Project Report

Food Trend Customer Preference Analysis

Submitted by

Abhishek Sarodaya

Group C

October 15, 2025

Contents

1 Abstract

The rapid growth of online food delivery platforms such as Swiggy and Zomato has significantly reshaped consumer behavior in the food industry. As competition intensifies, gaining deep insights into customer preferences, satisfaction levels, and behavioral trends has become essential for business sustainability and growth.

This project, "FoodTrends: Understanding Customer Preferences through Data Analysis and Visualization using Power BI," focuses on uncovering evolving food consumption patterns, customer demographics, and satisfaction drivers within the online food delivery ecosystem. Using a structured dataset sourced from Kaggle, the project explores key trends such as popular cuisines, preferred ordering times, influence of offers, and service expectations.

The dataset includes both demographic variables (e.g., age, income, family size) and service experience factors (e.g., food quality, delivery speed, discounts, and customer feedback). Through data cleaning, modeling, and interactive Power BI dashboards, the project visualizes these insights to reveal critical patterns and correlations.

The final dashboard-driven analysis not only highlights customer preferences and satisfaction trends but also identifies factors contributing to customer churn. These insights empower food delivery businesses to make informed, data-driven decisions aimed at enhancing user experience, personalizing marketing strategies, and boosting customer retention.

2 Introduction

2.1 Background – Understanding Food Trends and Customer Preferences in Online Food Delivery

The online food delivery industry has experienced a transformational shift over the past decade, becoming one of the fastest-growing sectors in the global food service market. In India, this growth has been particularly pronounced due to increased smartphone adoption, changing urban lifestyles, and the rapid rise of digital infrastructure. Valued at approximately 5 billion in 2021, the Indian online food delivery market is projected to reach 13 billion by 2025, reflecting a strong compound annual growth rate of 27%.

Beyond just growth, what truly defines the evolution of this industry is the emergence of distinct food trends and shifting customer preferences. Understanding these preferences from cuisine choices and order frequency to expectations around offers and delivery experience has become a critical differentiator for platforms competing in a saturated market.

Several key dynamics shape these emerging food trends:

- **Behavioral Shifts in Consumption Patterns:** Modern urban consumers, including professionals, students, and families, now favor convenience and variety over traditional cooking. This has led to a rise in frequent online ordering, with users in metro cities like Bangalore, Mumbai, and Delhi placing 6–8 orders per month on average.

- **Digital Transformation and Personalization:** Accelerated by the COVID-19 pandemic, the digital shift brought a wider demographic online, making personalization and understanding of individual preferences even more crucial. Platforms increasingly rely on data insights to tailor recommendations and promotions.

- **Competitive Innovation Driven by Customer Expectations:** Giants like Swiggy and Zomato, along with emerging hyperlocal players, continuously innovate in delivery speed, food variety, and customer engagement based on evolving user preferences and satisfaction feedback.

- **Role of Technology in Shaping Preferences:** Advanced payment systems, real-time tracking, and AI-driven recommendation engines have made food delivery more accessible, while also providing businesses with valuable data to analyze customer likes, dislikes, and trends.

However, with growing options and higher expectations, retaining customers and ensuring satisfaction have become significant challenges. The industry continues to face high churn rates (25–35%), often linked to delivery delays, food quality concerns, or a mismatch in customer expectations. This underscores the importance of analyzing food trends and customer preferences to improve service, enhance loyalty, and gain competitive advantage.

This project — FoodTrends: Understanding Customer Preferences — aims to explore these dynamics through data analysis and visualization, uncovering actionable insights that can help food delivery businesses better align with what their customers truly want.

2.2 Leveraging Customer Analytics for Food Delivery Insights

In the hyper-competitive food delivery ecosystem, data-driven decision making has transitioned from a competitive advantage to a business necessity. Customer analytics provides the foundation for several critical business functions:

- **Personalization and Targeting:** By understanding demographic patterns, preference clusters, and behavioral trends, platforms can deliver personalized experiences, targeted promotions, and relevant recommendations that increase engagement and loyalty.
- **Operational Optimization:** Analysis of delivery patterns, timing preferences, and geographic concentrations enables optimized resource allocation, route planning, and restaurant partnerships.
- **Churn Prediction and Prevention:** Identifying early warning signs of customer dissatisfaction allows for proactive intervention, retention campaigns, and service recovery initiatives.
- **Product Development:** Insights into meal preferences, cuisine trends, and pricing sensitivity inform menu development, bundle creation, and partnership strategies.
- **Quality Assurance:** Monitoring satisfaction drivers and pain points enables continuous improvement in food quality, packaging, delivery efficiency, and customer service.

The transition from intuition-based to data-driven decision making represents a fundamental shift in how food delivery platforms compete and grow. Companies that effectively leverage customer analytics demonstrate significantly higher retention rates, increased customer lifetime value, and stronger competitive positioning.

2.3 Role of Data Visualization and Power BI in Customer Analytics

In the era of big data, collecting information is no longer sufficient — organizations must transform raw data into actionable insights. Data visualization plays a vital role by converting complex datasets into intuitive visual formats, enabling quick and informed decision-making.

For this project, Microsoft Power BI was chosen as the primary tool due to its advanced visualization capabilities, seamless integration with multiple data sources, and support for real-time analytics. Power BI empowers analysts and business stakeholders to create interactive dashboards that uncover patterns, monitor performance, and communicate insights clearly.

