**Group 5** 

# QUANTIFYING THE AIR TRAVEL EXPERIENCE:

# A Comprehensive Analysis of Influential Factors in Passenger Satisfaction

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- 3 Evaluation
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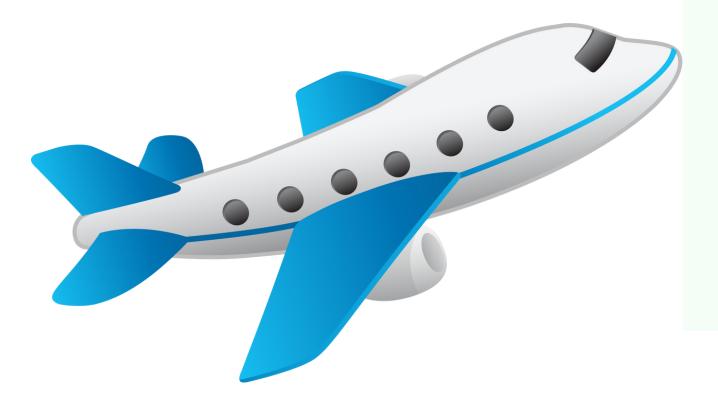
# INTRODUCTION

**Summary of Project** 

# **Project Background**

#### **Aviation Industry**

- Major tourism driver
- Contributes 7.6% to global tourism GDP (WTC 2023)
- Highly competitive industry (focused on the journey)



#### **Problem Statement**

- What are the key contributing factors that impact the passengers overall experience while flying?
- What is the impact of flight delays and arrival delays on overall passenger's experience?

#### **Project Objective**

- To identify and analyse
   the key contributing
   factors that impact the
   overall customer
   experience in the context
   of airline travel.
- To investigate the specific impacts of departure and arrival delays on overall customer experience.
- To predict customer satisfaction using machine learning models.

# Mechanics

#### Hardware



- Minimum hardware requirement for R.
- Operating system:
   Windows 10
- CPU Architecture: Intel
   Core i3 or AMD Ryzen
   3250u (64-bit)
- 1GB RAM, 2GB harddisk space

#### **Software**



- The programming language used in this project is R.
- Chose R for familiarity and extensive libraries.
- Simplified syntax in R, beginner-friendly and easy to learn

#### **Platform**







- Employ Shiny for interactive web apps.
- Use GitHub for version control to ensure reproducible research.
- Use Team to hold meetings and share documents

# Data Science Pipeline

#### Phase 1

- Define Problem & Goals
- Data Procurement
- Data Understanding
- Data Preparation
- Data Cleaning
- Exploratory Data Analysis

#### Phase 2

- Modeling
- Evaluation
- Deployment
- Results and Discussion

# DATA MODELING

**Experiment & Results** 

## **Experiment & Results - Result Matrices**

## **Machine Learning**

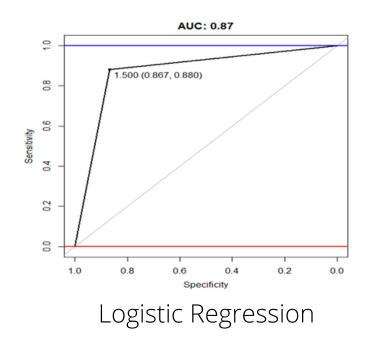
- Create data partition (75:25)
   using "set.seed(100)" for
   reproducibility
- Using caret package to streamline model training
- Employed 5 classification models
- Performed cross-validation
   for 5 times

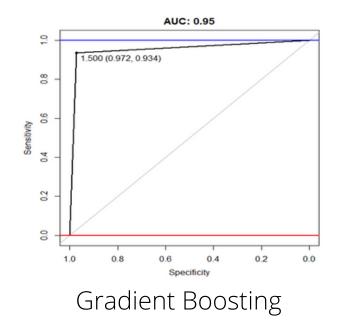
|                          | Accuracy | Sensitivity | Specificity | F1-Score | AUC . |
|--------------------------|----------|-------------|-------------|----------|-------|
| Logistic<br>Regression   | 87%      | 90%         | 83%         | 89%      | 87%   |
| Decision<br>Tree         | 87%      | 87%         | 88%         | 89%      | 87%   |
| Gradient<br>Boosting     | 96%      | 97%         | 93%         | 96%      | 95%   |
| K-Nearest<br>L-Neighbour | 92%      | 97%         | 87%         | 93%      | 92%   |
| Random<br>Forest         | 96%      | 98%         | 94%         | 97%      | 96%   |

