# AIRPORT FINANCIAL PERFORMANCE: A HYBRID FRAMEWORK TO EVALUATE NON-AERONAUTICAL REVENUES GENERATION EFFICIENCY

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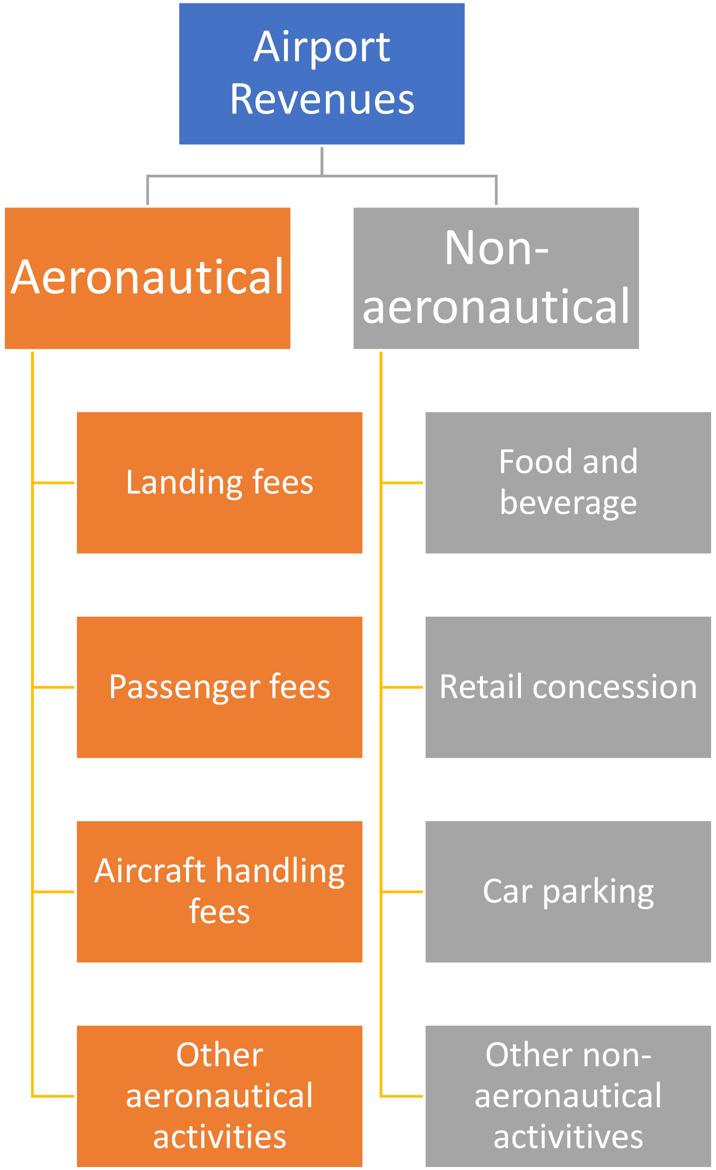
# Introduction




Graham (2008) and IATA (2019)