With features like Data Analysis Expressions (DAX) for custom calculations, dynamic filtering, and report sharing, Power BI provides a powerful platform for visual analytics. This project leverages these strengths to build insightful dashboards that highlight customer preferences, satisfaction trends, and potential churn indicators in the food delivery industry — enabling stakeholders to make more effective, data-driven decisions.

3 Problem Statement & Objectives

3.1 Business Problem

The rapid expansion of the online food industry has created vast opportunities for growth, yet understanding the evolving food trends and customer preferences remains a critical challenge. As consumer behaviors shift toward convenience, personalization, and variety, food delivery platforms and restaurants must adapt quickly to stay competitive.

Despite collecting large volumes of customer data, many businesses struggle to extract meaningful insights that reveal what customers truly want — such as preferred cuisines, ordering patterns, value sensitivity, and satisfaction drivers.

This project addresses the core question:

> *"How can data visualization using Power BI uncover food trends and customer preferences to support data-driven decision-making in the online food industry?"*

By analyzing structured customer data and creating interactive dashboards, the project aims to help stakeholders identify key patterns in customer behavior, understand satisfaction factors, and optimize service offerings based on real user insights.

3.2 Project Objectives

This project aims to leverage data analysis and visualization to better understand customer behavior and preferences within the online food delivery industry, while generating actionable insights for business improvement. The specific objectives are:

- **Customer Behavior Understanding:**
  Develop a comprehensive understanding of customer demographics, ordering patterns, preference drivers, and satisfaction determinants throughout the customer lifecycle.

- **Food Trend and Preference Analysis:**
  Analyze emerging food trends and customer preferences to identify popular cuisines, ordering habits, and value sensitivities.

- **Churn Analysis and Prediction:**
  Identify key indicators of customer churn, at-risk segments, and critical intervention points to support retention strategies.

- **Satisfaction Driver Identification:**
  Quantify the impact of service attributes such as food quality, delivery timeliness, pricing, and offers on overall customer satisfaction and loyalty.
- **Operational Insight Generation:**
  Provide actionable insights to optimize delivery operations, resource allocation, route planning, and service quality management.
- **Interactive Dashboard Development:**
  Design and implement an interactive Power BI dashboard for effective data storytelling and real-time visualization of customer preferences and satisfaction trends.
- **Actionable Business Recommendations:**
  Derive strategic recommendations based on data insights to enhance customer retention, improve service quality, and inform marketing strategies.

4 Literature Review / Related Work

This section reviews previous studies related to food delivery analytics, customer satisfaction, churn prediction, and data visualization. It provides a foundation for the methodologies and tools applied in this project.

4.1 The Growth of Online Food Delivery

India's online food delivery market is expected to reach USD 24 billion by 2030, driven by rapid urbanization, smartphone penetration, and changing lifestyles. However, this growth brings challenges in maintaining service quality, ensuring customer retention, and delivering efficient logistics. As a result, organizations increasingly turn to data analytics to personalize experiences, identify pain points, and optimize operations.

Studies like Saha et al. (2023) highlight the role of consumer behavior analysis and churn modeling in this sector, pointing to the effectiveness of predictive techniques in boosting customer retention strategies.

4.2 Role of Data Visualization in Business Intelligence

Data visualization transforms raw datasets into meaningful visual formats, aiding decision-makers in identifying insights quickly. As Few (2006) puts it, the goal is to "see what you need to know, not everything you can know."

Modern BI tools like Power BI offer advanced features such as DAX-based modeling, real-time dashboards, and drill-through analysis, which are vital for tracking key performance indicators (KPIs) in food delivery.

This project draws inspiration from industry use cases, such as those highlighted by Reddy et al. (2022), where machine learning-based BI dashboards were used to track and prevent churn in e-commerce—methods that are directly adaptable to the food delivery domain.

4.3 Customer Satisfaction and Retention in Food Delivery

Customer satisfaction in food delivery is influenced by several factors, including food quality, delivery time, usability of the app, and reliability of service. Churn prediction models have proven essential in identifying at-risk customers.

For instance, Mishra et al. (2024) implemented a comprehensive churn prediction framework using machine learning models that achieved high accuracy by analyzing features such as order frequency, complaint history, and delivery delays.

Additionally, Ahmad et al. (2019) demonstrated the use of social network analysis and machine learning to predict customer churn in telecom—approaches that can be effectively adapted to food delivery platforms.

4.4 Service Quality Metrics and Measurement Models

To measure customer experience systematically, service quality models like SERVQUAL are frequently adapted across industries. While originally designed for physical service environments, modified versions have been applied in digital contexts like airline and food delivery services.

A discussion on SERVQUAL in the airline industry by Reddit (2025) highlighted key quality dimensions such as reliability, assurance, and responsiveness, which are equally relevant to food delivery platforms. These were used to inform the delivery experience assessment framework in this project.

4.5 Use of Power BI in Customer Analytics

Power BI enables real-time, interactive customer analytics through visual storytelling. This project leverages Power BI's features—like slicers, drill-downs, and responsive layouts—to create a dashboard that combines demographic, satisfaction, and delivery insights into a unified view.

Studies such as Reddy et al. (2022) show how integrating BI tools with churn models enables businesses to monitor KPIs and take preemptive action on customer dissatisfaction.