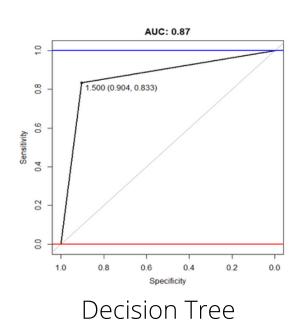
#### Result

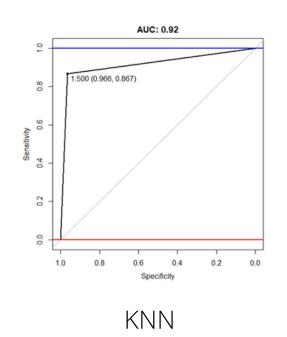
Random Forest Model, the best performance model, is better to fit the data and predict passenger satisfaction.

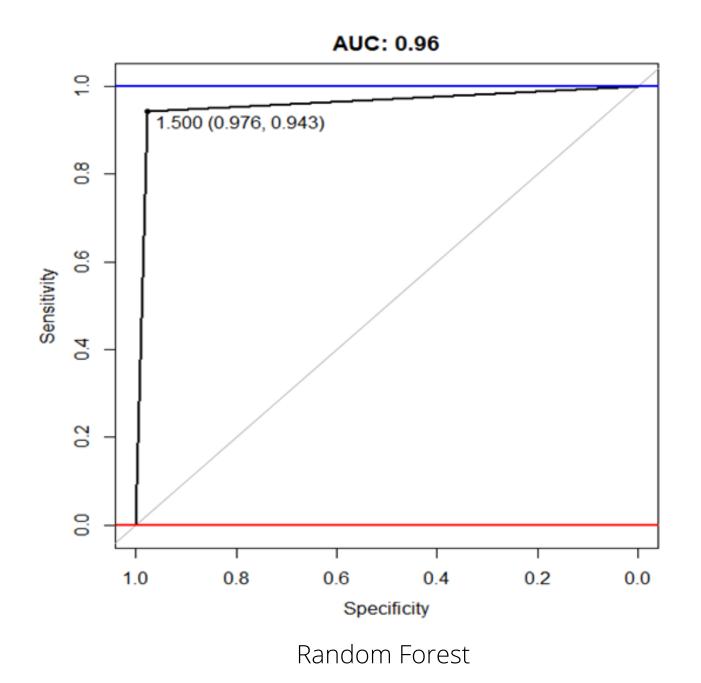
# Experiment & Results -Result Matrices











# **Experiment & Results - Rated Features**

Based on the analysis conducted in the previous chapter we can do a cross analysis of the Highest rated features that is recognized by each model.

| Logistic   | Decision      | Gradient      | K-Nearest | Random Forest |
|------------|---------------|---------------|-----------|---------------|
| Regression | Tree          | Boosting      | Neighbour | Random Forest |
| Type of    | Class         | Online        | NI/A      | Online        |
| travel     | Class         | Boarding      | N/A       | Boarding      |
| Customer   | Online        | In-flight     | N/A       | In-flight     |
| Type       | Boarding      | Wi-Fi         | IN/A      | Wi-Fi         |
| Online     | Type of       | Type of       | N/A       | Class         |
| Booking    | Travel        | Travel        | IN/A      | Class         |
| Check In   | In-flight     | Class         | N/A       | Type of       |
| service    | entertainment | Class         | IN/A      | Travel        |
| In flight  | In-flight     | In-flight     | N/A       | In-flight     |
| Wi-Fi      | Wi-Fi         | entertainment | IN/A      | entertainment |

#### Result

In answering the problem statement highlighted earlier, the **top 3 features** based of the feature importance analysis across the models trained are:

- Online Boarding
- In-Flight WiFi
- Type of Travel

|                   | Arrival Delay Ranked | Departure Delay Ranked |
|-------------------|----------------------|------------------------|
| Logistic          | 16/26                | 18/26                  |
| Regression        |                      |                        |
| Decision Tree     | 29/29                | 29/29                  |
| Gradient Boosting | 16/29                | 20/29                  |
| K-Nearest         | N/A                  | N/A                    |
| Neighbour         |                      |                        |
| Random Forest     | 18/29                | 19/29                  |

# EVALUATION

Comparison & Results Future Studies

# Comparative Study - Methods

#### **Evaluation**

Identify similar studies that utilized the same datasets and comparing their conclusions to this study forms the table below on the features

| Characteristics      | This Study                 | Study 1          | Study 2              |
|----------------------|----------------------------|------------------|----------------------|
|                      | Binning (Ages, Flight      | Normalization    | Binning (Type of     |
| Preprocessing        |                            |                  | Travel),             |
| Methods              | Distance)                  | (Arrival Delay,  | Dropped Columns      |
|                      |                            | Departure Delay) | (Departure Delay)    |
| Handle Missing  Data | MICE Imputation            | MICE Imputation  | Dropped Column       |
|                      | Decision Tree, Logistic    |                  | K-Nearest Neighbour, |
| Models Used          | Regression, Random         | Catboost         | Decision Tree,       |
| Models Osed          | Forest, Gradient Boosting, | Classification   | Random Forest,       |
|                      | K-Nearest Neighbour        |                  | LASSO Regression     |

# Comparative Study-Features

#### Result

Despite difference in ranking, the **overall features** that are present are the same.

| Rank | Feature (This Study) | Feature (Study 1) | Feature (Study 2) |
|------|----------------------|-------------------|-------------------|
| 1    | Online Boarding      | In-Flight WiFi    | Online Boarding   |
| 2    | In-Flight WiFi       | Type of Travel    | In-Flight WiFi    |
| 3    | Type of Travel       | Online Boarding   | Type of Travel    |

Further analysing the outcomes of the studies, the team has filtered the features for only service-based features.

| Rank | Feature (This Study)    | Feature (Study 1) | Feature (Study 2)       |
|------|-------------------------|-------------------|-------------------------|
| 1    | Online Boarding         | In-Flight WiFi    | Online Boarding         |
| 2    | In-Flight WiFi          | Online Boarding   | In-Flight WiFi          |
| 3    | In-Flight Entertainment | Check-In Service  | In-Flight Entertainment |

## **Future Studies**

- More airlines for a clearer comparison
- A bigger set of data from different places to help understand what makes customers satisfied
- **Diverse models** to improve potentially better use-cases

|   | Aspect                              | Improvement  | Argument  |
|---|-------------------------------------|--|---|
|   | Data<br>Constraints                 | Data is limited to US Airlines, expanding the scope of data to include data from other countries/airlines.   | Provides deeper insight into an overall view of airlines not limited to potential US related biases.  |
|   | Data geo-<br>temporal<br>aspects    | Expanding the data by adding a Geo-temporal aspect to the data such as location and date-time of the survey. | This helps by allowing the study of geographical cluster biases within a given area as well as showing the changes of sentiments over time via a temporal aspect. |
| 3 | Diverse<br>Classification<br>Models | Utilizing more robust models and exploring the potential usage of ensemble models.                           | Increasing the scope of models may identify potentially better use-cases as compared to the ones utilized in this study.  |

