DISCOVERING CUSTOMER BEHAVIOUR PATTERNS IN AIRLINE HOLIDAY BOOKINGS USING ASSOCIATION RULES

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CHAPTER I

INTRODUCTION

1.1 PROJECT BACKGROUND

The airline industry is marked by intense competition, with customer satisfaction and retention playing crucial roles in maintaining a competitive edge. Booking platforms, in-flight amenities, and promotional strategies significantly influence customer decisions. Despite these efforts, many travel agencies struggle to optimize their services due to a lack of clear insights into customer behaviour.

As a travel agency committed to delivering exceptional services, our primary goal is to provide unparalleled travel experiences and establish ourselves as a trusted partner in our customers' journeys. Understanding customer behaviour and preferences, particularly in relation to airline bookings, is pivotal in achieving this mission.

This project focuses on analysing customer behaviour and booking preferences to identify the challenges faced during the purchase and booking process. By leveraging association rule analysis, we aim to uncover key patterns and actionable insights that will enable us to address these challenges effectively and enhance the overall customer experience.

1.2 PROBLEM STATEMENT

The airline travel industry faces significant challenges in understanding and addressing customer behaviour during the booking process. For instance, booking completion rates vary between platforms, with websites often performing better than mobile apps. Additionally, while longer flights prompt customers to opt for meals and preferred seating, short purchase lead times frequently result in incomplete bookings.

These gaps hinder the ability of travel agencies to maximize customer satisfaction and revenue. Without actionable insights into these patterns, agencies risk falling short of customer expectations. This study aims to address these challenges by:

1. Identifying the booking platform with the highest conversion rates.

2. Analysing customer preferences for ancillary services based on flight duration.

3. Investigating the relationship between purchase lead times and booking completion rates.

1.3 OBJECTIVE OF PROJECT

The main objectives of this analysis are:

1. To determine which platform has the highest confidence level for booking completion.

2. To investigate the likelihood of passengers requesting preferred seats and in-flight meals based on flight duration.

3. To analyze if shorter purchase lead times correlate with higher booking completion rates.

CHAPTER II

METHODOLOGY

2.1 DATA PREPARATION

2.1.1 Data Source

The data we used was sourced from:

https://www.kaggle.com/datasets/manishkumar7432698/airline-passangers-booking-data?select=Passanger_booking_data.csv

2.1.2 Data Cleaning

As part of the data preparation, a few steps of data cleaning was done. The steps are as below.

1. Load Data into R

```
travel <- read.csv('Passanger_booking_data.csv')
```

2. Load necessary libraries

```
library(arules)
```

```
## Warning: package 'arules' was built under R version 4.4.2

## Loading required package: Matrix

##
## Attaching package: 'arules'

## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

```
library(arulesViz)
```

```
## Warning: package 'arulesViz' was built under R version 4.4.2
```

3. Investigate the details of the dataset

```
head(travel)
```

```
##   num_passengers sales_channel trip_type purchase_lead length_of_stay
## 1              1      Internet RoundTrip            21             12
## 2              2      Internet RoundTrip           262             19
## 3              1      Internet RoundTrip           112             20
## 4              2      Internet RoundTrip           243             22
## 5              1      Internet RoundTrip            96             31
## 6              2      Internet RoundTrip            68             22
##   flight_hour flight_day  route booking_origin wants_extra_baggage
## 1           6        Tue AKLHGH      Australia                   0
## 2           7        Sat AKLDEL    New Zealand                   1
## 3           3        Sat AKLDEL    New Zealand                   0
## 4          17        Wed AKLDEL          India                   1
## 5           4        Sat AKLDEL    New Zealand                   0
## 6          15        Wed AKLDEL          India                   1
##   wants_preferred_seat wants_in_flight_meals flight_duration booking_complete
## 1                    0                     0            7.21                1
## 2                    0                     0            5.52                0
## 3                    0                     0            5.52                0
## 4                    1                     0            5.52                0
## 5                    0                     1            5.52                0
## 6                    0                     1            5.52                0
```

