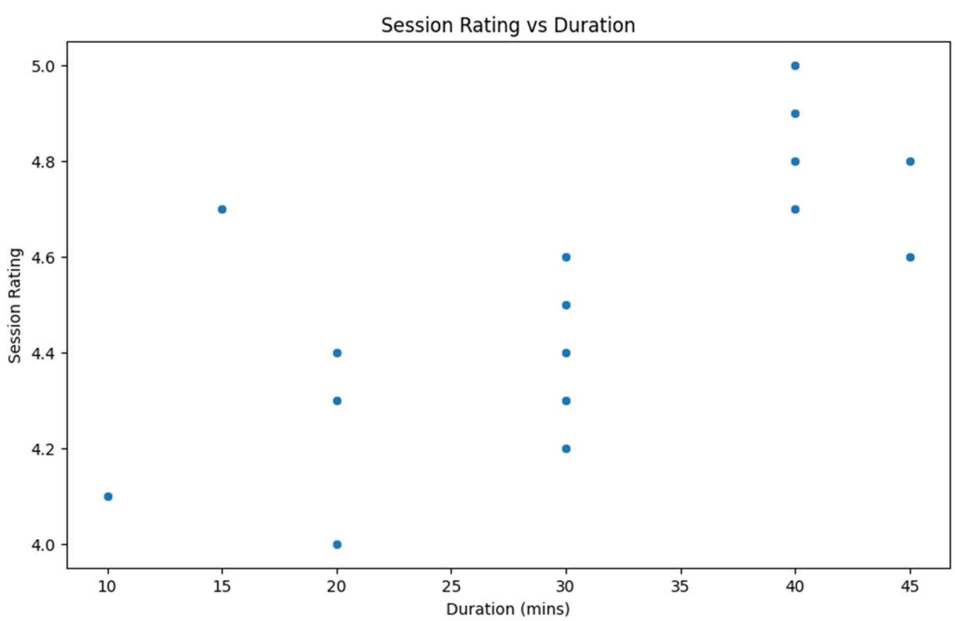
  Those values have been imputed using mode since most of the data points appear to have a rating of 4 or 5, and it's imputed with the most frequent rating.

- Data Merging

  I have merged the three datasets based on User ID, and the merged dataset is as follows:

```
Data columns (total 25 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   User ID             38 non-null     object
 1   User Name           38 non-null     object
 2   Age                 38 non-null     int64
 3   Location            38 non-null     object
 4   Registration Date   38 non-null     datetime64[ns]
 5   Phone               38 non-null     object
 6   Email               38 non-null     object
 7   Favorite Meal       38 non-null     object
 8   Total Orders        38 non-null     int64
 9   Session ID_x        38 non-null     object
 10  Dish Name_x         38 non-null     object
 11  Meal Type_x         38 non-null     object
 12  Session Start       38 non-null     datetime64[ns]
 13  Session End         38 non-null     datetime64[ns]
 14  Duration (mins)     38 non-null     int64
 15  Session Rating      38 non-null     float64
 16  Order ID            38 non-null     int64
 17  Order Date          38 non-null     datetime64[ns]
 18  Meal Type_y         38 non-null     object
 19  Dish Name_y         38 non-null     object
 20  Order Status        38 non-null     object
 21  Amount (USD)        38 non-null     float64
 22  Time of Day         38 non-null     object
 23  Rating              38 non-null     float64
 24  Session ID_y        38 non-null     object
```

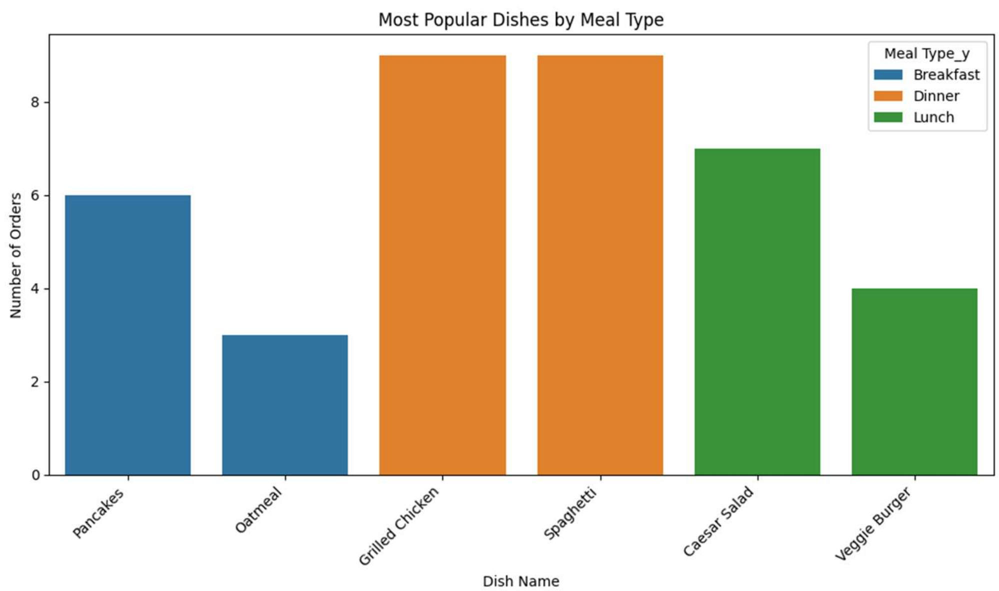
## Relationship between Cooking Sessions and Orders



