RGR Case Study - 14122019

December 15, 2019

1 Deliveroo "Rider Get Rider" Case Study

1.0.1 By Edd Webster

Notebook last updated: 14/12/2019

```
In [1]: from IPython.display import Image
        Image(url= "./images/deliveroologo.png", width=250)
```

```
Out[1]: <IPython.core.display.Image object>
```

Click Section **??** to jump straight to the Exploratory Data Analysis section and skip the Section **??** and Section **??** sections. Or you can click Section **??** to jump straight to the Conclusion.

1.1 Introduction

This notebook is an Exploratory Data Analysis (EDA) of Rider data for Deliveroo, analysing the performance of the 'Rider Get Rider' (RGR) scheme, an incentivised referral scheme targeting current Deliveroo Riders, determining whether or not it is successful. The dataset provided is explored and the findings summarised.

For more information about this notebook and the author, I'm available through all the following channels: * EddWebster.com, * edd.j.webster@gmail.com, * LinkedIn.com/in/eddwebster, and * GitHub/eddwebster.

1.2 Notebook Contents

1. Section **??**
2. Section **??**
3. Section **??**
4. Section **??**
5. Section **??**
6. Section **??**
7. Section **??**

1.3 1. Notebook Setup

First we will import all the required libraries for this notebook. These include: * IPython * NumPy * Pandas * Seaborn

```
In [2]: # Import modules

        # Python 3.5 (ideally)
        import sys
        assert sys.version_info >= (3, 5)

        # Data preprocessing
        import numpy as np
        import pandas as pd
        import os

        # Plotting figures
        %matplotlib inline
        import matplotlib.pyplot as plt
        import seaborn as sns
        import missingno as msno    # pip install missingno if you don't have it

        # Display in Jupyter
        from IPython.display import Image
        from IPython.core.display import HTML

        # Ignore warnings
        import warnings
        warnings.filterwarnings(action="ignore", message="^internal gelsd")

        print("Setup Complete")
```

```
Setup Complete
```

1.4 2. Task Brief

The following brief has been copied and pasted from the Word document provided and is included in this Jupyter notebook for reference. Click Section **??** to skip to the next section where the proper coding begins.

1.4.1 Background

At Deliveroo, we want to understand our customers, rider and restaurants in as much detail as possible. As we attempt to build and maintain the optimal rider fleet we utilise a series of marketing channels and schemes to attract new Riders. One of these channels is referred to as 'Rider Get Rider' or 'RGR', which is an incentivised referral scheme targeting current Deliveroo Riders.

1.4.2 The Task

Imagine a senior manager has asked you to analyse the performance of the RGR scheme and determine if it is successful. They have asked you to take them through your findings later that day. Analyse the dataset provided and summarise your findings.

The overarching question you should answer with your analysis is: "Is the RGR scheme successful, and why have you reached that conclusion?" * You should define what success is * How has RGR performed compared with other channels? * How does rider performance / behaviour vary between the channels?

Summarise your findings * Your summary could be a short document, one tab of a spreadsheet or a notebook * Please do not spend time creating a presentation / slide deck * It should be logically set out so the reader can follow your main findings and any conclusions you have arrived at * It should make appropriate use of visualisations to convey your findings

Note - We have provided a clean data set and you do not need to do any data cleaning.

1.5 3. Data Source

1.5.1 Data Import

First, let's import the CSV file provided, 'rgr_take_home_v3_dataset.csv', to this Jupyter notebook as a Pandas DataFrame.

```
In [3]: # Import CSV to a Pandas DataFrame
        filepath = "data/rgr_take_home_v3_dataset.csv"
        df_raw = pd.read_csv(filepath)
```

1.5.2 Initial Data Handling

Let's quality of the dataset by looking first and last rows, using the head() and tail() methods.

```
In [4]: # Display the first 5 rows of the raw DataFrame, df_raw
        df_raw.head()
```

```
Out[4]:    RIDER_ID  LOCATION APPLICATION_DATE APPLICATION_APPROVED_DATE  \
        0      1864  Roo York       05/03/2017                31/03/2017
        1      1864  Roo York       05/03/2017                31/03/2017
        2      1864  Roo York       05/03/2017                31/03/2017
        3      1864  Roo York       05/03/2017                31/03/2017
        4      1864  Roo York       05/03/2017                31/03/2017

          FIRST_WORK_DATE ACQUISITION_CHANNEL           VEHICLE_TYPE  \
        0      03/04/2017             Digital  Scooter / Motorcycle
        1      03/04/2017             Digital  Scooter / Motorcycle
        2      03/04/2017             Digital  Scooter / Motorcycle
        3      03/04/2017             Digital  Scooter / Motorcycle
        4      03/04/2017             Digital  Scooter / Motorcycle

           WEEKS_SINCE_FIRST_WORK  RIDER_ACTIVE  HOURS_WORKED  \
        0                       0          True     18.918334
        1                       1          True     33.625274
        2                       2          True     10.539444
        3                       3          True     10.268887
        4                       4          True     17.463331
```

```
   HOURS_WORKED_CUMULATIVE  ORDERS_DELIVERED  ORDERS_DELIVERED_CUMULATIVE  \
0                18.918334              44.0                         44.0
1                52.543608              78.0                        122.0
2                63.083052              30.0                        152.0
3                73.351939              38.0                        190.0
4                90.815270              58.0                        248.0

   THROUGHPUT  THROUGHPUT_CUMULATIVE  REFERRALS  REFERRALS_CUMULATIVE  \
0    2.325786               2.325786        NaN                   NaN
1    2.319684               2.321881        NaN                   NaN
2    2.846450               2.409522        NaN                   NaN
3    3.700498               2.590252        NaN                   NaN
4    3.321245               2.730818        NaN                   NaN

   SUCCESSFUL_REFERRALS  SUCCESSFUL_REFERRALS_CUMULATIVE
0                   NaN                              NaN
1                   NaN                              NaN
2                   NaN                              NaN
3                   NaN                              NaN
4                   NaN                              NaN
```

In [5]:
```python
# Display the last 5 rows of the raw DataFrame, df_raw
df_raw.tail()
```

Out[5]:
```
        RIDER_ID  LOCATION APPLICATION_DATE APPLICATION_APPROVED_DATE  \
113520    103776  Roo York       28/03/2017                07/04/2017
113521    103776  Roo York       28/03/2017                07/04/2017
113522    103776  Roo York       28/03/2017                07/04/2017
113523    103776  Roo York       28/03/2017                07/04/2017
113524    103776  Roo York       28/03/2017                07/04/2017

       FIRST_WORK_DATE ACQUISITION_CHANNEL          VEHICLE_TYPE  \
113520      08/04/2017            Referral  Scooter / Motorcycle
113521      08/04/2017            Referral  Scooter / Motorcycle
113522      08/04/2017            Referral  Scooter / Motorcycle
113523      08/04/2017            Referral  Scooter / Motorcycle
113524      08/04/2017            Referral  Scooter / Motorcycle

        WEEKS_SINCE_FIRST_WORK  RIDER_ACTIVE  HOURS_WORKED  \
113520                      20         False           NaN
113521                      21          True      2.080833
113522                      22          True      0.664722
113523                      23         False      0.000000
113524                      24         False           NaN

        HOURS_WORKED_CUMULATIVE  ORDERS_DELIVERED  \
113520               283.251111               NaN
113521               285.331944               4.0
```

```
113522              285.996666             2.0
113523              285.996666             NaN
113524              285.996666             NaN

        ORDERS_DELIVERED_CUMULATIVE  THROUGHPUT  THROUGHPUT_CUMULATIVE  \
113520                        638.0         NaN               2.252418
113521                        642.0    1.922307               2.250011
113522                        644.0    3.008777               2.251775
113523                        644.0         NaN               2.251775
113524                        644.0         NaN               2.251775

        REFERRALS  REFERRALS_CUMULATIVE  SUCCESSFUL_REFERRALS  \
113520        NaN                   NaN                   NaN
113521        NaN                   NaN                   NaN
113522        NaN                   NaN                   NaN
113523        NaN                   NaN                   NaN
113524        NaN                   NaN                   NaN

        SUCCESSFUL_REFERRALS_CUMULATIVE
113520                              NaN
113521                              NaN
113522                              NaN
113523                              NaN
113524                              NaN
```

In [6]:
```
# Print the Shape of the raw DataFrame, df_raw
print(df_raw.shape)
```

```
(113525, 19)
```

The raw DataFrame has: * 113,525 observations (rows), each observation represents one Rider per week, and * 19 attributes (columns).