```
str(travel)
```

```
## 'data.frame':    50002 obs. of  14 variables:
##  $ num_passengers       : int  1 2 1 2 1 2 1 3 2 1 ...
##  $ sales_channel        : chr  "Internet" "Internet" "Internet" "Internet" ...
##  $ trip_type            : chr  "RoundTrip" "RoundTrip" "RoundTrip" "RoundTrip" ...
##  $ purchase_lead        : int  21 262 112 243 96 68 3 201 238 80 ...
##  $ length_of_stay       : int  12 19 20 22 31 22 48 33 19 22 ...
##  $ flight_hour          : int  6 7 3 17 4 15 20 6 14 4 ...
##  $ flight_day           : chr  "Tue" "Sat" "Sat" "Wed" ...
##  $ route                : chr  "AKLHGH" "AKLDEL" "AKLDEL" "AKLDEL" ...
##  $ booking_origin       : chr  "Australia" "New Zealand" "New Zealand" "India" ...
##  $ wants_extra_baggage  : int  0 1 0 1 0 1 1 1 1 0 ...
##  $ wants_preferred_seat : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ wants_in_flight_meals: int  0 0 0 0 1 1 1 1 1 1 ...
##  $ flight_duration      : num  7.21 5.52 5.52 5.52 5.52 5.52 5.52 5.52 5.52 5.52 ...
##  $ booking_complete     : int  1 0 0 0 0 0 0 0 0 0 ...
```

```
dim(travel)
```

```
## [1] 50002    14
```

4. Change the value for sales_channel from "Internet" and "Mobile" into "Website" and "Mobile_App", respectively.

5. Group the flight_duration column into 5 groups.

6. Group the purchase_lead column into 3 groups.

7. Change the value of all binary columns from 1 and 0 into Yes and No, respectively.

```
# changing the value for sales_channel from "Internet" and "Mobile" into "Website" and "Mobile_App" respectively
travel$sales_channel[travel$sales_channel %in% "Internet"] = "Website"
travel$sales_channel[travel$sales_channel %in% "Mobile"] = "Mobile_App"

# grouping the value in the flight_duration in 5 groups
travel$flight_duration <- cut(travel$flight_duration, breaks = 5, labels = c(1, 2, 3, 4, 5))

# grouping the value in the purchase_lead in 3 groups
travel$purchase_lead <- cut(travel$purchase_lead, breaks = 3, labels = c(1, 2, 3))

# changing the binary collumn into Yes and No respectively
columns_to_convert <- c("wants_extra_baggage", "wants_preferred_seat", "wants_in_flight_meals", "booking_complete")
travel[columns_to_convert] <- lapply(travel[columns_to_convert], function(x) ifelse(x == 1, "Yes", "No"))
```

8. Create a new data frame with all of the column of interest

```
travel_a <- travel[, c("num_passengers", "sales_channel", "trip_type", "purchase_lead",
                       "booking_origin", "wants_extra_baggage", "wants_preferred_seat",
                       "wants_in_flight_meals", "flight_duration", "booking_complete")]
```

9. Convert the columns into factor

10. Convert the new dataset into transaction format

```
# converting character columns to factors
change_into_factor <- c("num_passengers", "sales_channel", "trip_type", "booking_origin",
                        "wants_extra_baggage", "wants_preferred_seat",
                        "wants_in_flight_meals", "booking_complete")
travel_a[change_into_factor] <- lapply(travel_a[change_into_factor], as.factor)

# converting dataset into transaction format
transactions <- as(travel_a, "transactions")
```

2.2 DATA MINING WITH ASSOCIATION RULE

To analyse the data in order to achieve our objectives, we decided to use association rule. Below are the steps we took to analyse our data.

1. Generated apriori rule to determine which platform between website and mobile application that have the highest likelihood of booking completion.

```
# 1. Between Website and Mobile_App, which one have the highest confidence level for booking_complete as Yes?
## Generate rules for Website
rules_website <- apriori(transactions,
                         parameter = list(supp = 0.01, conf = 0.1),
                         appearance = list(lhs = c("sales_channel=Website"),
                                           rhs = c("booking_complete=Yes")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5    0.01      1

##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 500
##
## set item appearances ...[2 item(s)] done [0.00s].
## set transactions ...[2 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [2 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [2 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Website

```
# Generate rules for Mobile_App
rules_mobile_app <- apriori(transactions,
                            parameter = list(supp = 0.01, conf = 0.1),
                            appearance = list(lhs = c("sales_channel=Mobile_App"),
                                              rhs = c("booking_complete=Yes")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5    0.01      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 500
##
## set item appearances ...[2 item(s)] done [0.00s].
## set transactions ...[2 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [2 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [2 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Mobile Application

2. Generated apriori rule to determine the likelihood of customers who book longer duration flight to opt for preferred seats and in-flight meals.