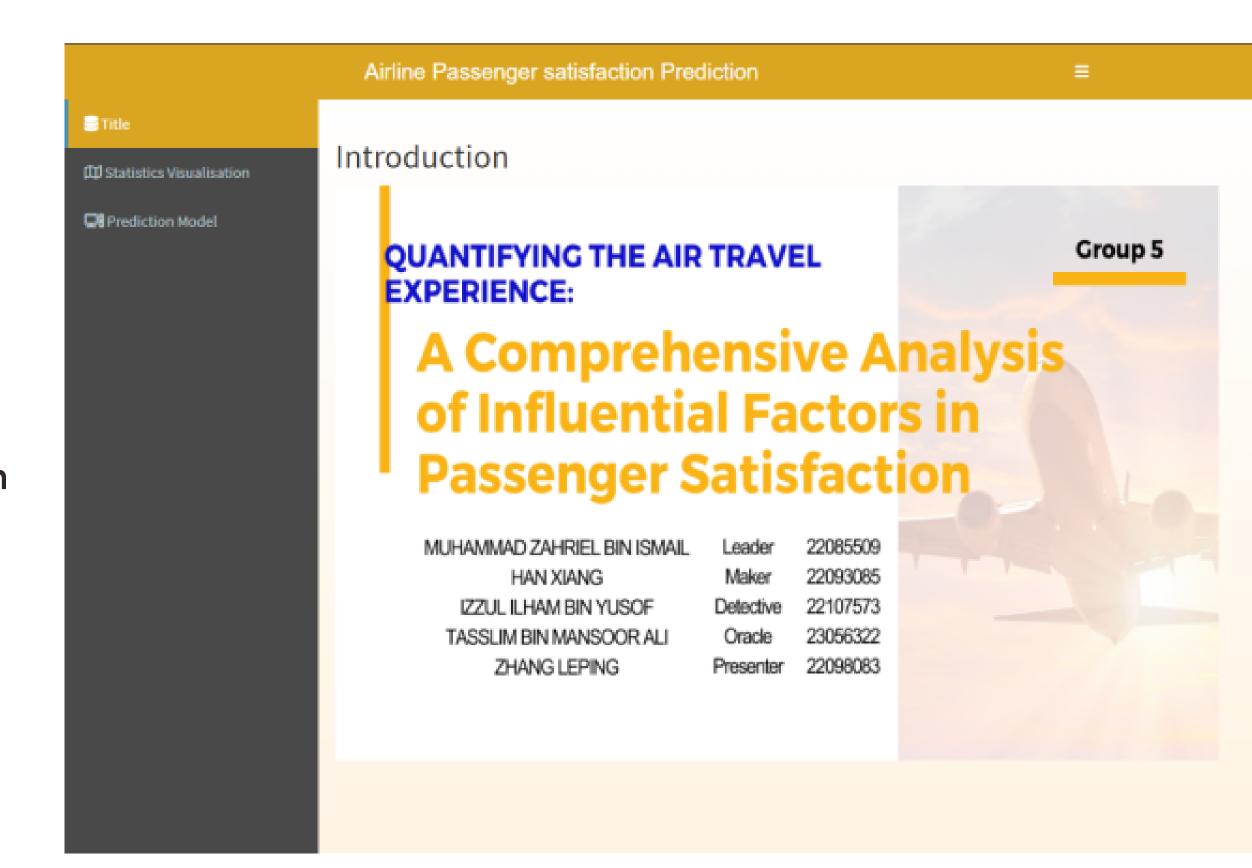
# DEPLOYMENT

**Data Product** 

# **Main Page**

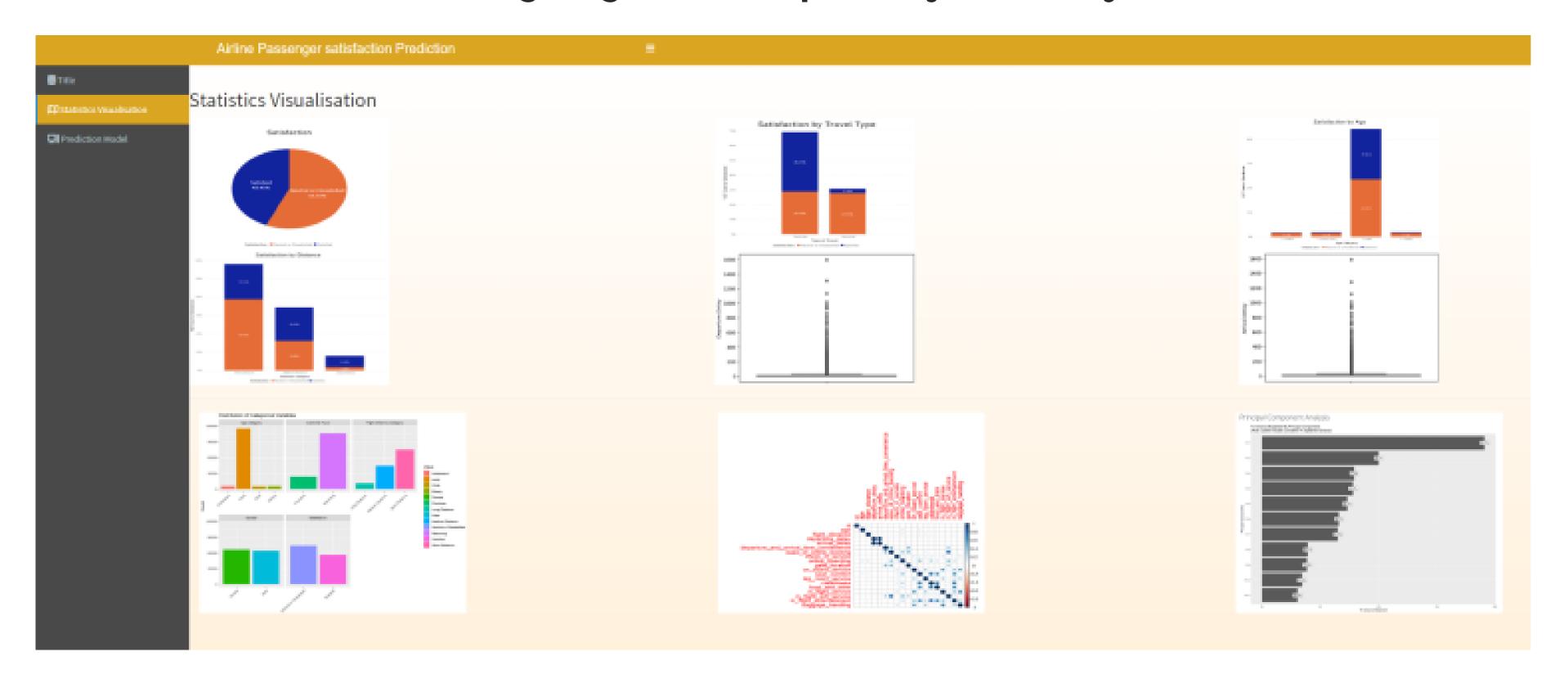
#### **Data Product**

An interactive web application on **Shiny** which can predict passenger satisfaction based on the facilities provided by the airline.