In [7]:
```
# Features (column names) of the raw DataFrame, df_raw
df_raw.columns
```

Out[7]:
```
Index(['RIDER_ID', 'LOCATION', 'APPLICATION_DATE', 'APPLICATION_APPROVED_DATE',
       'FIRST_WORK_DATE', 'ACQUISITION_CHANNEL', 'VEHICLE_TYPE',
       'WEEKS_SINCE_FIRST_WORK', 'RIDER_ACTIVE', 'HOURS_WORKED',
       'HOURS_WORKED_CUMULATIVE', 'ORDERS_DELIVERED',
       'ORDERS_DELIVERED_CUMULATIVE', 'THROUGHPUT', 'THROUGHPUT_CUMULATIVE',
       'REFERRALS', 'REFERRALS_CUMULATIVE', 'SUCCESSFUL_REFERRALS',
       'SUCCESSFUL_REFERRALS_CUMULATIVE'],
      dtype='object')
```

The Dataset has nineteen features (columns): * `RIDER_ID`: a unique rider identifier * `LOCATION`: the city the rider applied in * `APPLICATION_DATE`: the date the rider applied to work for Deliveroo * `APPLICATION_APPROVED_DATE`: * `FIRST_WORK_DATE`: the date that the rider application was approved * `ACQUISITION_CHANNEL`: the last touch marketing channel recorded for the rider/applicant * VEHICLE_TYPE: the type of vehicle the rider uses * WEEKS_SINCE_FIRST_WORK: the number of weeks since the first_work_date, from 0-24 * RIDER_ACTIVE: Boolean flag if the rider worked in that week or not * HOURS_WORKED: the number of hours worked by the rider that week * HOURS_WORKED_CUMULATIVE: the cumulative number of hours worked by the rider to date * ORDERS_DELIVERED: the number of orders delivered by the rider that week * ORDERS_DELIVERED_CUMULATIVE: the cumulative number of orders delivered by the rider to date * THROUGHPUT: the orders per hour (orders / hours) of the rider that week * THROUGHPUT_CUMULATIVE_REFERRALS: the cumulative throughput of the rider to date * REFERRALS: the number of referrals made by that rider that week * REFERRALS_CUMULATIVE: the cumulative number of referrals made by that rider to date * SUCCESSFUL_REFERRALS: the number of successful (approved) referrals made by the rider in that week * SUCCESSFUL_REFERRALS_CUMULATIVE: the cumulative number of successful (approved) referrals made by the rider to date

The dtypes method returns the data types of each attribute in the DataFrame.

In [8]:
```
# dtypes of the features of the raw DataFrame, df_raw
df_raw.dtypes
```

Out[8]:
```
RIDER_ID                             int64
LOCATION                            object
APPLICATION_DATE                    object
APPLICATION_APPROVED_DATE           object
FIRST_WORK_DATE                     object
ACQUISITION_CHANNEL                 object
VEHICLE_TYPE                        object
WEEKS_SINCE_FIRST_WORK               int64
RIDER_ACTIVE                          bool
HOURS_WORKED                       float64
HOURS_WORKED_CUMULATIVE            float64
ORDERS_DELIVERED                   float64
ORDERS_DELIVERED_CUMULATIVE        float64
THROUGHPUT                         float64
THROUGHPUT_CUMULATIVE              float64
REFERRALS                          float64
REFERRALS_CUMULATIVE               float64
SUCCESSFUL_REFERRALS               float64
SUCCESSFUL_REFERRALS_CUMULATIVE    float64
dtype: object
```

The info method to get a quick description of the data, in particular the total number of rows, and each attribute's type and number of non-null values.

In [9]:
```
# Info for the raw DataFrame, df_raw
df_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 113525 entries, 0 to 113524
Data columns (total 19 columns):
RIDER_ID                           113525 non-null int64
LOCATION                           113525 non-null object
```

```
APPLICATION_DATE                   113525 non-null object
APPLICATION_APPROVED_DATE          113525 non-null object
FIRST_WORK_DATE                    113525 non-null object
ACQUISITION_CHANNEL                113525 non-null object
VEHICLE_TYPE                       113525 non-null object
WEEKS_SINCE_FIRST_WORK             113525 non-null int64
RIDER_ACTIVE                       113525 non-null bool
HOURS_WORKED                       55001 non-null float64
HOURS_WORKED_CUMULATIVE            113525 non-null float64
ORDERS_DELIVERED                   51774 non-null float64
ORDERS_DELIVERED_CUMULATIVE        111362 non-null float64
THROUGHPUT                         51774 non-null float64
THROUGHPUT_CUMULATIVE              111362 non-null float64
REFERRALS                          2409 non-null float64
REFERRALS_CUMULATIVE               17068 non-null float64
SUCCESSFUL_REFERRALS               2409 non-null float64
SUCCESSFUL_REFERRALS_CUMULATIVE    17068 non-null float64
dtypes: bool(1), float64(10), int64(2), object(6)
memory usage: 15.7+ MB
```

The describe method to show some useful statistics for each numerical column in the DataFrame.

In [10]:
```
# Description of the raw DataFrame, df_raw, showing some summary statistics for each 
df_raw.describe()
```

Out[10]:

	RIDER_ID	WEEKS_SINCE_FIRST_WORK	HOURS_WORKED
count	113525.000000	113525.000000	55001.000000
mean	80873.171989	12.000000	16.333247
std	12798.378932	7.211134	14.652287
min	1864.000000	0.000000	0.000000
25%	70838.000000	6.000000	5.484444
50%	77621.000000	12.000000	11.976390
75%	94220.000000	18.000000	22.985834
max	103776.000000	24.000000	122.296665

	HOURS_WORKED_CUMULATIVE	ORDERS_DELIVERED	ORDERS_DELIVERED_CUMULATIVE
count	113525.000000	51774.000000	111362.000000
mean	117.987786	37.995287	252.875532
std	166.645993	35.692802	389.403744
min	0.167500	1.000000	1.000000
25%	19.801390	12.000000	35.000000
50%	55.344720	26.000000	104.000000
75%	143.990280	53.000000	294.000000
max	2075.802227	284.000000	5046.000000

	THROUGHPUT	THROUGHPUT_CUMULATIVE	REFERRALS	REFERRALS_CUMULATIVE

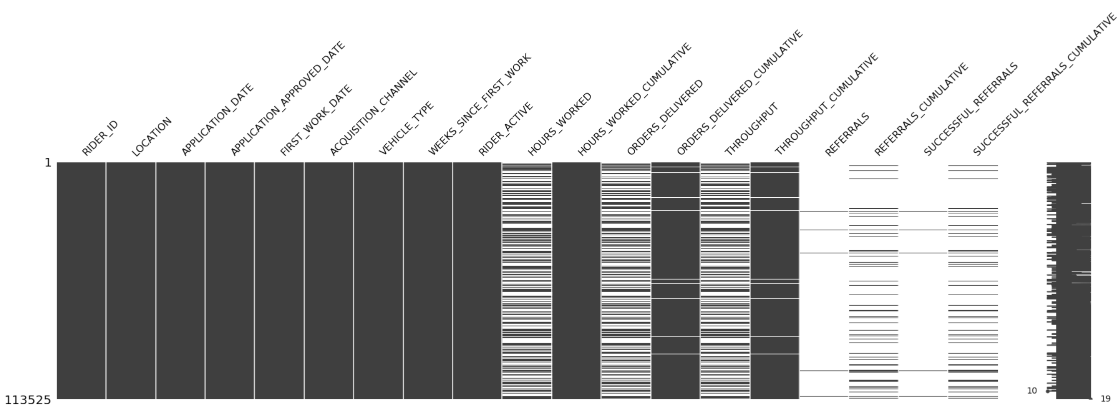
count	51774.000000	111362.000000	2409.000000	17068.000000
mean	2.185034	1.945347	1.077210	2.067495
std	0.781561	0.663847	1.717319	5.127942
min	0.023303	0.025417	0.000000	0.000000
25%	1.696575	1.521931	1.000000	1.000000
50%	2.210061	1.993766	1.000000	1.000000
75%	2.686744	2.403426	1.000000	2.000000
max	30.000300	6.326892	37.000000	285.000000

	SUCCESSFUL_REFERRALS	SUCCESSFUL_REFERRALS_CUMULATIVE
count	2409.000000	17068.000000
mean	0.233707	0.396649
std	0.476797	0.801456
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	1.000000
max	5.000000	28.000000

Next, we will look at the number of NULL values in the dataset. This can be plotted nicely using the missingno library (pip install missingno).