*There's a positive correlation between session duration and rating. Sessions longer than 35 minutes tend to receive higher ratings (4.6-5.0). Shorter sessions (10-20 minutes) generally receive lower ratings (4.0-4.4). The highest ratings (5.0) appear around the 40-minute mark. This suggests that users are more satisfied with longer duration, more comprehensive cooking sessions*

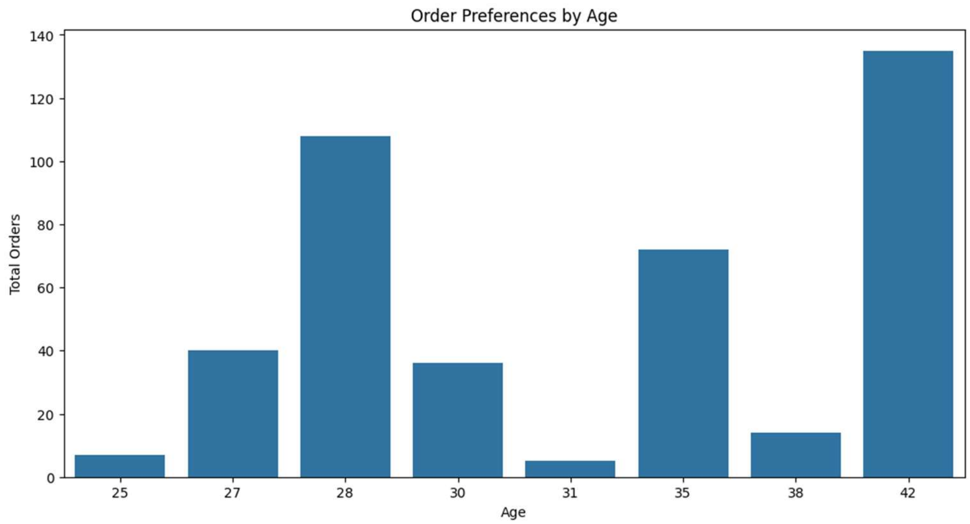
## Popular Dishes

```
Most Popular Dishes by Meal Type:
Meal Type_y     Dish Name_y  Order ID
  Breakfast        Pancakes         6
  Breakfast         Oatmeal         3
     Dinner Grilled Chicken         9
     Dinner       Spaghetti         9
      Lunch    Caesar Salad         7
      Lunch    Veggie Burger        4
```




*For dinner, grilled chicken and spaghetti are tied to the most ordered dinner items. In the case of breakfast, Pancakes are more popular than Oatmeal. And in the case of lunch, Caesar Salad is more popular than Veggie Burger.*

# Demographic Factors and User Behavior

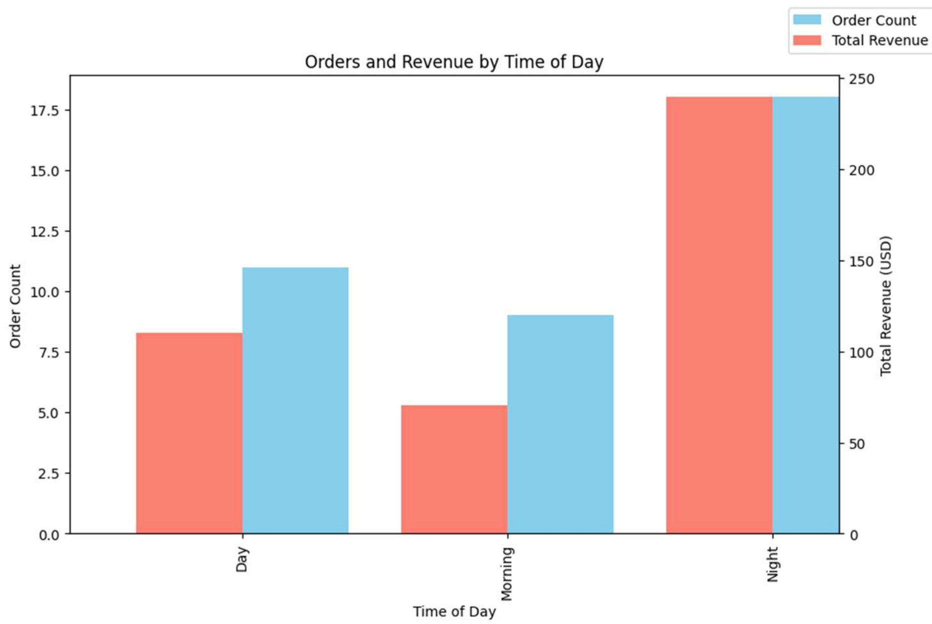



*There are distinct peaks in ordering activity at ages 28 and 42. Age 42 shows the highest number of orders (approximately 135 orders). Age 28 is the second most active group (about 110 orders). There's notably lower activity among users in their early 30s, with age 31 showing the lowest ordering frequency. The distribution suggests that the orders are most popular among both young professionals (late 20s) and established adults (early 40s)*