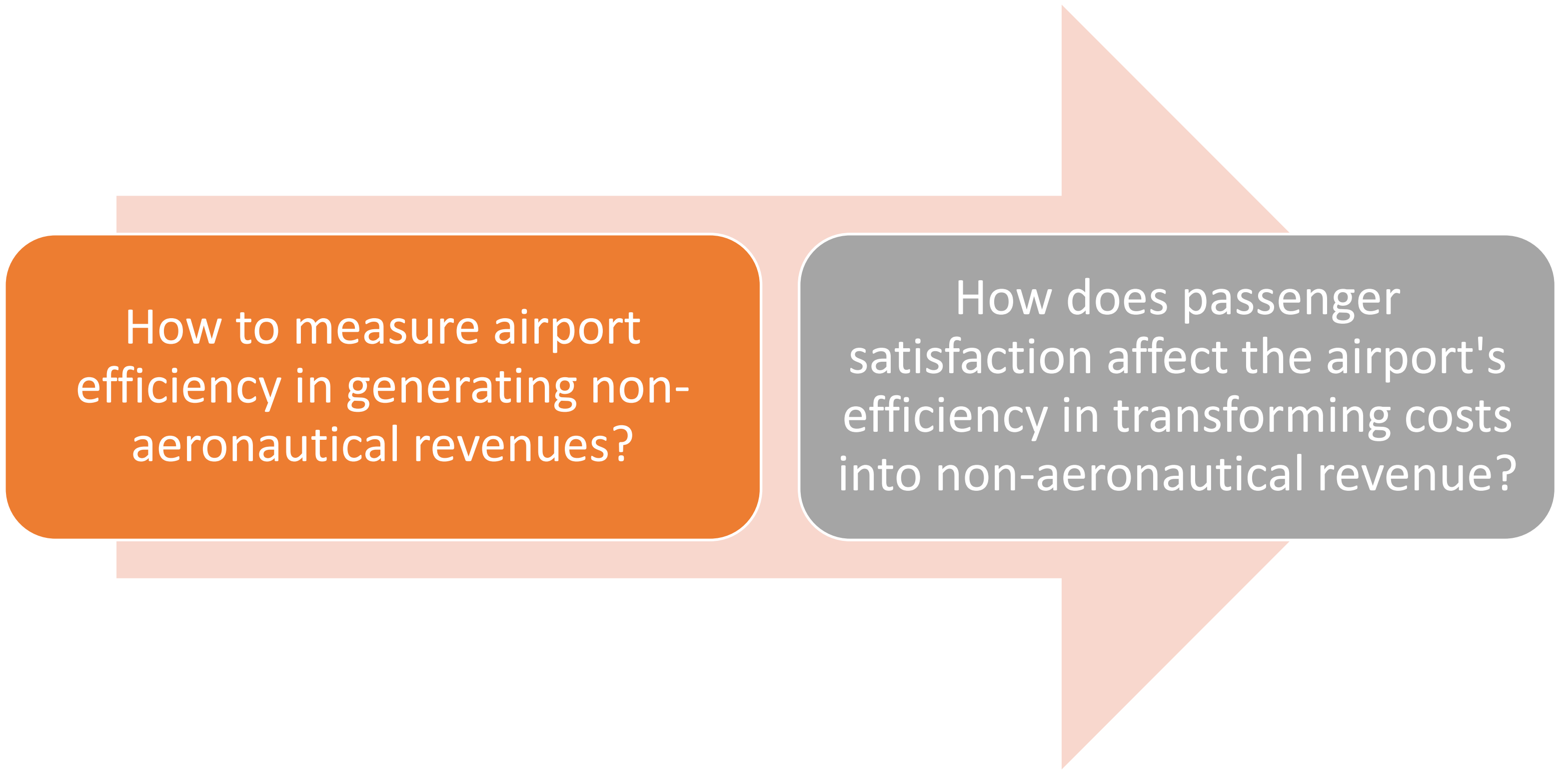
# Introduction

- Wu and Chen (2019) => non-aeronautical revenues are potential sources to promote the sustainable financial development of airports

- ACI World Airport Economics Database (2023) => overall airport industry costs surged by 12.39% between 2015 and 2019

# Introduction

- The main objective of this paper is to construct a hybrid framework for calculating an airport efficiency index, specifically focusing on non-aeronautical revenue generation while incorporating the influence of passenger satisfaction levels.



# Literature Review

SUBJECTS

- Efficiency evaluation of an airport as a business-oriented structure
- Non-aeronautical revenues in current airport business scenario
- Passenger experience at airport terminals
- Literature Gaps

# Efficiency evaluation of an airport as a business-oriented structure

Merkert et al., 2012

Fernandes and Pacheco, 2018

Lai et al., 2012

Keskin and Köksal, 2019

Adler et al., 2013

Olariaga and Moreno, 2019

Maghbouli et al. (2014)

Fragoudaki and Giokas, 2020

Rely on operational efficiency

Merkert and Assaf, 2015

(EBITDA)

lo Storto, 2018

(General revenues)

Consider the operational efficiency and analyze financial performance

# Efficiency evaluation of an airport as a business-oriented structure

Schultz & Reitmann, 2019

Yilmaz et al., 2022

Implement machine learning (ML) techniques to predict performance or to complement a DEA model

Examples of ML applications:

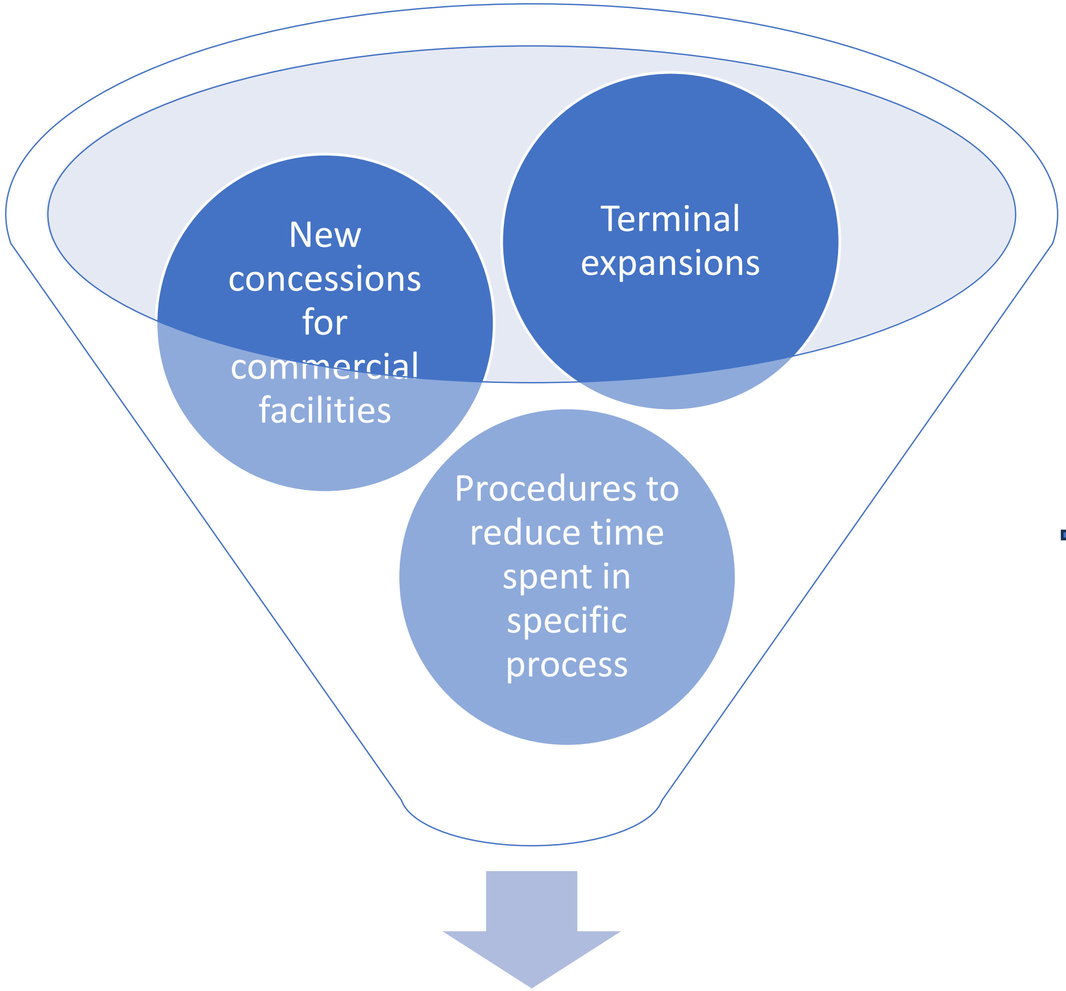
- Long Short-Term Memory (LSTM) -> Neural Network => aircraft boarding
- Self Organizing Maps (SOM) -> clusterizing => operational efficiency

# Non-aeronautical revenues in current airport business scenario

Kazda and Caves (2015) => many airport administrations obtain higher revenues from non-aeronautical services than from aeronautical services

In Brazil, for example, the airports privatization has started in 2012. Since then, the concessionaires financial report indicates an average growth of almost 65% in the participation of non-aeronautical revenues on airport revenues distribution after the first year of privatization.

# Non-aeronautical revenues in current airport business scenario




growth of non-aeronautical revenues

Yokomi, Wheat and Mizutani (2017)
Castillo-Manzano, Valpuesta and Braza (2018)
Fuerst and Gross (2018)
Nascimento et al. (2022)

Regression models

# Passenger experience at airport terminals

Brink and Madison (1975) => discussion about the level of service based on how much time a passenger spends at a terminal.

Castillo-Manzano (2010) => suggests that the expenditure levels increase as the waiting time increases.