In [11]:
```
# Plot visualisation of the missing values for each feature of the raw DataFrame, df_
msno.matrix(df_raw, figsize = (30, 7))
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11a6658fd68>
```



In [12]:
```
# Counts of missing values
null_value_stats = df_raw.isnull().sum(axis=0)
null_value_stats[null_value_stats != 0]
```

Out[12]:
```
HOURS_WORKED                      58524
ORDERS_DELIVERED                  61751
```

```
ORDERS_DELIVERED_CUMULATIVE          2163
THROUGHPUT                          61751
THROUGHPUT_CUMULATIVE                2163
REFERRALS                          111116
REFERRALS_CUMULATIVE                96457
SUCCESSFUL_REFERRALS               111116
SUCCESSFUL_REFERRALS_CUMULATIVE     96457
dtype: int64
```

Even though it is good practice to look at the null values in a new dataset, as stated in the brief, the dataset is clean and no data cleaning is required. We therefore will leave null values here.

1.5.3 Data Wrangling

As stated in the brief, the dataset has 113,525 records in which one each row refers to one rider per week i.e. each of the 4,541 Riders has 25 rows of data (including week 0 as the week they joined).

For my analysis, I want to separate the latest version of each Rider's data, i.e. week 24, from the previous week's data, to analyse only their total performance of the Riders over the 24 week period. This will leave a dataset of 4,541 records, one per Rider, each with the total value of the following data points: `WEEKS_SINCE_FIRST_WORK`, `HOURS_WORKED_CUMULATIVE`, `ORDERS_DELIVERED_CUMULATIVE`, `THROUGHPUT_CUMULATIVE_REFERRALS`, `REFERRALS_CUMULATIVE`, and `SUCCESSFUL_REFERRALS_CUMULATIVE`.

To do this, we can take the rows only where `WEEKS_SINCE_FIRST_WORK` is equal to 24 i.e. the final week and create the new Dataframe that we'll be working with, using the standard naming convention `df`.

```
In [13]: # Week 24 only of each Rider
         df = df_raw.loc[df_raw['WEEKS_SINCE_FIRST_WORK'] == 24]
```

Again we will perform some of the data handling checks that we performed with the raw dataset.

```
In [14]: df.head()
```

```
Out[14]:      RIDER_ID  LOCATION APPLICATION_DATE APPLICATION_APPROVED_DATE  \
         24       1864  Roo York       05/03/2017                31/03/2017
         49       3062  Roo York       03/10/2016                22/10/2016
         74       5276  Roo York       24/03/2017                31/03/2017
         99       9510  Roo York       05/10/2016                22/10/2016
         124     16977  Roo York       18/03/2017                20/03/2017

             FIRST_WORK_DATE ACQUISITION_CHANNEL          VEHICLE_TYPE  \
         24       03/04/2017             Digital  Scooter / Motorcycle
         49       30/10/2016             Offline               Bicycle
         74       01/04/2017             Organic  Scooter / Motorcycle
         99       28/10/2016             Digital               Bicycle
         124      24/03/2017            Referral               Bicycle

              WEEKS_SINCE_FIRST_WORK  RIDER_ACTIVE  HOURS_WORKED  \
```

```
24                          24        True     35.087779
49                          24       False           NaN
74                          24       False           NaN
99                          24       False           NaN
124                         24       False           NaN

     HOURS_WORKED_CUMULATIVE  ORDERS_DELIVERED  ORDERS_DELIVERED_CUMULATIVE  \
24                820.883044              70.0                       1977.0
49                 15.555832               NaN                         26.0
74                 23.326944               NaN                         70.0
99                 74.400552               NaN                         97.0
124                23.710833               NaN                         67.0

     THROUGHPUT  THROUGHPUT_CUMULATIVE  REFERRALS  REFERRALS_CUMULATIVE  \
24     1.994997               2.408382        NaN                   1.0
49          NaN               1.671399        NaN                   NaN
74          NaN               3.000822        NaN                   1.0
99          NaN               1.303754        NaN                   NaN
124         NaN               2.825713        NaN                   NaN

     SUCCESSFUL_REFERRALS  SUCCESSFUL_REFERRALS_CUMULATIVE
24                    NaN                              1.0
49                    NaN                              NaN
74                    NaN                              0.0
99                    NaN                              NaN
124                   NaN                              NaN
```

In [15]:
```
df.tail()
```

Out[15]:
```
        RIDER_ID  LOCATION APPLICATION_DATE APPLICATION_APPROVED_DATE  \
113424    103762  Roo York       31/03/2017                07/04/2017
113449    103764  Roo York       20/03/2017                07/04/2017
113474    103774  Roo York       26/02/2017                07/04/2017
113499    103775  Roo York       25/03/2017                07/04/2017
113524    103776  Roo York       28/03/2017                07/04/2017

       FIRST_WORK_DATE ACQUISITION_CHANNEL          VEHICLE_TYPE  \
113424      08/04/2017            Referral  Scooter / Motorcycle
113449      07/04/2017            Referral  Scooter / Motorcycle
113474      07/04/2017             Organic  Scooter / Motorcycle
113499      07/04/2017            Referral  Scooter / Motorcycle
113524      08/04/2017            Referral  Scooter / Motorcycle

        WEEKS_SINCE_FIRST_WORK  RIDER_ACTIVE  HOURS_WORKED  \
113424                      24          True     19.114722
113449                      24         False           NaN
113474                      24         False           NaN
113499                      24          True     23.698056
```

```
113524                        24         False           NaN

        HOURS_WORKED_CUMULATIVE  ORDERS_DELIVERED  \
113424               903.356102              59.0
113449               216.875004               NaN
113474               278.383333               NaN
113499               338.583337              83.0
113524               285.996666               NaN

        ORDERS_DELIVERED_CUMULATIVE  THROUGHPUT  THROUGHPUT_CUMULATIVE  \
113424                       2259.0    3.086626               2.500675
113449                        321.0         NaN               1.480115
113474                        783.0         NaN               2.812668
113499                       1107.0    3.502397               3.269505
113524                        644.0         NaN               2.251775

        REFERRALS  REFERRALS_CUMULATIVE  SUCCESSFUL_REFERRALS  \
113424        NaN                   NaN                   NaN
113449        NaN                   4.0                   NaN
113474        NaN                   NaN                   NaN
113499        NaN                   5.0                   NaN
113524        NaN                   NaN                   NaN

        SUCCESSFUL_REFERRALS_CUMULATIVE
113424                              NaN
113449                              2.0
113474                              NaN
113499                              1.0
113524                              NaN
```

In [16]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4541 entries, 24 to 113524
Data columns (total 19 columns):
RIDER_ID                           4541 non-null int64
LOCATION                           4541 non-null object
APPLICATION_DATE                   4541 non-null object
APPLICATION_APPROVED_DATE          4541 non-null object
FIRST_WORK_DATE                    4541 non-null object
ACQUISITION_CHANNEL                4541 non-null object
VEHICLE_TYPE                       4541 non-null object
WEEKS_SINCE_FIRST_WORK             4541 non-null int64
RIDER_ACTIVE                       4541 non-null bool
HOURS_WORKED                       1319 non-null float64
HOURS_WORKED_CUMULATIVE            4541 non-null float64
ORDERS_DELIVERED                   1223 non-null float64
ORDERS_DELIVERED_CUMULATIVE        4464 non-null float64
```