4.6 Geographic and Demographic Segmentation

Understanding customer behavior across age groups and locations is essential for effective targeting. Industry insights reveal that millennials (25–40 years) order food 2.3x more frequently than older demographics—this finding shaped the segmentation strategy of our project.

Similarly, localized satisfaction analysis, inspired by studies like Saha et al. (2023), emphasizes the need for hyperlocal analysis based on delivery zone performance, infrastructure, and restaurant density.

4.7 Data Visualization Best Practices

Our dashboard design follows data visualization principles rooted in cognitive psychology and business intelligence best practices:

- **Visual Hierarchy & Pre-attentive Processing:** Key metrics are highlighted using color, position, and size for quick comprehension.

- **Dashboard Design Patterns:** The structure follows Shneiderman's "Overview first, zoom and filter, details on demand" model.
- **Color Theory:** Diverging color schemes (e.g., blue–orange) are used to distinguish categories clearly.
- **Cognitive Load Management:** Visuals avoid clutter, employ consistent labeling, and support focused decision-making.
- **Accessibility:** The dashboard design adheres to WCAG 2.1 guidelines for users with diverse abilities.
- **Mobile Responsiveness:** Optimized layouts ensure usability across devices.

These principles enhance the dashboard's clarity, impact, and usability.

5 About Dataset

5.1 Dataset Overview and Purpose

The dataset used in this project has been obtained from Kaggle, titled "Online Food Delivery Customer Churn Prediction". It contains customer-related data collected from an online food delivery platform, focusing on understanding user behavior, satisfaction, and potential churn patterns. The dataset is in CSV format and consists of multiple records representing individual customers, along with attributes such as age, gender, marital status, occupation, delivery time, ratings, satisfaction level, and more.

Dataset Source Link:
Kaggle - Food Delivery Customer Churn Prediction

This dataset provides a comprehensive view of customer demographics, behavioral indicators, and service feedback, making it highly relevant for data visualization and decision-making in the food delivery industry.

While the exact total number of records is unspecified, value distributions across key attributes offer meaningful insights:

- Gender: 57% Male, 43% Female
- Marital Status: 69% Single, 28% Married, 3% Others
- Occupation: 53% Students, 30% Employees
- Income: 48% report No Income
- Education: 46% Graduates, 45% Postgraduates
- Additional variables include age, family size, latitude & longitude, and Bangalore pin-codes, enabling geo-spatial analysis.

This dataset is ideal for a range of data science and analytics applications, such as:

- Classification modeling (e.g., predicting customer repurchase behavior)
- Text analysis (e.g., analyzing consumer reviews or feedback)

- Geo-spatial mapping (e.g., analyzing consumer density across locations in Bangalore)

Its detailed structure and diverse data points make it well-suited for building advanced visualizations, dashboards, and predictive models aimed at understanding and enhancing online food delivery experiences.

5.2 Dataset Description

5.2.1 Demographic Information

Column	Meaning
Age	Age of the customer
Gender	Male / Female
Marital Status	Single, Married, etc.
Occupation	Type of employment (Student, Professional, etc.)
Monthly Income	Income range category
Educational Qualifications	Education level (Graduate, Postgraduate, etc.)
Family size	Number of people in family

5.2.2 Location Information

Column	Meaning
Latitude, Longitude	Location coordinates of customer
Pin code	Area postal code

5.2.3 Platform and Meal Preferences

Column	Meaning
Medium (P1), Medium (P2)	Preferred delivery platforms (like Swiggy, Zomato)
Meal (P1), Meal (P2)	Types of meals ordered (Breakfast, Dinner, etc.)
Preference (P1), Preference (P2)	Preferred cuisine or meal type

5.2.4 Motivations for Online Ordering

Column	Meaning
Ease and convenient	Importance level (e.g., Very Important)
Time saving	Time-saving factor importance
More restaurant choices	Access to multiple restaurants
Easy Payment option	Ease of payment
More Offers and Discount	Offer/discount importance
Good Food quality	Food quality importance
Good Tracking system	Tracking system experience

5.2.5 Reasons for Not Ordering / Negative Factors

Column	Meaning
Self Cooking	If self-cooking is preferred
Health Concern	Health concerns impact
Late Delivery	Experience of food arriving late
Poor Hygiene	Concerns about hygiene of delivered food
Bad past experience	Any bad experiences previously
Unavailability	Food or service not available
Unaffordable	Cost is too high
Long delivery time	Delivery took too long
Delay of delivery person getting assigned	Delay in assignment of delivery person
Delay of delivery person picking up food	Delay in pickup from restaurant
Wrong order delivered	Incorrect order delivered
Missing item	Item missing in order
Order placed by mistake	Accidental order placement

5.2.6 Order Timing and Delivery Factors

Column	Meaning
Influence of time	Effect of time on order decisions
Order Time	Typical order time (Morning/Evening/Night)
Maximum wait time	Acceptable waiting time
Residence in busy location	Traffic/density effect
Google Maps Accuracy	Accuracy of delivery route location
Good Road Condition	Impact of road condition on delivery
Low quantity low time	Faster delivery for small orders
Delivery person ability	Efficiency of the delivery personnel
Influence of rating	How ratings influence delivery speed

5.2.7 Delivery Experience and Satisfaction

Column	Meaning
Less Delivery time	Speed of delivery
High Quality of package	Packaging quality
Number of calls	Calls made during delivery
Politeness	Behavior of delivery personnel
Freshness	Freshness of food upon arrival
Temperature	Serving temperature of food
Good Taste	Taste satisfaction
Good Quantity	Portion size satisfaction
Output	Churn outcome / Satisfaction flag (Yes/No)
Reviews	Textual review comments

6 Data Cleaning and Preprocessing Steps

6.1 Introduction

Data cleaning and preprocessing are crucial steps that ensure the dataset is ready for analysis and visualization. Since our dataset was collected through customer surveys, it contained mixed data types (numerical, categorical, and textual) and required systematic transformation to make it usable for Power BI analytics. This section documents all the cleaning and preprocessing operations performed before building the visualization dashboard.