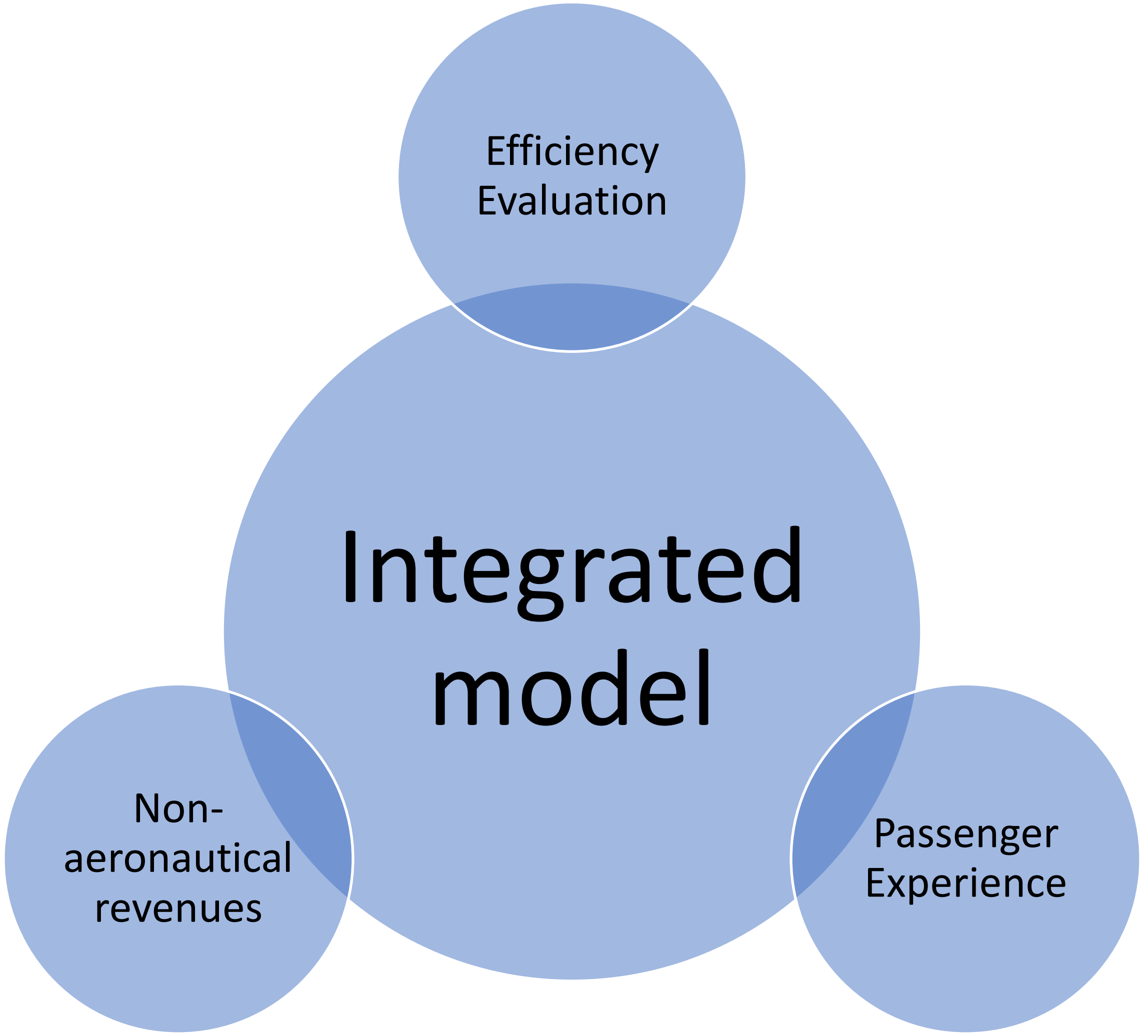
# Passenger experience at airport terminals

Kiliç and Çadirci (2020) => ambient conditions and terminal facilities as two of the top 10 attributes that have positive impact on passenger experience.

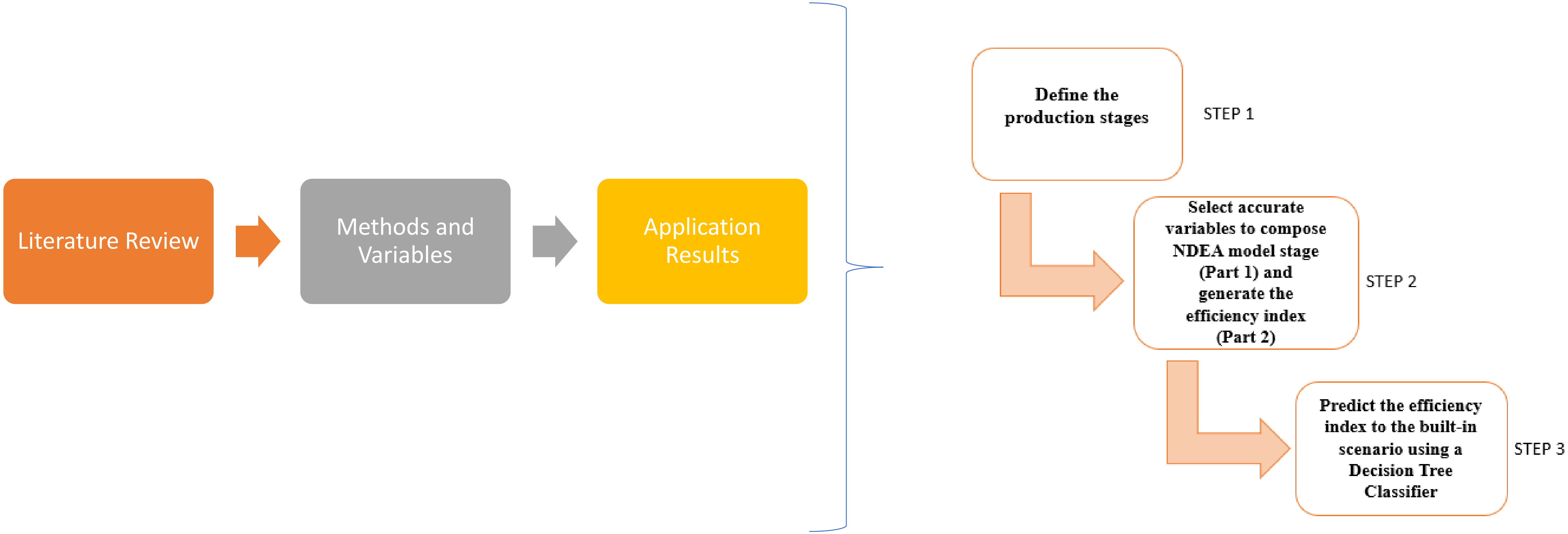
Nascimento et al. (2022) => positive passenger evaluation of products price on commercial establishments has a negative impact on non-aeronautical revenues.