```
THROUGHPUT                          1223 non-null float64
THROUGHPUT_CUMULATIVE               4464 non-null float64
REFERRALS                           74 non-null float64
REFERRALS_CUMULATIVE                1002 non-null float64
SUCCESSFUL_REFERRALS                74 non-null float64
SUCCESSFUL_REFERRALS_CUMULATIVE     1002 non-null float64
dtypes: bool(1), float64(10), int64(2), object(6)
memory usage: 678.5+ KB
```

In [17]:
```
df.describe()
```

Out[17]:

	RIDER_ID	WEEKS_SINCE_FIRST_WORK	HOURS_WORKED	\
count	4541.000000	4541.0	1319.000000	
mean	80873.171989	24.0	19.372840	
std	12799.731993	0.0	16.926589	
min	1864.000000	24.0	0.000000	
25%	70838.000000	24.0	5.693751	
50%	77621.000000	24.0	14.942779	
75%	94220.000000	24.0	30.296527	
max	103776.000000	24.0	89.775555	

	HOURS_WORKED_CUMULATIVE	ORDERS_DELIVERED	ORDERS_DELIVERED_CUMULATIVE	\
count	4541.000000	1223.000000	4464.000000	
mean	197.829756	50.528209	440.673835	
std	259.929947	43.825879	621.260672	
min	0.178888	1.000000	1.000000	
25%	29.188333	15.000000	53.000000	
50%	90.675278	38.000000	172.000000	
75%	262.693056	75.000000	573.250000	
max	2075.802227	251.000000	5046.000000	

	THROUGHPUT	THROUGHPUT_CUMULATIVE	REFERRALS	REFERRALS_CUMULATIVE	\
count	1223.000000	4464.000000	74.000000	1002.000000	
mean	2.403633	1.990289	1.270270	2.589820	
std	0.717144	0.667197	2.216361	9.369239	
min	0.056955	0.025861	0.000000	0.000000	
25%	1.965016	1.568525	1.000000	1.000000	
50%	2.440885	2.051430	1.000000	1.000000	
75%	2.888611	2.461074	1.000000	3.000000	
max	5.396876	5.191057	19.000000	285.000000	

	SUCCESSFUL_REFERRALS	SUCCESSFUL_REFERRALS_CUMULATIVE
count	74.000000	1002.000000
mean	0.310811	0.561876
std	0.547114	1.215396
min	0.000000	0.000000
25%	0.000000	0.000000

```
50%                   0.000000                              0.000000
75%                   1.000000                              1.000000
max                   2.000000                             28.000000
```

The new dataset, `df`, is now only 1/25 of it's original size, containing only the final row for each Rider and their total performance in the recorded metrics. The original dataset is still accessible using the DataFrame `df_raw`.

Next we will explore the new DataFrame and plot the key metrics for further analysis.

1.6 4. Exploratory Data Analysis

The exploratory data analysis aims to answer the question, **"Is the RGR scheme successful, and if so, how have you reached that conclusion?"**.

As per the project brief, I will separate my answer to this section into the following three subsections: * Defining what success is (Section **??**) * How has RGR performed compared with other channels? (Section **??**) * How does rider performance / behaviour vary between the channels? (Section **??**)

We will be using the Pandas library for DataFrames and the Seaborn library for plotting.

1.6.1 4.1. Definition of a successful RGR scheme

Some gig economy startups can have a turnover of staff as high as 500% per year (source 1) and (source 2). It is therefore important for these companies to focus on recruitment, how it can be done smarter and at less cost.

It is difficult to define what success for an RGR scheme would be, I would consider the following three components: * a system whereby current staff recommend a sufficient number potential employees to the application process, * of those candidates that apply, a significant percentage meet the standards to be eligible to work for the company, and * of these potential employees, those that are hired perform go on to meet the required standards and expected commitment to the role.

These three requirements are analysed in much further detail in the following sections Section **??** and Section **??**.

To throw out some rough numbers, if for every two members of staff, one potential employee can be referred and then of those candidates, 1/4 are successful, I would say that is quite a successful recruitment process.

Let's take a look at the rough numbers for our dataset:

```
In [18]: total_riders = df['RIDER_ID'].count()
         total_referrals = df['REFERRALS_CUMULATIVE'].sum()
         total_successful_referrals = df['SUCCESSFUL_REFERRALS_CUMULATIVE'].sum()

         print("Total Riders: " + str(total_riders))
         print("Total Referrals: " + str(total_referrals))
         print("Total Successful Referrals: " + str(total_successful_referrals))

         print("Rate of Successful Referalls to Referrals (%): " + str(round((total_successful_
         print("Rate of Successful Referalls to Riders (%): " + str(round((total_successful_re
```

```
Total Riders: 4541
Total Referrals: 2595.0
Total Successful Referrals: 563.0
Rate of Successful Referalls to Referrals (%): 21.7%
Rate of Successful Referalls to Riders (%): 12.4%
```

Looking at the overall dataset, of the 4,531 Riders, 2,595 referrals were made and of these referrals, 563 were successful. That means that for every candidate, 0.573 candidates are referred and 0.124 successful candidates are referred. Of the candidates that are referred, the success rate is about 21.7% i.e. 1 in 5. Looking at these rough numbers, I would suggest that Deliveroo's RGR scheme is extremely productive. We will however dive much deeper into these numbers in the following sections.

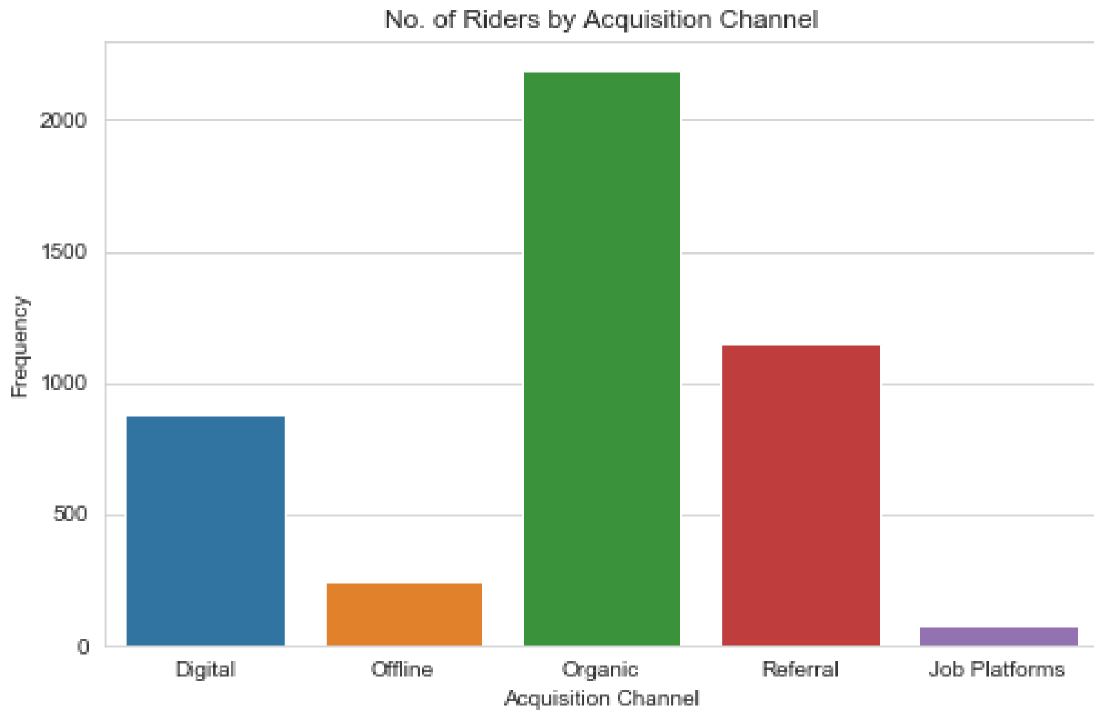
To make better comments on defining what is a successful RGR scheme, I would like to know what the turnover rate of Riders for Deliveroo and the average length of employment of Riders with the company, for example.

1.6.2 4.2. How has RGR performed compared with other channels?

Let's plot the data for Riders by Acquisition Channel to see the volumes of Riders recruited by each different channel. These are: * Digital * Job Platforms * Offline * Organic * Referral

Plot the data