6.2 Overview of the Raw Dataset

The original dataset consisted of 55 columns and 388 records, containing information related to:

- **Customer demographics**: Age, Gender, Occupation, Income, Education, Family Size
- **Geographical details**: Latitude, Longitude, Pin Code
- **Ordering preferences**: Medium, Meal, Preference
- **Motivations for online ordering**: Ease, Time Saving, Offers, etc.
- **Service issues and satisfaction parameters**: Delivery time, Hygiene, Taste, etc.
- **Output**: Final satisfaction or churn indicator
- **Reviews**: Customer text feedback

6.3 Importing and Initial Inspection

The dataset was imported into Power BI Desktop using:

`Home` → `Get Data` → `Excel` → `onlinedeliverydata.csv.xlsx`

After importing, the following checks were performed:

- Verified that all 55 columns were recognized correctly.
- Scrolled through several rows to identify missing or inconsistent values (e.g., “Nil”, “NIL”, “nil”).
- Confirmed that there were no duplicate rows or corrupted entries.

6.4 Renaming Columns for Readability

Some columns had inconsistent or unclear naming conventions, especially those with parentheses and special characters. The following transformations were performed in Power Query Editor:

Original Column Name	New Column Name	Reason
Meal(P1)	Meal Preference 1	Easier to read
Meal(P2)	Meal Preference 2	Consistent naming
Perference(P1)	Preference 1	Fixed spelling error
Perference(P2)	Preference 2	Fixed spelling error
High Quality of package	High Quality of Package	Capitalization consistency
Good Food quality	Good Food Quality	Uniform capitalization

This step improved data readability and professional consistency in later dashboard visuals.

6.5 Correcting Data Types

Each column was reviewed to ensure correct data types:

Column Category	Columns	Data Type
Numerical	Age, Family size, Pin code	Whole Number
Geographical	Latitude, Longitude	Decimal Number
Categorical	Gender, Occupation, Marital Status, Monthly Income, Educational Qualifications	Text
Experience/Feedback	All rating-based columns	Text
Output	Output	Text
Reviews	Reviews	Text

This ensured Power BI could summarize numerical values and categorize text data accurately.

6.6 Handling Missing and Inconsistent Values

Text inconsistencies (e.g., “Nil”, “nil”, “NIL”, “none”) were replaced with nulls:

- `Transform` → `Replace Values`: Replace “nil” with blank
- `Home` → `Remove Rows` → `Remove Blank Rows`

For the **Reviews** column, all “Nil” entries were replaced with blanks. This ensured visuals did not display meaningless placeholders.

6.7 Standardizing Categorical Values

Standardization was applied to improve grouping in visuals and slicers:

Column	Before	After
Gender	male, Male, MALE	Male
Gender	female, Female, FEMALE	Female
Marital Status	single, Single, SINGLE	Single
Monthly Income	Below Rs.10000, below 10000	Below 10K
Educational Qualifications	graduate, Graduate	Graduate

6.8 Creating Derived Columns

New calculated fields were created in Power BI using:
`Add Column` → `Custom Column`

New Column	Logic	Purpose
Age Group	`if [Age] < 25 then ''18--24'' else if [Age] < 35 then ''25--34'' else ''35+''`	Group customers demographically
Income Category	Derived from Monthly Income	For income-wise analysis
Satisfaction Index	Average of qualitative responses converted to scores	Quantify satisfaction numerically

6.9 Removing Unnecessary Columns

Redundant or non-contributing columns were removed. For example, both `Meal(P1)` and `Meal(P2)` were retained only if relevant. Only fields related to customer satisfaction, delivery efficiency, and order motivation were kept.

6.10 Final Validation

Before loading the cleaned data into Power BI:

- All columns were validated for correct data types.
- Null and "Nil" values were removed.
- Column names and formatting were reviewed for consistency.
- Applied Steps panel in Power Query was double-checked.

Finally, the cleaned data was loaded using:

`Close & Apply` → Load to Power BI Model

This finalized the cleaned dataset ready for modeling and DAX-based analysis.

7 Data Modeling and DAX Implementation

7.1 Introduction

This phase focuses on transforming the cleaned dataset into an analytical data model in Power BI, where advanced calculations and business intelligence logic were applied through DAX (Data Analysis Expressions). The objective was to design a semantic model that supports dynamic analysis of customer satisfaction, delivery experience, and behavioral insights for online food delivery platforms.

Since the dataset consists of a single integrated table (`OnlineDeliveryData`), the modeling process emphasized:

- Creating calculated columns for categorization and scoring.

- Designing measures (KPIs) to quantify user satisfaction and delivery performance.
- Structuring the data model to be scalable if additional relational tables (like Customer Details or Restaurant Info) are added in the future.