```
# Generate rules for flight_duration = 1 (shortest flight duration group)
rules_flight_duration_1 <- apriori(transactions,
                                   parameter = list(supp = 0.01, conf = 0.1),
                                   appearance = list(lhs = c("flight_duration=1"),
                                                     rhs = c("wants_preferred_seat=Yes", "wants_preferred_seat=No",
                                                             "wants_in_flight_meals=Yes", "wants_in_flight_meals=No")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5    0.01      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 500
##
## set item appearances ...[5 item(s)] done [0.00s].
## set transactions ...[5 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [5 item(s)] done [0.00s].
## creating transaction tree ... done [0.01s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [8 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Short Flight Duration

```
# Generate rules for flight_duration = 5 (longest flight duration group)
rules_flight_duration_5 <- apriori(transactions,
                                   parameter = list(supp = 0.01, conf = 0.1),
                                   appearance = list(lhs = c("flight_duration=5"),
                                                     rhs = c("wants_preferred_seat=Yes", "wants_preferred_seat=No",
                                                             "wants_in_flight_meals=Yes", "wants_in_flight_meals=No")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5    0.01      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 500
##
## set item appearances ...[5 item(s)] done [0.00s].
## set transactions ...[5 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [5 item(s)] done [0.00s].
## creating transaction tree ... done [0.01s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [8 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Long Flight Duration

3. Generated apriori rule to know if customer with shorter purchase lead will complete their booking.

```
# Generate rules for purchase_lead = 1
rules_purchase_lead_1 <- apriori(transactions,
                                 parameter = list(supp = 0.01, conf = 0.1),
                                 appearance = list(lhs = c("purchase_lead=1"),
                                                   rhs = c("booking_complete=Yes", "booking_complete=No")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5    0.01      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 500
##
## set item appearances ...[3 item(s)] done [0.00s].
## set transactions ...[3 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [3 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [4 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Short Term Purchase Lead

```
# Generate rules for purchase_lead = 2
rules_purchase_lead_2 <- apriori(transactions,
                                 parameter = list(supp = 0.01, conf = 0.1),
                                 appearance = list(lhs = c("purchase_lead=2"),
                                                   rhs = c("booking_complete=Yes", "booking_complete=No")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5    0.01      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 500
##
## set item appearances ...[3 item(s)] done [0.00s].
## set transactions ...[3 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [3 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [3 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Medium Term Purchase Lead

```
# Generate rules for purchase_lead = 3
rules_purchase_lead_3 <- apriori(transactions,
                                 parameter = list(supp = 0.00001, conf = 0.1),
                                 appearance = list(lhs = c("purchase_lead=3"),
                                                   rhs = c("booking_complete=Yes", "booking_complete=No")))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.1    0.1    1 none FALSE            TRUE       5   1e-05      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 0
##
## set item appearances ...[3 item(s)] done [0.00s].
## set transactions ...[3 item(s), 50002 transaction(s)] done [0.01s].
## sorting and recoding items ... [3 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 done [0.00s].
## writing ... [4 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

Rule for Long Term Purchase Lead

CHAPTER III

RESULTS AND DISCUSSION

3.1 RELATIONSHIP BETWEEN SALES CHANNEL AND BOOKING COMPLETION

Based on our analysis in the previous chapter, we found that the probability of booking completion is higher via the website compared to the mobile app. This is because the confidence level of booking completion = Yes when sales_channel is “website” is 0.155 while the confidence level of booking completion = Yes when sales_channel is “mobile app” is 0.108. (refer figure below)

```
# inspect the value
inspect(rules_website)

##     lhs                        rhs                     support   confidence
## [1] {}                      => {booking_complete=Yes} 0.1495740 0.149574
## [2] {sales_channel=Website} => {booking_complete=Yes} 0.1373945 0.154789
##     coverage  lift     count
## [1] 1.0000000 1.000000 7479
## [2] 0.8876245 1.034866 6870

inspect(rules_mobile_app)

##     lhs                           rhs                     support    confidence
## [1] {}                         => {booking_complete=Yes} 0.14957402 0.1495740
## [2] {sales_channel=Mobile_App} => {booking_complete=Yes} 0.01217951 0.1083823
##     coverage  lift      count
## [1] 1.0000000 1.0000000 7479
## [2] 0.1123755 0.7246063  609
```

Results for Relationship between Sales Channel and Booking Completion

With that being said, we can make a decision to enhance the website’s user interface and optimize the booking process to make it more user-friendly and efficient.