```
In [19]: # Set the width and height of the figure
         plt.figure(figsize=(8,5))

         # Plot style
         sns.set_style("whitegrid")

         # Add title
         plt.title("No. of Riders by Acquisition Channel")

         # Bar chart showing
         sns_plot_4_2 = sns.countplot(df['ACQUISITION_CHANNEL'])

         # Add labels for axes
         plt.xlabel("Acquisition Channel")
         plt.ylabel("Frequency")

         # Save plot
         fig_4_2 = sns_plot_4_2.get_figure()
         fig_4_2.savefig("./figures/4_2.png")
```




```
In [20]: print(df['ACQUISITION_CHANNEL'].describe())

count        4541
unique          5
top       Organic
freq         2190
Name: ACQUISITION_CHANNEL, dtype: object
```

```
In [21]: print(df.groupby('ACQUISITION_CHANNEL')[['RIDER_ID']].count())

                     RIDER_ID
ACQUISITION_CHANNEL
Digital                   882
Job Platforms              77
Offline                   242
Organic                  2190
Referral                 1150
```

Analysis The data shows that of the 4,541 total Riders in the dataset, 1,150 joined Deliveroo through the Referral channel, making up just over a quarter (25.3%) of the total workforce. This is the second most popular Acquisition Channel after Organic, which makes up 2,190 of the Riders in the dataset (48.2%).

The key thing to notice here is that even though the Referral scheme is the second best Acquisition Measure, it is actually the best performing channel in which Deliveroo is actively involved in when driving recruitment. Half of the Riders in the dataset came are said to have come to Deliveroo Organically which presumably means that Deliveroo had no active participation in finding the Riders before their application.

When comparing channel to Job Platforms, presumably sites like LinkedIn, Indeed, Monster, Reed etc., this channel recruited only 77 Riders (1.70% of the Riders in the dataset). The next best Acquisition Channel is Digital, making up a considerable number of the Riders with 882 (19.4% of the dataset). Offline makes up the remaining 242 Riders (5.33%).

Considering quarter of the Riders came to Deliveroo through Referrals and it is the best performing active measure, I would say I would say that the RGR scheme is performing very well and is a key component for Deliveroo maintaining its staff and high performance levels regarding the delivery of the food.

1.6.3 4.3. How does Rider performance / behaviour vary between the channels?

Wrangle the data For this section, before we can make any plots, we need to wrangle the data to a form that's more suited to our needs. We need to take the existing DataFrame of Riders data for the 24th week, `df`, and use the groupby and aggregate methods to create a new DataFrame, `df_channel`, that counts the number of Riders in each channel by unique rider id and the total sum for key performance metrics, defined below.

For this exercise, the first performance metrics are: Hours Worked, Cumulative Orders Delivered, Orders Delivered Cumulative, and Cumulative Throughput. We will also next look at Cummulative Referrals, and Cumulative Successful Referrals to see the 'performance' of the Riders regarding the referring new candidates to the business.

Using this new DataFrame, we can produce calibrated metrics (discussed further in next steps) taking averages per Rider and use these create plots that determine the performance and behaviour of the Riders by channel.

The code for this is as follows:

```
In [22]: # Created groupedby DataFrame, by channel
         df_channel = df.groupby(
            ['ACQUISITION_CHANNEL']
         ).agg(
             {
                  'RIDER_ID': 'count',                          # the total number of Riders
                  'HOURS_WORKED_CUMULATIVE': 'sum',             # the sum total of cumulative ho
                  'ORDERS_DELIVERED_CUMULATIVE': 'sum',         # the sum total of cumulative de
                  'THROUGHPUT_CUMULATIVE': 'sum',               # the sum total of cumulative th
                  'REFERRALS_CUMULATIVE': 'sum',                # the sum total of cumulative re
                  'SUCCESSFUL_REFERRALS_CUMULATIVE': 'sum'      # the sum total of cumulative su
             }
         ).reset_index()

         # Rename the RIDER_ID column to TOTAL_RIDERS
         df_channel = df_channel.rename(columns={'RIDER_ID':'TOTAL_RIDERS'})

         df_channel
```

```
Out[22]:   ACQUISITION_CHANNEL  TOTAL_RIDERS  HOURS_WORKED_CUMULATIVE  \
        0             Digital           882            140313.938052
        1       Job Platforms            77             14923.873923
        2             Offline           242             37820.421062
        3             Organic          2190            407886.645300
        4            Referral          1150            297400.045266

           ORDERS_DELIVERED_CUMULATIVE  THROUGHPUT_CUMULATIVE  REFERRALS_CUMULATIVE  \
        0                     292481.0            1625.277691                 533.0
        1                      32032.0             139.768841                   6.0
        2                      79032.0             434.241888                 113.0
        3                     924513.0            4453.435329                 962.0
        4                     639110.0            2231.928393                 981.0

           SUCCESSFUL_REFERRALS_CUMULATIVE
        0                             75.0
        1                              3.0
        2                             17.0
        3                            193.0
        4                            275.0
```

```
In [23]: df_channel.dtypes
```

```
Out[23]: ACQUISITION_CHANNEL                 object
         TOTAL_RIDERS                         int64
         HOURS_WORKED_CUMULATIVE            float64
         ORDERS_DELIVERED_CUMULATIVE        float64
         THROUGHPUT_CUMULATIVE              float64
         REFERRALS_CUMULATIVE               float64
         SUCCESSFUL_REFERRALS_CUMULATIVE    float64
         dtype: object
```

As previously discussed in Section **??** and again in the grouped table, `df_channel`, we have different numbers of Riders for each of the Acquisition Channels. We will therefore calibrate the metrics in question regarding performance, these being: `HOURS_WORKED_CUMULATIVE`, `ORDERS_DELIVERED_CUMULATIVE`, `THROUGHPUT_CUMULATIVE`, `REFERRALS_CUMULATIVE`, and `SUCCESSFUL_REFERRALS_CUMULATIVE`. These will be calibrated by taken an average per rider i.e. dividing the sum total by the number of Riders. These new metrics can be identified with the suffix '_PR' (per rider) e.g. `HOURS_WORKED_CUMULATIVE_PR` is the cumulative hours worked per rider.

```
In [24]: # Create per Rider (PR) columns
         df_channel['HOURS_WORKED_CUMULATIVE_PR'] = df_channel['HOURS_WORKED_CUMULATIVE'] / df_
         df_channel['ORDERS_DELIVERED_CUMULATIVE_PR'] = df_channel['ORDERS_DELIVERED_CUMULATIVE
         df_channel['THROUGHPUT_CUMULATIVE_PR'] = df_channel['THROUGHPUT_CUMULATIVE'] / df_chan
         df_channel['REFERRALS_CUMULATIVE_PR'] = df_channel['REFERRALS_CUMULATIVE'] / df_channe
         df_channel['SUCCESSFUL_REFERRALS_CUMULATIVE_PR'] = df_channel['SUCCESSFUL_REFERRALS_CU
```

```
# Drop unnamed channel (created 2nd index)
df_channel = df_channel.loc[:, ~df_channel.columns.str.contains('^Unnamed')]
```

In [25]:
```
df_channel.head()
```

Out[25]:
```
  ACQUISITION_CHANNEL  TOTAL_RIDERS  HOURS_WORKED_CUMULATIVE  \
0             Digital           882            140313.938052
1       Job Platforms            77             14923.873923
2             Offline           242             37820.421062
3             Organic          2190            407886.645300
4            Referral          1150            297400.045266

   ORDERS_DELIVERED_CUMULATIVE  THROUGHPUT_CUMULATIVE  REFERRALS_CUMULATIVE  \
0                     292481.0            1625.277691                 533.0
1                      32032.0             139.768841                   6.0
2                      79032.0             434.241888                 113.0
3                     924513.0            4453.435329                 962.0
4                     639110.0            2231.928393                 981.0

   SUCCESSFUL_REFERRALS_CUMULATIVE  HOURS_WORKED_CUMULATIVE_PR  \
0                             75.0                  159.086098
1                              3.0                  193.816544
2                             17.0                  156.282732
3                            193.0                  186.249610
4                            275.0                  258.608735