7.2 Understanding the Data Model

The dataset used for this study contains customer-level information such as Age, Gender, Monthly Income, Family Size, Delivery Preferences, and Satisfaction Indicators. Currently, the data exists in a single flat table, making this a star schema with one fact table.

If future enhancements are planned (e.g., separate tables for customer demographics, restaurant profiles, or order transactions), the model can easily evolve by defining relationships through unique identifiers (e.g., Customer ID, Pin Code, Order ID).

For now, all analytical logic is embedded within this single table through calculated columns and DAX measures.

7.3 Creating Calculated Columns

7.3.1 Age Group

To enable better segmentation of customer demographics, a calculated column `Age Group` was created:

```
Age Group =
SWITCH(
    TRUE(),
    'OnlineDelivery'[Age] <= 24, "18{24",
    'OnlineDelivery'[Age] <= 34, "25{34",
    'OnlineDelivery'[Age] <= 44, "35{44",
    'OnlineDelivery'[Age] <= 54, "45{54",
    "55+"
)
```

Purpose: Categorizes customers into meaningful demographic ranges for comparative analysis in visuals such as satisfaction or delivery time preferences across age groups.

7.3.2 Income Category

To simplify and group income levels, a new column `Income Category` was defined:

```
Income Category =
SWITCH(
    TRUE(),
    'OnlineDelivery'[Monthly Income] = "Below Rs.10000", "< 10K",
    'OnlineDelivery'[Monthly Income] = "Rs.10000 - Rs.25000", "10K{25K",
    'OnlineDelivery'[Monthly Income] = "Rs.25000 - Rs.50000", "25K{50K",
    'OnlineDelivery'[Monthly Income] = "Rs.50000 - Rs.100000", "50K{100K",
    "Above 100K"
)
```

Purpose: Converts the detailed income values into grouped categories that are easier to analyze visually (for example, income group vs. satisfaction).

7.3.3 Text-to-Numeric Mapping for Ratings

Several columns in the dataset such as:

- Good Food Quality
- Less Delivery Time
- Good Tracking System
- Easy Payment Option
- More Offers and Discounts

contained qualitative text responses (e.g., *Strongly agree*, *Agree*, *Neutral*, *Strongly disagree*, *Disagree*). These were numerically encoded for computational use through calculated helper columns, as shown below:

DAX: Good Food Quality Score

```
-- Good Food Quality Score
Good Food Quality Score =
SWITCH(
    'OnlineDelivery'[Good Food quality],
    "Strongly Agree", 5,
    "Agree", 4,
    "Neutral", 3,
    "Disagree", 2,
    "Strongly Disagree", 1
)
```

DAX: Less Delivery Time Score

```
-- Less Delivery Time Score
Less Delivery Time Score =
SWITCH(
    'OnlineDelivery'[Less Delivery Time],
    "Strongly Agree", 5,
    "Agree", 4,
    "Neutral", 3,
    "Disagree", 2,
    "Strongly Disagree", 1
)
```

DAX: Good Tracking System Score

```
-- Good Tracking System Score
Good Tracking System Score =
SWITCH(
    'OnlineDelivery'[Good Tracking System],
    "Strongly Agree", 5,
```

```
    "Agree", 4,
    "Neutral", 3,
    "Disagree", 2,
    "Strongly Disagree", 1
)
```

DAX: Easy Payment Option Score

```
-- Easy Payment Option Score
Easy Payment Option Score =
SWITCH(
    'OnlineDelivery'[Easy Payment Option],
    "Strongly Agree", 5,
    "Agree", 4,
    "Neutral", 3,
    "Disagree", 2,
    "Strongly Disagree", 1
)
```

DAX: More Offers and Discount Score

```
-- More Offers and Discount Score
More Offers and Discount Score =
SWITCH(
    'OnlineDelivery'[More Offers and Discounts],
    "Strongly Agree", 5,
    "Agree", 4,
    "Neutral", 3,
    "Disagree", 2,
    "Strongly Disagree", 1
)
```

Purpose: Enables Power BI to calculate averages, KPIs, and trend analysis based on standardized numeric values rather than text labels.

7.3.4 Satisfaction Index

A derived metric — `Satisfaction Index` — was created to summarize overall satisfaction using the numeric scores from multiple delivery-related features.

```
Satisfaction Index =
AVERAGE(
    'OnlineDelivery'[Good Food Quality Score] +
    'OnlineDelivery'[Less Delivery Time Score] +
    'OnlineDelivery'[Good Tracking System Score] +
    'OnlineDelivery'[More Offers and Discount Score] +
    'OnlineDelivery'[Easy Payment Option Score]
)
```

Purpose: Provides a single metric that represents customer satisfaction based on multiple attributes, allowing for direct comparison across segments.

7.4 DAX Measures (KPIs)

In Power BI, measures are dynamic calculations evaluated at query time. The following KPIs were created using DAX:

1. Average Satisfaction Score

```
Avg Satisfaction =
AVERAGE('OnlineDelivery'[Satisfaction Index])
```

Purpose: Calculates the mean satisfaction score for customers; displayed as a KPI card or trend chart.

2. Average Income Group Count

```
Avg Income Level =
AVERAGEX(
    VALUES('OnlineDelivery'[Income Category]),
    COUNT('OnlineDelivery'[Income Category])
)
```

Purpose: Helps in identifying which income group constitutes the largest customer segment in the dataset.