Silva et al. (2024) => expenditure levels increase as the waiting time and the passenger satisfaction increases.

# Literature final consideration

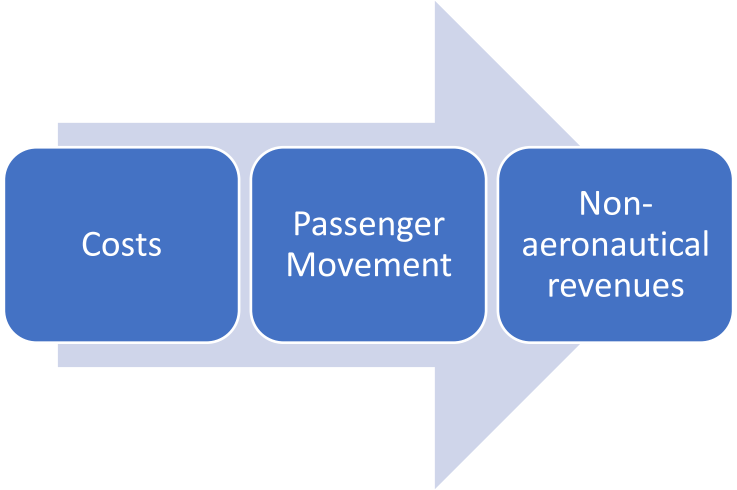


# Proposed Method



# Proposed Method

STEP 1: **Define the production stages (cost-revenues stage)**



# Proposed Method

- STEP 2: **Select accurate variables to compose each NDEA model stage (part 1)**

| Variable | Measurement | Explanation | Variable function Stage 1 | Variable function Stage 2 |
|---|---|---|---|---|
| **Operational Costs** | R$MM | Represents the main necessary operational costs to maintain the airport operation | Input | - |
| **Personal Costs** | R$MM | Represents the main necessary personal costs to maintain the airport operation | Input | - |
| **Domestic Passenger** | Number | Total domestic passenger movement | Output | Input |
| **International Passenger** | Number | Total international passenger movement establishments | Output | Input |
| **Non-aeronautical revenues** | Value of non-aeronautical revenues x1000000 | Non-aeronautical revenue during a specific period | - | Output |

# Proposed Method

STEP 2: **Generate the efficiency index using the NDEA model (part 2)**

$$E_0 = \max \sum_{r=1}^{s} u_r . y_{r0}$$

$$\sum_{i=1}^{m} v_i . x_{i0} = 1$$

$$\sum_{d=1}^{q} w_d . z_{dj} - \sum_{i=1}^{m} v_i . x_{ij} \leq 0, \; j = 1,2,\ldots,n.$$

$$\sum_{r=1}^{s} u_r . y_{rj} - \sum_{d=1}^{q} w_d . z_{dj} \leq 0, \; j = 1,2,\ldots,n.$$

$$u_r, v_i, w_d \geq \varepsilon, \; i = 1,2,\ldots,m; \; r = 1,2,\ldots,s; \; d = 1,2,\ldots,D.$$