# Visualization Page

#### Presenting insights from Exploratory Data Analysis (EDA)



# **Prediction Model Page**

#### **Model Used: Random Forest**

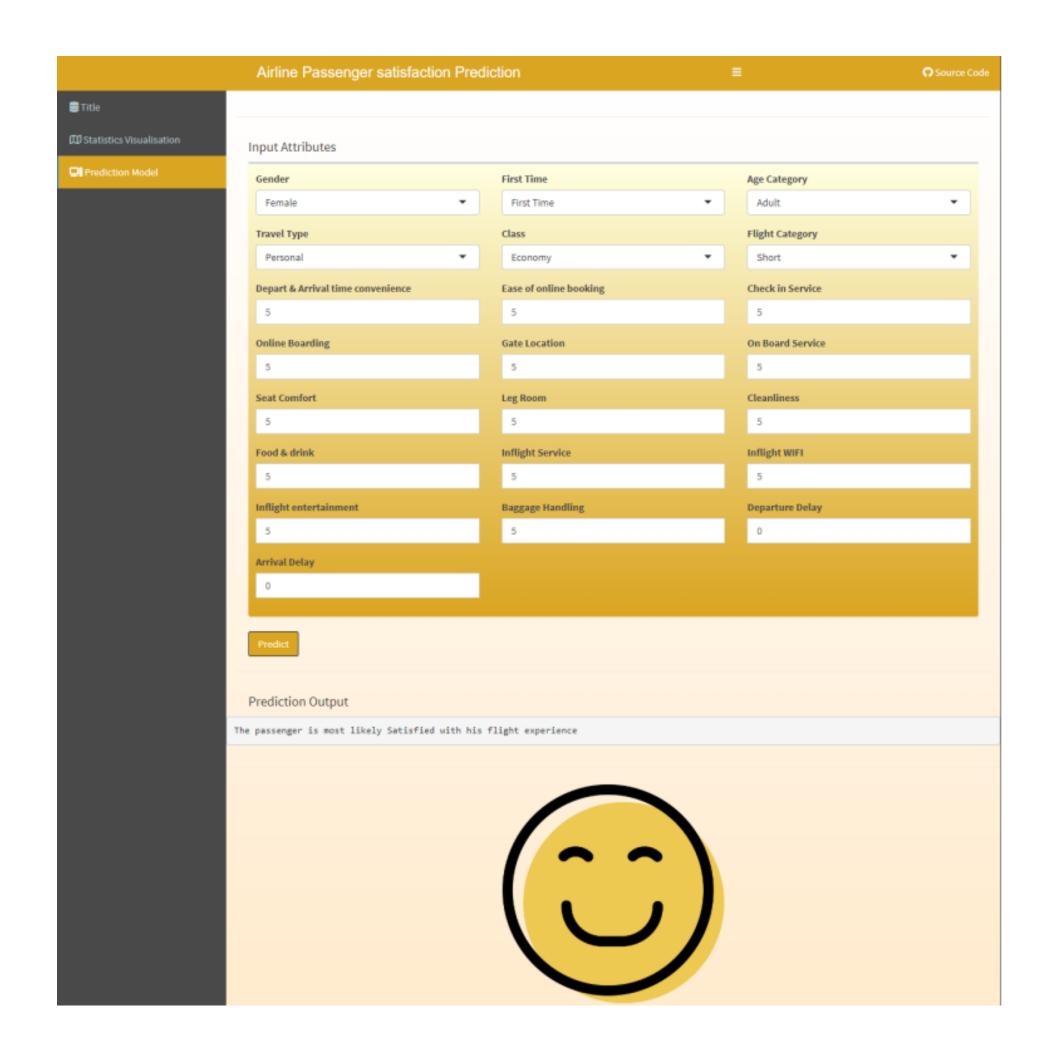
#### Instructions

#### Input

- Gender
- First-time flying status
- Age
- Category
- Travel type
- Class and flight category
- Ratings for specific facilities

#### **Output**

- Satisfaction level
- Relevant emoji



# CONCLUSION

Reproducible Research Insights

# Plan for Reproducible Research

### Reproducibility Validation

To ensure that the data is accessible as well as the code for this study, all the steps involved will be posted on GitHub and be publicly available for researchers to reproduce the study.

#### **Code Document**

Furthermore, to ensure that the model training will produce the same results, the team has preset the seed in R using "set.seed(100)" to ensure that no variation occurs.

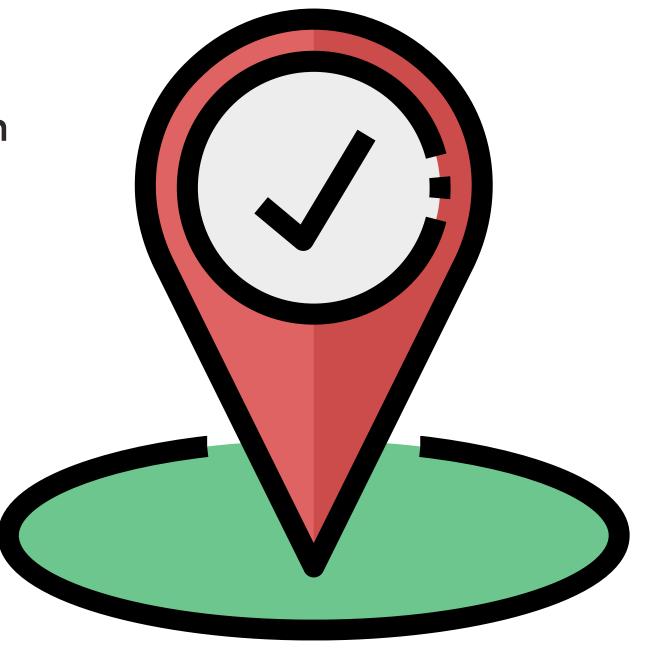
### **Data Repository**

Added on to this, documentation, datasets as well as dependencies (Libraries, etc.) will also be listed within the GitHub repository.

https://github.com/ZahrielIsmail/WQD7001\_Group\_5\_Assignment

## Conclusion

- According to customer reviews, Online Check-In, In-Flight WiFi, and In-Flight Entertainment services are areas that need improvement.
- Arrival/departure delays have a relatively low impact on overall satisfaction.
- These findings help airlines prioritize their efforts to improve customer experience and retention.



## Reference

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# THANK YOU!