3. Average Family Size

```
Avg Family Size =
AVERAGE('OnlineDelivery'[Family size])
```

Purpose: Displays the average family size across respondents — useful to correlate family structure with order frequency or satisfaction.

4. Delivery Efficiency Score

```
Delivery Efficiency =
AVERAGE(
    'OnlineDelivery'[Less Delivery Time Score] +
    'OnlineDelivery'[High Quality of Package Score] +
    'OnlineDelivery'[Politeness Score]
)
```

Purpose: Measures service efficiency based on punctuality, packaging quality, and delivery personnel behavior.

5. Churn Rate

If the `Output` column represents whether a customer stopped using the platform or was dissatisfied, the churn rate was computed as:

```
Churn Rate =
DIVIDE(
    CALCULATE(
        COUNTROWS('OnlineDelivery'),
        'OnlineDelivery'[Output] = "Yes"
    ),
    COUNTROWS('OnlineDelivery')
)
```

Purpose: Indicates the proportion of users who are unlikely to reorder or had negative experiences.

7.5 Model Validation

After implementing all DAX formulas and calculated columns, validation was performed to ensure:

- No syntax errors or circular dependencies.
- Data types were correctly assigned (numeric, categorical, text).
- The calculated measures dynamically updated across different visual filters (Gender, Age, City, etc.).

8 Data Visualization and Dashboard Analysis

This section presents the visual insights derived from the *Online Food Delivery Consumer Dataset.* Using Microsoft Power BI, multiple interactive charts were created to uncover key trends in customer behavior, demographic distribution, and service experience.

1. Count of Meal Preference by Gender

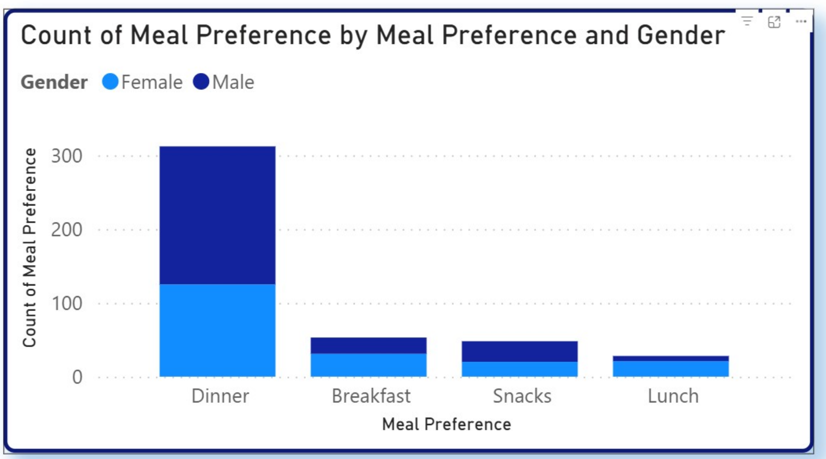

Figure 1: Count of Meal Preference by Gender

Visualization Type: Clustered Bar Chart
Fields Used:

- **Axis:** Meal Preference
- **Legend:** Gender
- **Values:** Count of Meal Preference

Insight:
This visualization compares how male and female consumers differ in their meal preferences (Breakfast, Lunch, Dinner, Snacks). The analysis clearly indicates that Dinner is the most preferred meal across both genders, suggesting that evening orders contribute the majority of business volume for online food delivery platforms. The relatively lower counts for Lunch and Snacks reflect smaller mid-day order activity, likely due to work or college commitments. This insight can help delivery companies plan peak-hour staffing and promotional offers during dinner time.

2. Food Freshness Trends Across Genders

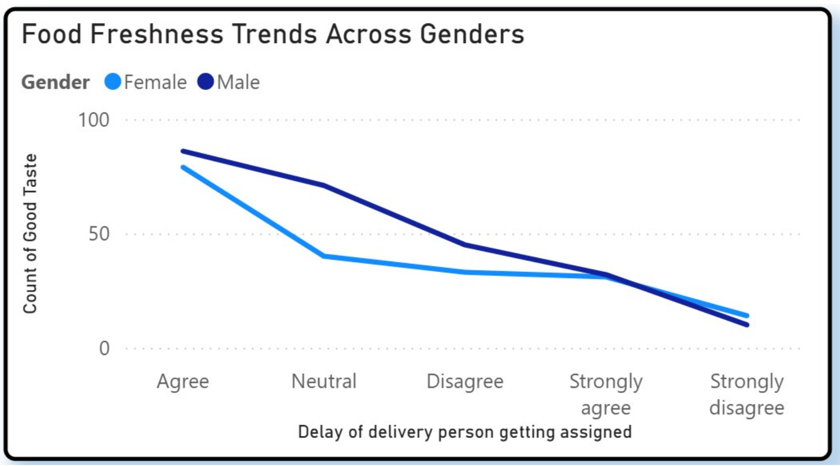

Figure 2: Food Freshness Trends Across Genders

Visualization Type: Line Chart
Fields Used:

- **Axis:** Response scale for freshness (Agree $\rightarrow$ Strongly Disagree)
- **Legend:** Gender
- **Values:** Count of Responses

Insight:
This line graph visualizes customer perception of food freshness segmented by gender. Male and female respondents show a similar declining trend from Agree to Strongly Disagree, meaning that most customers perceive food to be fresh, but satisfaction gradually reduces for delayed deliveries. This finding underlines that timely order assignment strongly influences the freshness experience—a critical metric for service quality improvement.