# Proposed Method

- STEP 3: **Prediction the efficiency index to the built-in scenario using passenger satisfaction**

| Variables | Definition |
|---|---|
| CHECKIN PROCESS | Score for passenger satisfaction regarding Check-in process |
| SECURITY INSPECTION | Score for passenger satisfaction regarding Security Inspection process |
| QUALITY OF COMMERCIAL ESTABLISHMENTS | Score for passenger satisfaction regarding the quality of Commercial Services |
| QUANTITY OF COMMERCIAL ESTABLISHMENTS | Score for passenger satisfaction regarding the quantity of Commercial Services |
| QUALITYOF FOOD & BEVERAGE ESTABLISHMENTS | Score for passenger satisfaction regarding the quality of Food & Beverage Services |
| QUANTITY OF FOOD & BEVERAGE ESTABLISHMENTS | Score for passenger satisfaction regarding the quantity of Food & Beverage Services |
| PRICE OF FOOD & BEVERAGE ESTABLISHMENTS | Score for passenger satisfaction regarding the price of Food & Beverage Services |

# Method Application

## Data Collection

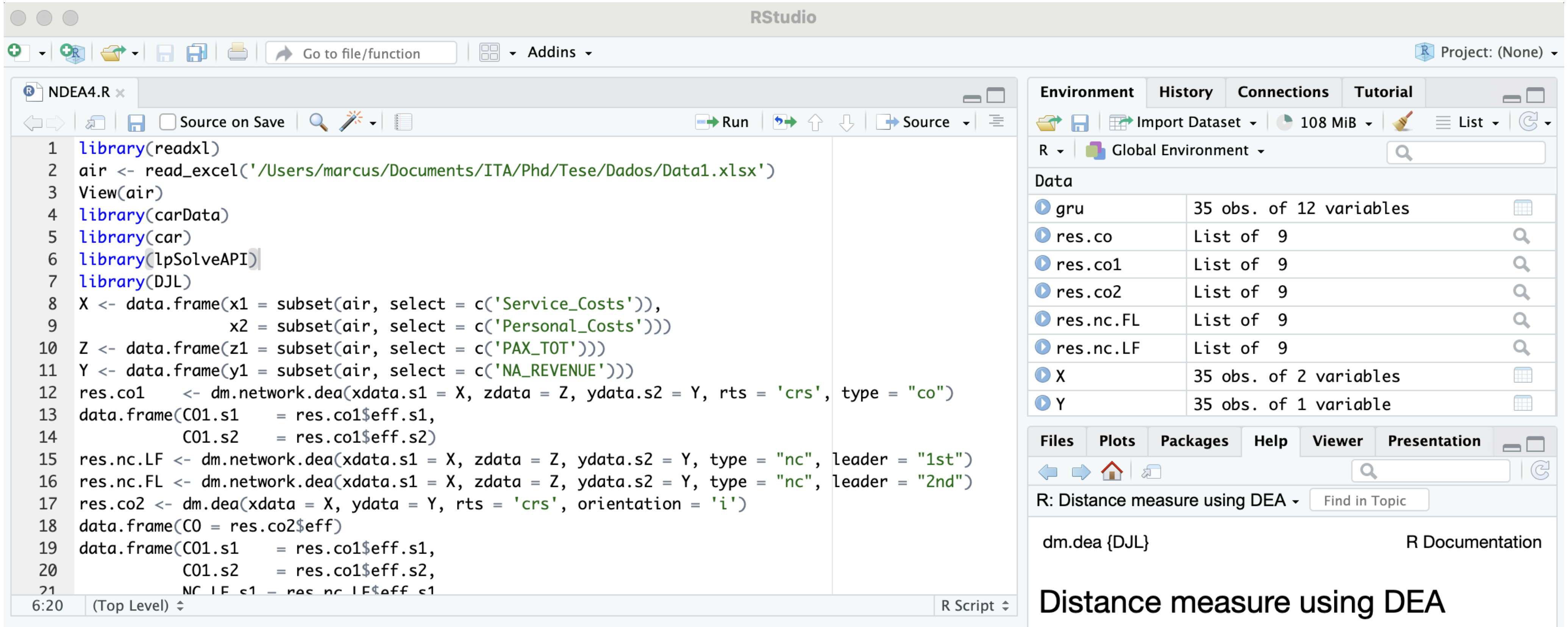
All data for has been collected since 2013 until 2022