3.2 RELATIONSHIP BETWEEN FLIGHT DURATION AND EXTRA PURCHASES

When it comes to determining the likelihood of customers to purchase preferred seats and in-flight meals, we analyzed its relationship with short flight duration and long flight duration.

What we found was the longer the flight duration, its more likely for the customers to purchase in-flight meals but not preferred seats. On the contrary, the shorter the flight duration, its less likely for the customers to want preferred seats nor in-flight meals. These findings are backed up by the confidence level of each analysis.

```
# Inspect the rules
inspect(sort(rules_flight_duration_1, by = "confidence", decreasing = TRUE))

##     lhs                    rhs                          support    confidence
## [1] {flight_duration=1} => {wants_preferred_seat=No}   0.19965201 0.7517319
## [2] {}                  => {wants_preferred_seat=No}   0.70303188 0.7030319
## [3] {flight_duration=1} => {wants_in_flight_meals=No}  0.17323307 0.6522590
## [4] {}                  => {wants_in_flight_meals=No}  0.57285709 0.5728571
## [5] {}                  => {wants_in_flight_meals=Yes} 0.42714291 0.4271429
## [6] {flight_duration=1} => {wants_in_flight_meals=Yes} 0.09235631 0.3477410
## [7] {}                  => {wants_preferred_seat=Yes}  0.29696812 0.2969681
## [8] {flight_duration=1} => {wants_preferred_seat=Yes}  0.06593736 0.2482681
##     coverage  lift      count
## [1] 0.2655894 1.0692715  9983
## [2] 1.0000000 1.0000000 35153
## [3] 0.2655894 1.1386069  8662
## [4] 1.0000000 1.0000000 28644
## [5] 1.0000000 1.0000000 21358
## [6] 0.2655894 0.8141092  4618
## [7] 1.0000000 1.0000000 14849
## [8] 0.2655894 0.8360092  3297
```

Short flight duration

```
inspect(sort(rules_flight_duration_5, by = "confidence", decreasing = TRUE))
```

```
##     lhs                    rhs                          support   confidence
## [1] {}                  => {wants_preferred_seat=No}    0.7030319 0.7030319
## [2] {flight_duration=5} => {wants_preferred_seat=No}    0.2945082 0.6595011
## [3] {}                  => {wants_in_flight_meals=No}   0.5728571 0.5728571
## [4] {flight_duration=5} => {wants_in_flight_meals=Yes}  0.2301108 0.5152940
## [5] {flight_duration=5} => {wants_in_flight_meals=No}   0.2164513 0.4847060
## [6] {}                  => {wants_in_flight_meals=Yes}  0.4271429 0.4271429
## [7] {flight_duration=5} => {wants_preferred_seat=Yes}   0.1520539 0.3404989
## [8] {}                  => {wants_preferred_seat=Yes}   0.2969681 0.2969681
##     coverage  lift      count
## [1] 1.0000000 1.0000000 35153
## [2] 0.4465621 0.9380814 14726
## [3] 1.0000000 1.0000000 28644
## [4] 0.4465621 1.2063738 11506
## [5] 0.4465621 0.8461203 10823
## [6] 1.0000000 1.0000000 21358
## [7] 0.4465621 1.1465840  7603
## [8] 1.0000000 1.0000000 14849
```

Long flight duration

As we can see, when flight duration is short, the confidence levels of wanting in-flight meals is 0.348 and wanting preferred seat is 0.248. In addition, the confidence levels of not purchasing in-flight meals and not preferring seats for short flight duration are 0.652 and 0.752, respectively. On the other hand, when flight duration is long, the confidence levels of opting for in-flight meals and preferred seats are 0.515 and 0.340, respectively. Besides that, the confidence levels for not wanting in-flight meals and preferred seats are 0.485 and 0.660, respectively.