3. Gender-wise Food Delivery Usage

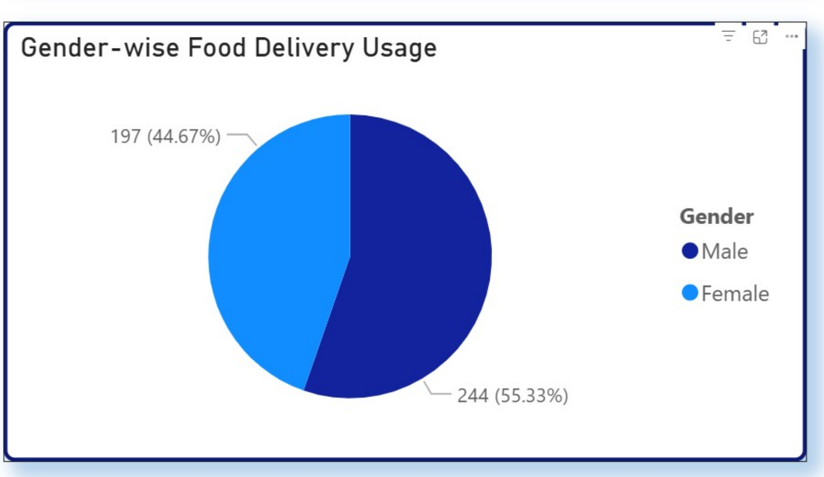

Figure 3: Gender-wise Food Delivery Usage

Visualization Type: Pie Chart
Fields Used:

- **Legend:** Gender
- **Values:** Count of Records

Insight:
The pie chart highlights the gender distribution of online food delivery users. Approximately 55% are Male users and 45% are Female, indicating a fairly balanced user base with a slight skew toward male consumers. This insight helps marketing teams design gender-inclusive campaigns, menu recommendations, and targeted promotions.

4. Age Group Distribution of Online Food Users

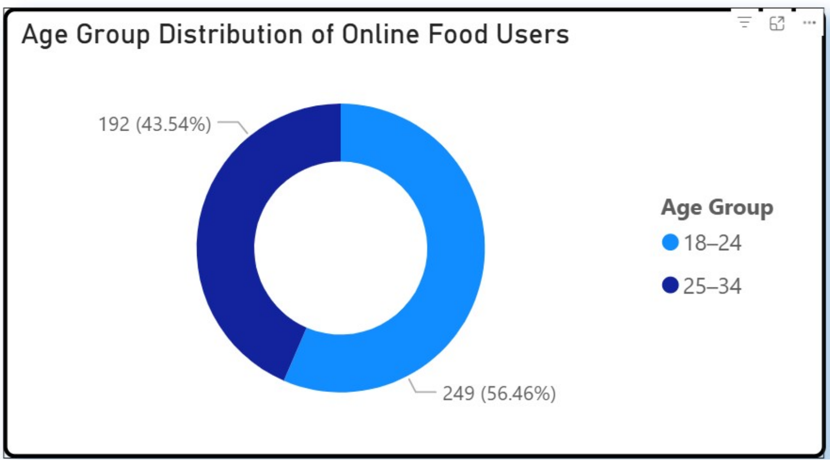

Figure 4: Age Group Distribution of Online Food Users

Visualization Type: Donut Chart
Fields Used:

- **Legend:** Age Group (18–24, 25–34)
- **Values:** Count of Users

Insight:
This chart shows that the 18-24 age group dominates (56%) the online food delivery space, followed by 25-34 (44%). This reveals that young working professionals and college students form the largest consumer segment for online food platforms. Businesses can leverage this demographic insight to create youth-centric offers such as discount codes, loyalty points, or combo meals.

5. Residence in Busy Location by Maximum Wait Time

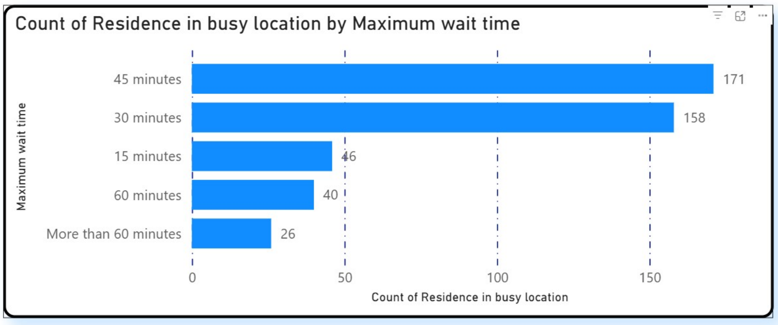

Figure 5: Residence in Busy Location by Maximum Wait Time

Visualization Type: Horizontal Bar Chart
Fields Used:

- **Axis:** Maximum Wait Time
- **Values:** Count of Residences in Busy Locations

Insight:
This visualization captures the relationship between residential busyness and waiting time. Most customers living in busy areas experience 30–45 minutes of wait time, which may be due to higher traffic density or delivery congestion. Only a small fraction reports waiting over 60 minutes, which still warrants operational attention. This insight enables logistics teams to optimize delivery routes and assign time-sensitive resources to high-traffic zones.