   ORDERS_DELIVERED_CUMULATIVE_PR  THROUGHPUT_CUMULATIVE_PR  \
0                      331.611111                  1.842718
1                      416.000000                  1.815180
2                      326.578512                  1.794388
3                      422.152055                  2.033532
4                      555.747826                  1.940807

   REFERRALS_CUMULATIVE_PR  SUCCESSFUL_REFERRALS_CUMULATIVE_PR
0                 0.604308                            0.085034
1                 0.077922                            0.038961
2                 0.466942                            0.070248
3                 0.439269                            0.088128
4                 0.853043                            0.239130
```

You can now see the new DataFrame with the new per Rider metrics, including `HOURS_WORKED_CUMULATIVE_PR`, `ORDERS_DELIVERED_CUMULATIVE_PR`, `THROUGHPUT_CUMULATIVE_PR`, `REFERRALS_CUMULATIVE_PR`, `SUCCESSFUL_REFERRALS_CUMULATIVE_PR`, and `ORDERS_DELIVERED_PER_HOUR_PR`.

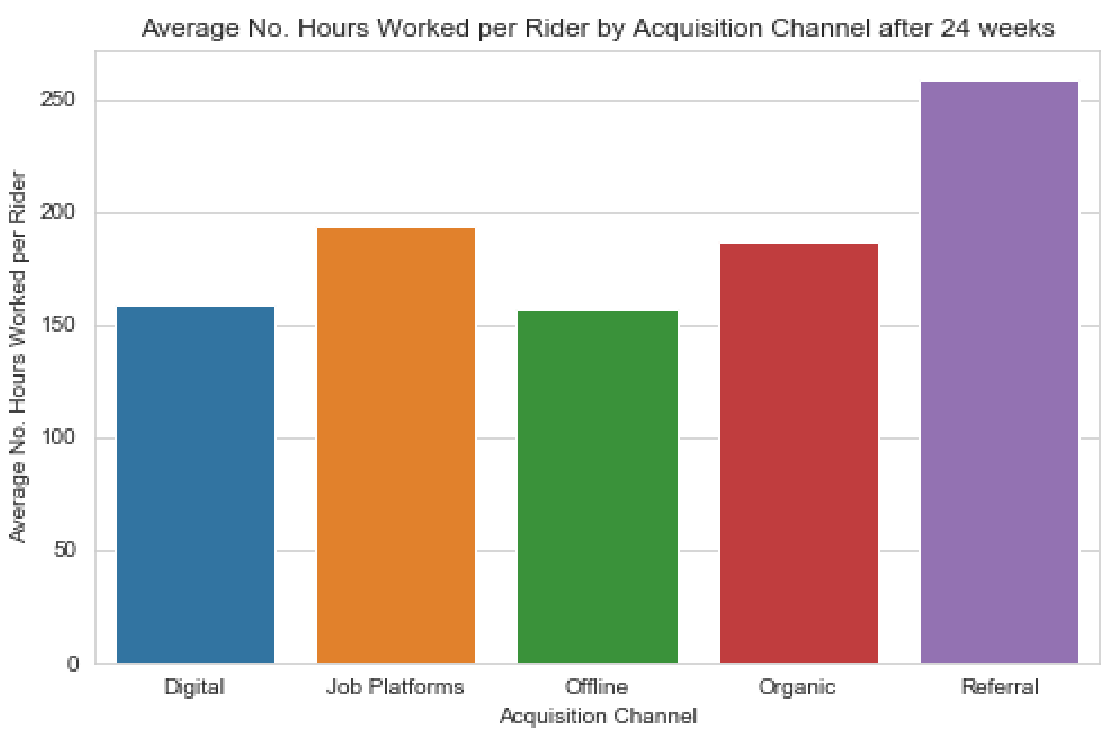
Before plotting this data, let's export the grouped and aggregated dataset in case we, or other analysts, would like to use it in future projects/analysis.

In [26]:
```
df_channel.to_csv(r'./data/rgr_take_home_v3_dataset_grouped.csv')
```

Plot the data

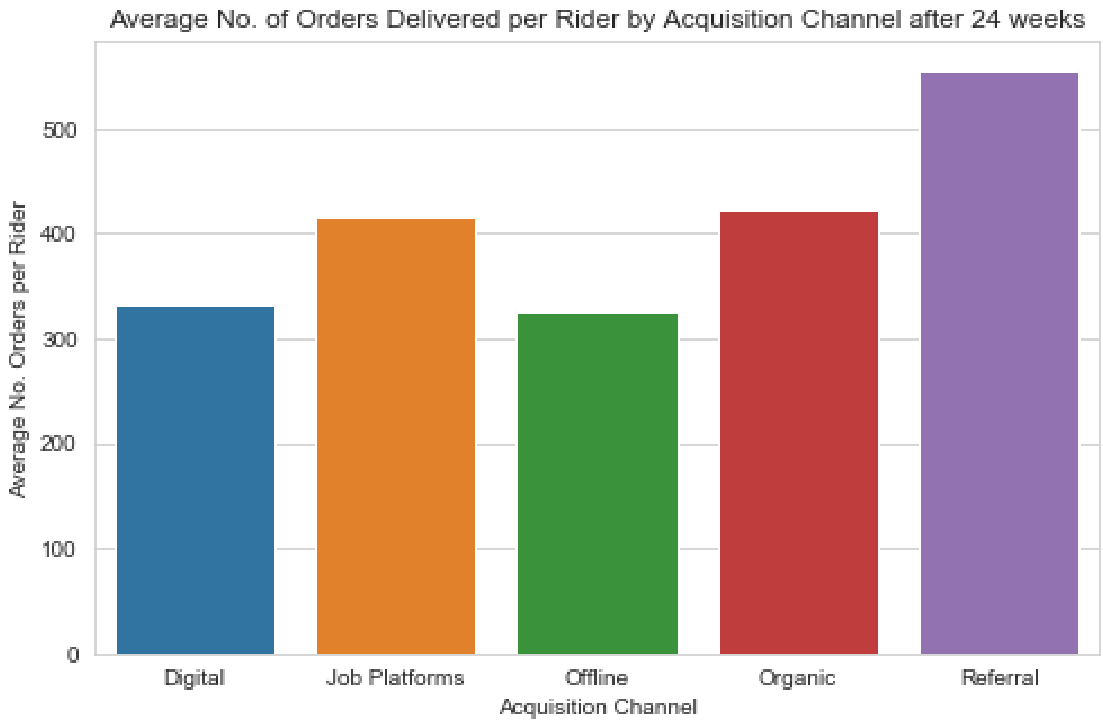
Plot 1: Average No. of Hours Worked per Rider by Acquisition Channel after 24 weeks

In [27]:
```
# Set the width and height of the figure
plt.figure(figsize=(8,5))

# Plot style
sns.set_style("whitegrid")

# Add title
plt.title("Average No. Hours Worked per Rider by Acquisition Channel after 24 weeks")

# Bar chart showing the Average No. Hours Worked per Rider by Acquisition Channel aft
sns_plot_4_3a = sns.barplot(x=df_channel['ACQUISITION_CHANNEL'], y=df_channel['HOURS_