# Additional Analysis

**Order Patterns by Time of Day**

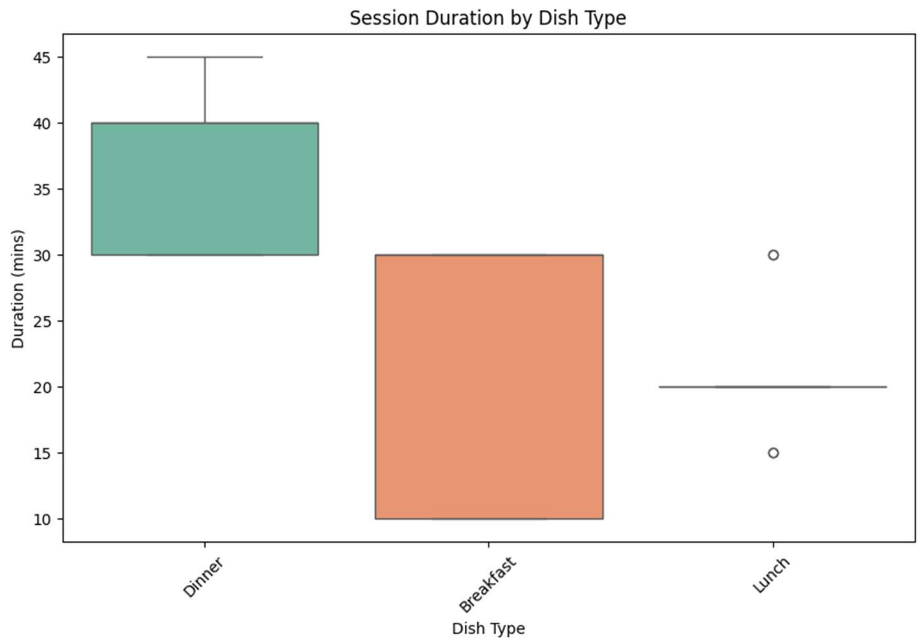
Analyze the number of orders and revenue generated during different times of the day (e.g., Morning, Afternoon, Night)




*This graph shows the order count and total revenue by the time of day. The highest number of orders and total revenue occurs during the night time. This suggests that customers tend to place more orders and spend more money in the evenings. The Morning period has the lowest order count and total revenue, indicating that this is the least active time for the business. The Day period has a moderate level of orders and revenue, falling between the higher Night period and the lower Morning period. The Day period has a moderate level of orders and revenue, falling between the higher Night period and the lower Morning period.*

**Duration and Dish Type**

Analyze which types of dishes (e.g., fast prep vs. slow prep) have longer cooking sessions




*This graph shows the average cooking session duration for different dish types. Dinner dishes have the longest average session duration at around 40 minutes. Breakfast dishes have the second-longest average session duration at around 30 minutes. Lunch dishes have the shortest average session duration at around 20 minutes. This suggests that customers tend to spend more time preparing and consuming dinner and breakfast dishes than lunch dishes.*

# BUSINESS RECOMMENDATIONS

Based on the data, here are business recommendations that I would think can help:

1. Session Duration Optimization

   Since longer cooking sessions (35+ minutes) correlate with higher satisfaction ratings (4.6-5.0), developing guided cooking experiences makes longer sessions more engaging.

2. Age-Targeted Marketing and Features

   - Focusing primary marketing efforts on two key demographics:
     - Young professionals (around age 28) - Emphasize quick, healthy cooking solutions for busy lifestyles
     - Established adults (around age 42) - Highlight family-friendly features and traditional recipe preservation
   - Addressing the engagement gap in the early 30s age group can be done by developing specific features or content that appeals to their needs

3. Meal-Specific Strategy

   - **Dinner Focus**: Expanding the dinner recipe collection with dishes similar in popularity and difficulty to Grilled Chicken and Spaghetti.

   - **Breakfast Innovation**: Build on pancake popularity with new breakfast varieties for busy mornings.

   - **Lunch Solutions**: Develop quick, healthy lunch options like Caesar Salad and meal prep features for office-goers.

4. Time-Based Features

   - Night-time Optimization: Since evening shows the highest usage and revenue, introducing special evening cooking assistance features will be good
   - Morning Engagement: Introducing breakfast meal planning and quick-start morning recipes.

These recommendations might align with Upliance.ai's mission to simplify cooking for young Indians while leveraging AI technology. These address both the data insights and the company's focus on being a disruptive force in home appliances.