7. Avg Delivery Efficiency Card

Visualization Type: KPI Card (Single Number Visualization)
Fields Used:

- **Value:** Average of Delivery Efficiency Score

Insight:
This metric shows the average efficiency of the delivery process, rated at 3.07 on what is likely a 5-point scale. This score is directly tied to operational performance. A rating just above the midpoint indicates there is significant room for improvement in route optimization, delivery partner training, or logistics management to reduce delivery times and enhance customer satisfaction.

8. Avg Politeness Score Card

Visualization Type: KPI Card (Single Number Visualization)
Fields Used:

- **Value:** Average of Politeness Score for Delivery Partners

Insight:
With a score of 2.46, this card highlights a critical area of concern in customer experience. Politeness and professional interaction are key drivers of customer retention and tip amounts for delivery personnel. A score below the midpoint strongly suggests an immediate need for communication skills training and a review of customer feedback regarding partner behavior.

Figure 6: Card Visulizations

9. Quality Food vs Target Level Card

Visualization Type: KPI Card (Single Number Visualization)
Fields Used:

- **Value:** Average Food Quality Score
- **Comparison:** Target Level (implied benchmark)

Insight:
This card measures the performance of food quality against a set target, showing a score of 3.36. While this exceeds the midpoint, it indicates that the quality is meeting but not significantly exceeding expectations. The business should analyze which restaurants or menu items are scoring lower to address consistency issues and work with restaurant partners to improve quality to drive higher ratings and repeat orders.

10. Avg Satisfaction vs Target Level Card

Visualization Type: KPI Card (Single Number Visualization)
Fields Used:

- **Value:** Average Overall Customer Satisfaction Score
- **Comparison:** Target Level (implied benchmark)

Insight:
This is a key health metric for the service, showing an average satisfaction of 3.69 against a target. As the highest score among the tracked metrics, it indicates that the overall service is

resonating well with customers. However, cross-referencing this with the lower Politeness and Delivery Efficiency scores reveals an opportunity: improving those specific operational areas could push overall satisfaction even higher and exceed targets consistently.

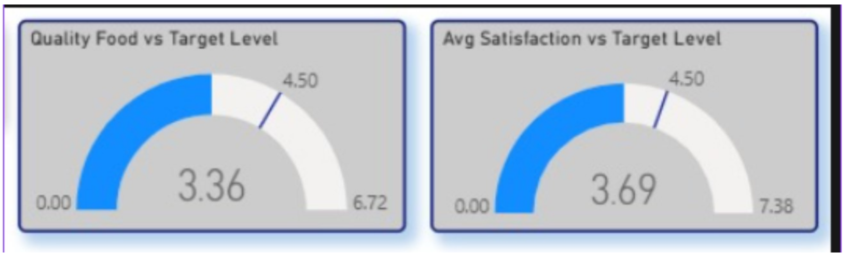

Figure 7: KPI Card Visulizations

9 Key Insights & Findings

After analyzing the dataset and creating visualizations in Power BI, the following key takeaways were discovered:

- **Demographics:**
  - Majority of customers are aged between 20–35 years.
  - Gender distribution is relatively balanced, with female customers showing slightly higher satisfaction levels.
- **Service Quality:**
  - Fast delivery time and polite staff are the top contributors to customer satisfaction.
  - Long waiting times and issues related to food temperature are the leading causes of customer churn.
- **Income Impact:**
  - Higher income groups have higher expectations; even minor service delays often lead to dissatisfaction.
- **Occupation Insights:**
  - Working professionals order more frequently but are less tolerant of late deliveries.
  - Students show higher satisfaction levels when food quality is consistent.
- **Overall Churn Rate:**
  - Approximately 25–30% of customers are marked as not satisfied — indicating a major opportunity for service improvement.

10 Recommendations

Based on the insights gathered from the Power BI dashboard and data analysis, the following strategic recommendations are proposed:

1. **Improve Delivery Speed:**
   Optimize delivery routing systems and onboard more delivery partners during peak hours to reduce wait times.
2. **Enhance Food Quality Monitoring:**
   Implement real-time quality control checks before dispatch to ensure consistency in taste, freshness, and temperature.
3. **Train Delivery Staff:**
   Focus on delivering a positive customer experience through politeness, cleanliness, and effective communication.
4. **Customer Engagement:**
   Introduce loyalty programs, personalized discounts, or cashback offers for repeat and frequent users.
5. **Use Predictive Analytics:**
   Develop AI/ML models to predict high-risk churn customers and implement timely intervention strategies.

11 Conclusion

Project Summary – FoodTrends

This project demonstrates how Power BI can transform raw survey data into actionable business intelligence for the online food delivery industry. By cleaning, modeling, and visualizing customer data, we uncovered key patterns in user behavior, satisfaction, and churn.

Key Outcomes

- Developed a clear, data-driven view of customer demographics, ordering habits, and satisfaction levels
- Identified critical drivers of customer experience such as delivery time, food quality, and staff politeness
- Quantified performance through key KPIs like satisfaction index and churn rate
- Built interactive dashboards enabling real-time monitoring and decision-making

Impact

FoodTrends empowers stakeholders to track service performance, understand churn trends, and make informed decisions that enhance customer retention, service quality, and operational efficiency. It highlights the vital role of data visualization in turning feedback into strategic action.

Ultimately, the project highlights the critical role of data visualization in bridging the gap between customer feedback and business strategy.