# Add labels for axes
plt.xlabel("Acquisition Channel")
plt.ylabel("Average No. Hours Worked per Rider")

# Save plot
fig_4_3a = sns_plot_4_3a.get_figure()
fig_4_3a.savefig("./figures/4_3a.png")
```



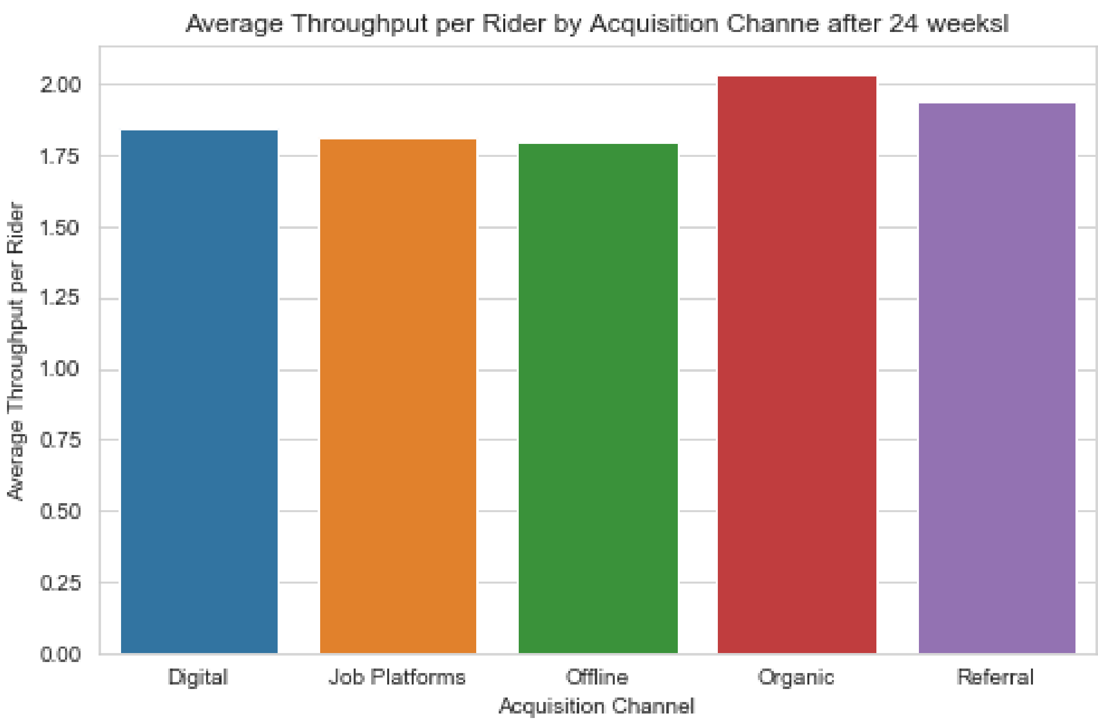
Plot 2: Average No. of Orders Delivered per Rider by Acquisition Channel after 24 weeks

In [28]:
```
# Set the width and height of the figure
plt.figure(figsize=(8,5))

# Plot style
sns.set_style("whitegrid")

# Add title
plt.title("Average No. of Orders Delivered per Rider by Acquisition Channel after 24 w

# Bar chart showing the Average No. of Orders Delivered per Rider by Acquisition Chan
sns_plot_4_3b = sns.barplot(x=df_channel['ACQUISITION_CHANNEL'], y=df_channel['ORDERS_

# Add labels for axes
plt.xlabel("Acquisition Channel")
plt.ylabel("Average No. Orders per Rider")

# Save plot
fig_4_3b = sns_plot_4_3b.get_figure()
fig_4_3b.savefig("./figures/4_3b.png")
```



Plot 3: Average Throughput per Rider by Acquisition Channel after 24 weeks

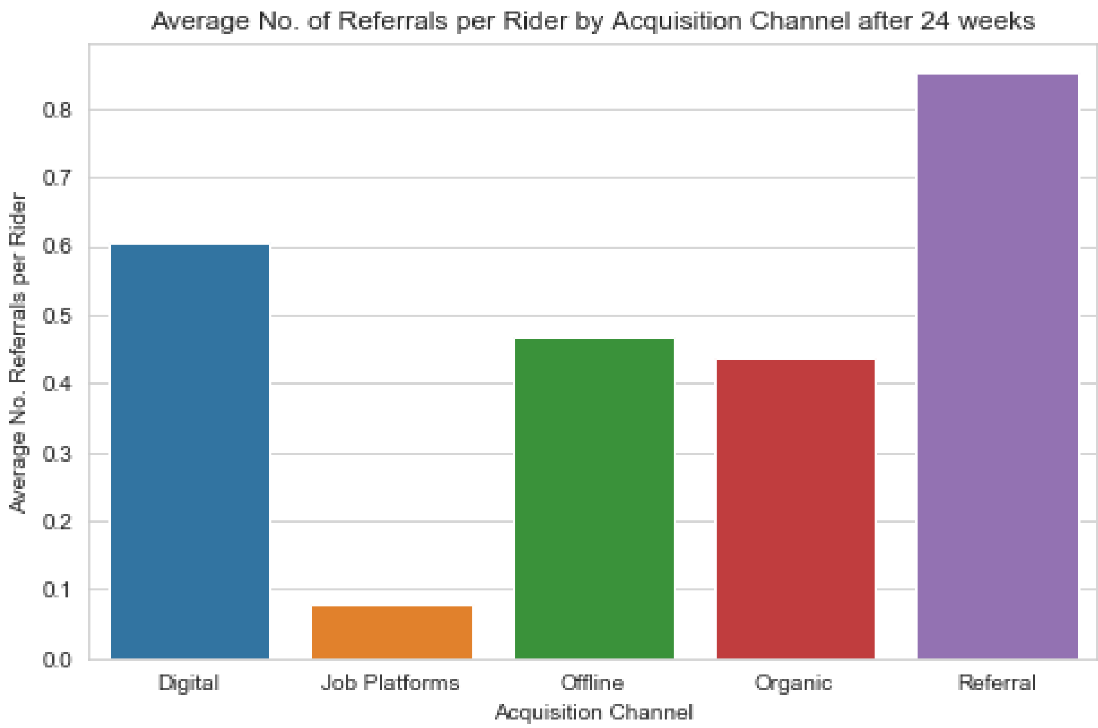
In [29]:
```
# Set the width and height of the figure
plt.figure(figsize=(8,5))

# Plot style
sns.set_style("whitegrid")

# Add title
plt.title("Average Throughput per Rider by Acquisition Channe after 24 weeksl")

# Bar chart showing the Average Throughput per Rider by Acquisition Channel after 24 w
sns_plot_4_3c = sns.barplot(x=df_channel['ACQUISITION_CHANNEL'], y=df_channel['THROUGH

# Add labels for axes
plt.xlabel("Acquisition Channel")
plt.ylabel("Average Throughput per Rider")

# Save plot
fig_4_3c = sns_plot_4_3c.get_figure()
fig_4_3c.savefig("./figures/4_3c.png")
```



Plot 4: Average No. of Referrals per Rider by Acquisition Channel after 24 weeks

In [30]:
```
# Set the width and height of the figure
plt.figure(figsize=(8,5))
```

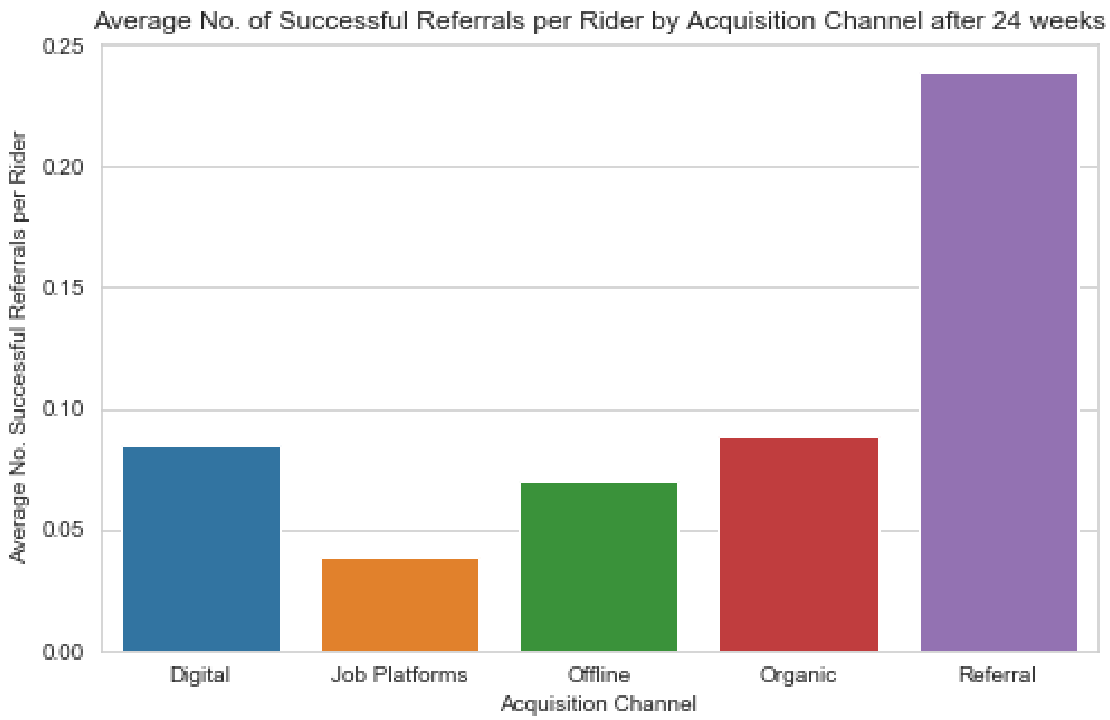
```
# Plot style
sns.set_style("whitegrid")