Confidence Levels	Short Flight Duration	Long Flight Duration
Want in-flight meals	0.348	0.515
Don’t want in-flight meals	0.652	0.485
Want preferred seats	0.248	0.340
Don’t want preferred seats	0.752	0.660

Table 1: Relationship between flight duration and extra purchases (in-flight meals and preferred seats)

Based on these findings, we can introduce promotional packages that include in-flight meals and seat preferences for long-haul flights to cater to customer needs and encourage bundled purchases.

3.3 RELATIONSHIP BETWEEN PURCHASE LEAD AND BOOKING COMPLETION

To analyse our third objective, we had generated association rule between purchase lead and the booking completion, as we saw in the previous chapter. From our analysis, we found that the likelihood of customers to complete their booking is higher when they make their purchase way earlier (long term purchase lead). The confidence levels are as below.

```
# Inspect the value
inspect(sort(rules_purchase_lead_1, by = "confidence", decreasing = TRUE))
```

```
##     lhs                  rhs                     support   confidence coverage
## [1] {}                => {booking_complete=No}  0.8504260 0.8504260  1.000000
## [2] {purchase_lead=1} => {booking_complete=No}  0.8083277 0.8498318  0.951162
## [3] {purchase_lead=1} => {booking_complete=Yes} 0.1428343 0.1501682  0.951162
## [4] {}                => {booking_complete=Yes} 0.1495740 0.1495740  1.000000
##     lift      count
## [1] 1.0000000 42523

## [2] 0.9993013 40418
## [3] 1.0039726  7142
## [4] 1.0000000  7479
```

Results for Short Term Purchase Lead

```
inspect(sort(rules_purchase_lead_2, by = "confidence", decreasing = TRUE))
```

```
##     lhs                  rhs                     support    confidence
## [1] {purchase_lead=2} => {booking_complete=No}  0.04195832 0.8623099
## [2] {}                => {booking_complete=No}  0.85042598 0.8504260
## [3] {}                => {booking_complete=Yes} 0.14957402 0.1495740
##     coverage   lift     count
## [1] 0.04865805 1.013974  2098
## [2] 1.00000000 1.000000 42523
## [3] 1.00000000 1.000000  7479
```

Results for Medium Term Purchase Lead

```
inspect(sort(rules_purchase_lead_3, by = "confidence", decreasing = TRUE))
```

```
##     lhs                  rhs                     support      confidence
## [1] {}                => {booking_complete=No}  0.8504259830 0.8504260
## [2] {purchase_lead=3} => {booking_complete=No}  0.0001399944 0.7777778
## [3] {purchase_lead=3} => {booking_complete=Yes} 0.0000399984 0.2222222
## [4] {}                => {booking_complete=Yes} 0.1495740170 0.1495740
##     coverage     lift      count
## [1] 1.0000000000 1.0000000 42523
## [2] 0.0001799928 0.9145743     7
## [3] 0.0001799928 1.4857007     2
## [4] 1.0000000000 1.0000000  7479
```

Results for Long Term Purchase Lead

Confidence Levels	Booking Complete	Booking Incomplete
Short Term Purchase Lead	0.150	0.850
Medium Term Purchase Lead	-	0.862
Long Term Purchase Lead	0.222	0.778

Table 2: Relationship between purchase lead and booking completion

However, we can still see that the probability of the customers to not complete their bookings is still higher overall. Hence, we can implement targeted strategies to encourage customers with short purchase lead times to finalize their bookings. These strategies could include offering time-sensitive discounts or sending timely reminders to create urgency.

CHAPTER IV

CONCLUSION AND FUTURE WORKS

In conclusion, by applying association rule analysis, we have identified critical patterns in customer behaviour related to airline holiday bookings. The insights derived from this analysis provide actionable recommendations to:

- Enhance the website for improved booking completion rates.
- Offer promotional packages tailored to the needs of long-haul passengers.
- Develop targeted strategies to convert short lead-time bookings into confirmed reservations.

These findings will help us address customer challenges more effectively and elevate their overall booking experience, strengthening our position as a trusted travel partner.