| Airport | Obs | YEAR | QUARTER | Service_Costs | Personal_Costs | PAX_DOM | PAX_INT | NA_REVENUE |
|---|---|---|---|---|---|---|---|---|
| GRU | 1 | 2013 | 1 | 182898 | 42299 | 5378957 | 3081354 | 128000 |
| GRU | 2 | 2013 | 2 | 235652 | 51600 | 5527920 | 2053952 | 157400 |
| GRU | 3 | 2013 | 3 | 225039 | 46941 | 6027057 | 3289396 | 154300 |
| GRU | 4 | 2013 | 4 | 217892 | 47880 | 6503937 | 3215917 | 186000 |
| GRU | 5 | 2014 | 1 | 233932 | 50953 | 6504451 | 3211829 | 176100 |
| GRU | 6 | 2014 | 2 | 265820 | 33529 | 6087265 | 3255317 | 241600 |
| GRU | 7 | 2014 | 3 | 316512 | 19456 | 6482004 | 3664111 | 251900 |
| GRU | 8 | 2014 | 4 | 278571 | 75789 | 6863009 | 3472006 | 245600 |
| GRU | 9 | 2015 | 1 | 301482 | 40048 | 6490994 | 3408322 | 240500 |
| GRU | 10 | 2015 | 2 | 499752 | 42460 | 5954793 | 3231682 | 239600 |

# Method Application

## NDEA Application

DJL package in the R language.



# Method Application

## NDEA RESULTS

| YEARQUARTER | Global1 | CCR | BCC |
|---|---|---|---|
| 2013Q1 | 0.60 | 0.56 | 0.74 |
| 2013Q2 | 0.54 | 0.55 | 0.65 |
| 2013Q3 | 0.59 | 0.57 | 0.69 |
| 2013Q4 | 0.64 | 0.70 | 0.77 |
| 2014Q1 | 0.60 | 0.62 | 0.70 |
| 2014Q2 | 0.72 | 0.94 | 0.94 |
| 2014Q3 | 0.77 | 1.00 | 1.00 |
| 2014Q4 | 0.58 | 0.65 | 0.69 |
| 2015Q1 | 0.66 | 0.81 | 0.81 |
| 2015Q2 | 0.54 | 0.56 | 0.57 |
| 2015Q3 | 0.67 | 0.79 | 0.81 |
| 2015Q4 | 0.75 | 1.00 | 1.00 |
| 2016Q1 | 0.63 | 0.73 | 0.76 |
| 2016Q2 | 0.62 | 0.74 | 0.76 |
| 2016Q3 | 0.62 | 0.73 | 0.74 |
| 2016Q4 | 0.62 | 0.73 | 0.75 |
| 2017Q1 | 0.62 | 0.71 | 0.75 |
| 2017Q2 | 0.64 | 0.77 | 0.80 |

The NDEA model results present:

- The aggregate efficiency of the cost-revenue cycle:
  - 1st phase -> transforming personal and service costs into passenger movement
  - 2nd phase -> transforming passenger movement into non-aviation revenues

In each phase, the inputs are setted to be 100% used.

# Method Application

## NDEA RESULTS

Efficiency Class:

1. Low Efficiency => NDEA efficiency from 0% to 33%
2. Regular Efficiency => NDEA efficiency from 33% to 66%
3. High Efficiency => NDEA efficiency from 66% to 100%