# Add title
plt.title("Average No. of Referrals per Rider by Acquisition Channel after 24 weeks")

# Bar chart showing the Average No. of Referrals per Rider by Acquisition Channel aft
sns_plot_4_3d = sns.barplot(x=df_channel['ACQUISITION_CHANNEL'], y=df_channel['REFERRA

# Add labels for axes
plt.xlabel("Acquisition Channel")
plt.ylabel("Average No. Referrals per Rider")

# Save plot
fig_4_3d = sns_plot_4_3d.get_figure()
fig_4_3d.savefig("./figures/4_3d.png")
```



Plot 5: Average No. of Successful Referrals per Rider by Acquisition Channel after 24 weeks

```
In [31]: # Set the width and height of the figure
         plt.figure(figsize=(8,5))

         # Plot style
```

```
sns.set_style("whitegrid")

# Add title
plt.title("Average No. of Successful Referrals per Rider by Acquisition Channel after

# Bar chart showing the Average No. of Successful Referrals per Rider by Acquisition
sns_plot_4_3e = sns.barplot(x=df_channel['ACQUISITION_CHANNEL'], y=df_channel['SUCCESS

# Add labels for axes
plt.xlabel("Acquisition Channel")
plt.ylabel("Average No. Successful Referrals per Rider")

# Save plot
fig_4_3e = sns_plot_4_3e.get_figure()
fig_4_3e.savefig("./figures/4_3e.png")
```



Analysis All analysis focuses on the Referral Acquisition Channel, comparing this to the other channels. Each of the five previous plots has a written paragraph, interpreting the results.

Plot 1: Average No. of Hours Worked per Rider by Acquisition Channel For the first plot, the Average No. of Hours Worked per Rider by Acquisition Channel, the data shows that Riders who joined Deliveroo by Referral came out on top, with an average no. of 258.6 total hours worked per Rider after 24 weeks, averaging at 10.8 hours a week. For reference, Riders work on average 15 hours a week in the UK (source). Of the total Hours Worked by all Riders in the dataset, this makes up 27.1% of total Hours Worked, suggesting that the Referral Riders are the hardest working and most committed demographic. The four other platform's share of the total percentage ranges between 16.7% and 20.3%, the next best channel being by Job Platform, with an average hours worked of 193.8 (20.3%).

Plot 2: Average No. of Orders Delivered per Rider by Acquisition Channel For the second plot, the Average No. of Orders Delivered per Rider by Acquisition Channel, the data shows that Riders who joined Deliveroo by Referral came out on top again, with an average no. of 555.7 orders delivered per Rider after 24 weeks. Of the total Orders Delivered by all Riders in the dataset, this makes up 27.1% of the total Orders Delivered, suggesting that the Referral Riders are the most productive demographic. The four other platform's share of the total percentage ranges between 15.9% and 20.6%, the next best channel being the Organic joiners, with an average Orders Delivered of 422.0 (20.6%).

Plot 3: Throughput per Rider by Acquisition Channel As a quick reminder before discussing the third plot, the Cumlative Throughput is the cumulative orders per hour (orders / hours) of the Rider.

As we can see from the data, the Average Throughput per Rider by Acquisition Channel of Riders who joined Deliveroo by Referral again came out very strongly, overall placing second with an average Throughput per Rider of 2.03. Of the total sum of Throughput per Rider in the dataset, this makes up 20.6%, suggesting that the Referral Riders are the some of the most product Riders and are very efficient in delivering the most orders per hour, as possible. The other platform's share of the total percentage are all very close, ranging between 19.0% (Offline) and 21.6% (Organic).

My instinct with this observation is that the Vehicle Type may be a more interesting indicator to use when looking at the Throughput of the Riders. However, I believe it's interesting analysis and has some value being in this report.

Plot 4: Average No. of Referrals per Rider by Acquisition Channel For the forth plot, the Average No. of Referrals per Rider by Acquisition Channel, the data shows that Riders who joined Deliveroo by Referral came out on top again, with an average no. of 0.853 Referrals per Rider after 24 weeks. Of the total Referrals by all Riders in the dataset, this makes up 34.9% of the total Referrals, suggesting that the Referral Riders are far more likely to Refer new Riders to the company. The four other platform's share of the total percentage ranges between 3.19% (Job Platforms) and 24.8% (Digital).

Plot 5: Average No. of Successful Referrals per Rider by Acquisition Channel For the fifth plot, the Average No. of Successful Referrals per Rider by Acquisition Channel, the data shows that Riders who joined Deliveroo by Referral continued to observe the previous trends, again leading the channels with an average no. of 0.239 Successful per Rider after 24 weeks. Of the total Successful Referrals by all Riders in the dataset, this makes up 45.9% of the total Successful Referrals, suggesting that not only are the Referral Riders are far more likely to Refer other Riders to the company (as seen in plot 4), but they are also far more likely to refer successful candidates. The four other platform's share of the total percentage ranges between 7.47% (Job Platforms) and 16.9% (Organic).

1.7 5. Summary and Conclusion

To answer the question "Is the RGR scheme successful and why?" using our limited dataset and restricted time for analysis, I believe that the answer is a resounding Yes!

Our analysis was divided into three sections: 1) We defined what a successful RGR scheme is; 2) We looked at how the RGR scheme performed compared with other channels; and 3) We analysed how Rider's performance and behaviour depending on their channel of recruitment.

We first looked at the 4,541 Riders and took a high level view to see through which channel they had come through to the company. The data showed that 1,150 employees joined Deliveroo through the Referral channel, making up just over a quarter (25.3%) of the workforce in the dataset, second only to Organic (48.2%), a demographic which is inherently our of Deliveroo's control. This therefore suggests that Referrals is Deliveroo's best active form of recruitment.

We next took our DataFrame and calibrated the key performance metrics of the Riders to determine average 'per Rider' values over the 24 week period for: Hours Worked, Orders Delivered, Orders Delivered, Throughput, Referrals, and Successful Referrals. Our plots show that in all but one of the categories, Referred Riders outperform other Riders in regarding these metrics, except for Throughput where Referrals placed second and as discussed in section 4.3, all channels performed quite simularly and I have suspicious that it's the form of transport that would have greater effect on improving this number i.e. using a car and not a bike.

To conclude, not only is 'Rider Get Rider' scheme a great way for Deliveroo to find new employees, the data suggests that these employees are some of the most productive, hardest working and efficient Riders in the business. The data also suggests that Riders who joined the business through the Referral scheme are more likely to go on to refer more future Riders and with a greater success rate.

1.8 6. Next Steps

This workbook was a short exploratory data analysis for Deliveroo Riders.

Some of the metrics and avenues not touched but may be of interest include: * Further address our definition of success using additional data of Riders including the turnover rate of Rider, the average length of employement of Riders with the company, for example. * Further analysis of the Rider's `VEHICLE_TYPE`, especially when considering it's effect on `THROUGHPUT` i.e. do car drivers deliver more orders per hours than cyclists. * Further analysis of the Rider `LOCATION`. We could maybe create a heatmap of Location vs. Aquisition Channel and see the hot spots. * Further analysis of the Rider's `RIDER_ACTIVITY` i.e. TRUE or FALSE. Does further inspection show any patterns?

1.9 7. Bibliography

1. https://www.businessinsider.com/uber-lyft-drivers-livable-wage-complaints-2019-5?r=US&IR=T
2. https://www.td.org/insights/has-the-gig-economy-jumped-the-shark
3. https://roocommunity.com/tech-round-up-statistics/

Visit my website EddWebster.com or my GitHub Repository for more projects. If you'd like to get in contact, my email is: edd.j.webster@gmail.com.

Section **??**