# Method Application

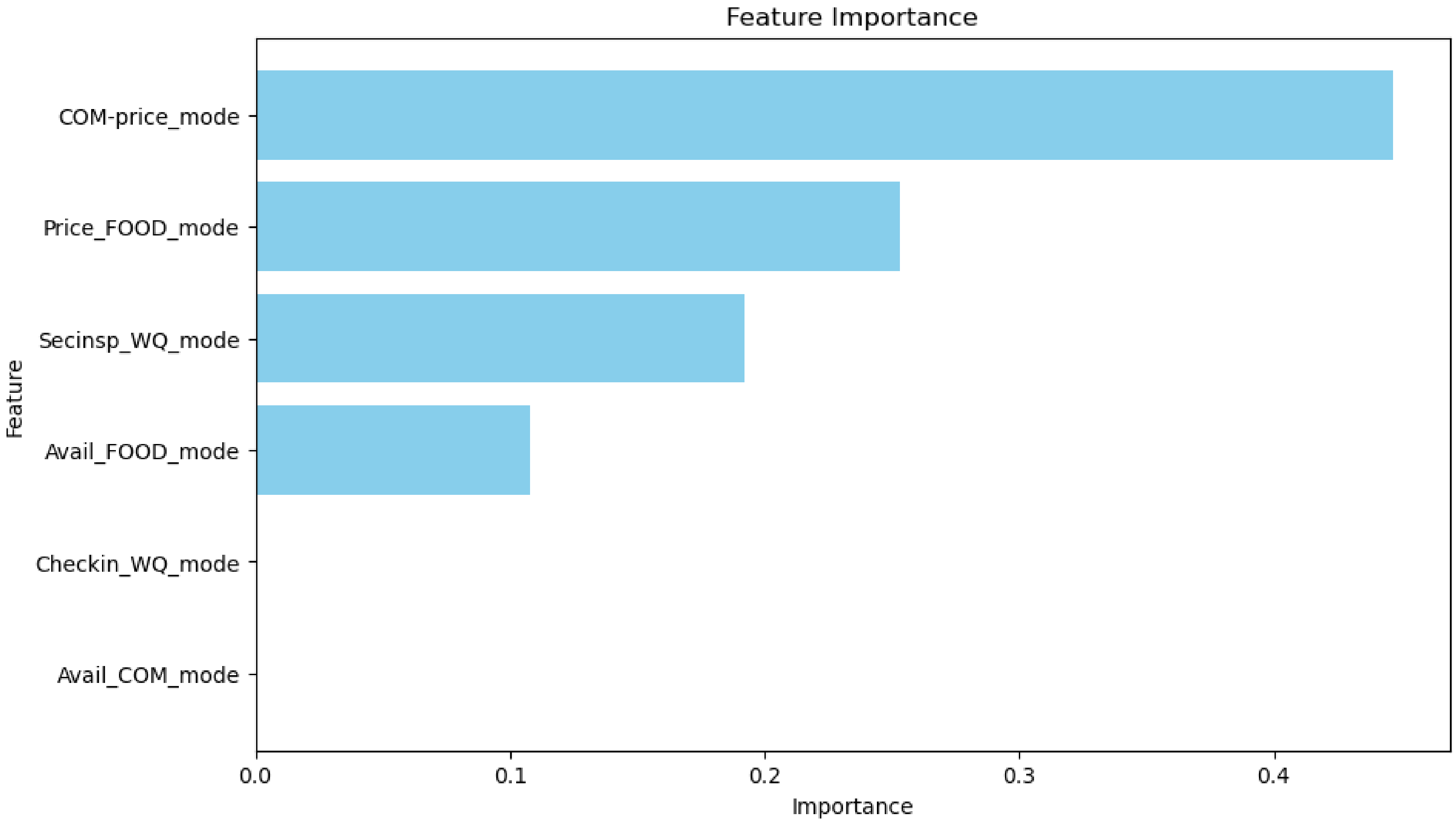
## Decision tree classifier

```python
import os
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, RandomizedSearchCV, StratifiedKFold
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from scipy.stats import randint


AIR = 'C:/Users/mvnma/iCloudDrive/Documents/ITA/Phd/Tese/Dados/'
df = pd.read_excel(AIR + 'GRU_Data_month.xlsx')


print(df.isnull().sum())


estat = 'mode'
features = [
    'Checkin_WQ',
    'Secinsp_WQ',
    'Avail_FOOD',
    'Price_FOOD',
    'Avail_COM',
    'COM-price'
]
X_clf = df[[f'{feature}_{estat}' for feature in features]]
y_clf = df['Class1']


X_train_clf, X_test_clf, y_train_clf, y_test_clf = train_test_split(X_clf, y_clf, test_size=0.25, random_state=42)


model_clf = DecisionTreeClassifier(random_state=42)


param_dist = {
    'max_depth': randint(2, 21),
    'min_samples_split': randint(2, 21),
    'min_samples_leaf': randint(2, 21)
```

A complete python code to run a Machine Learning model called Decision Tree Classifier

# Results and Final Considerations

## Feature Importance




Best cross-validation score: 0.875
Accuracy with the best model: 0.962

# Results and Final Considerations

## Feature Importance

**Key Features Influencing Classification**: The decision tree model revealed that pricing variables—COM-price_mode (44.7%) and Price_FOOD_mode (25.3%)—are the most important factors driving customer satisfaction or service quality classification.

This emphasizes the critical role economic factors play in customer behavior at airports, suggesting that administrators should focus on optimizing pricing strategies for commercial services and food to improve overall customer experience.

# Results and Final Considerations

## Feature Importance

**Model Performance and Generalization**: The model achieved strong performance with a cross-validation accuracy of 87.5% and a test set accuracy of 96.3%. However, cross-validation results varied across data folds, ranging from 68.2% to 95.2%, indicating some sensitivity to data partitioning.

Addressing class imbalances and diversifying data splits could improve consistency in generalization across different scenarios.

Feature Importance

# Results and Final Considerations

**Operational Insights for Efficiency**: Insights from feature importance show that operational variables like Checkin_WQ_mode and Avail_COM_mode had little to no influence on classification outcomes, while food availability and security inspections had moderate impact.

This suggests that airport administrators should prioritize optimizing pricing strategies, while also ensuring that food availability and security processes are efficient, to improve overall service quality and customer satisfaction.

Thank you!

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