Medical Appointment No Shows - [No-show appointments]

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In [ ]:

```

```

1. Introduction

In this section we briefly introduce the data and features we have, the setup for our analysis, and the hypothesis we will look into.

1.1. Dataset description

This dataset collects information from 110,527 medical appointments in Brazil and is focused on the question of whether or not patients show up for their appointment. 14 associated characteristics about the patient are included in each row.

PatientID

- Identification of a patient.

AppointmentID

- Identification of each appointment.

Gender

- Male or Female. Note: Female is the greater proportion, woman takes way more care of they health in comparison to man.

ScheduledDay

- The day patient set up their appointment.

AppointmentDay

- The day of the actual appointment.

Age

- Patient age

Neighbourhood

- Indicates the location of the hospital.

Scholarship

- Indicates whether or not the patient is enrolled in Brasilian welfare program Bolsa Família.

Hipertension

- Hipertension. True or False.

Diabetes

- Diabetes. True or False.

Alcoholism

- Alcoholism. True or False.

Handcap

- Handicapped. True or False.

SMS_received

- 1 or more messages sent to the patient.

No-show

- 'No' if the patient showed up to their appointment, and 'Yes' if they did show up

1.2. Initial statements

This section sets up import statements for all the packages that will be used throughout this python notebook.

In [1]:
```
# Data analysis packages:
import numpy as np
import pandas as pd

# Vusialization packages:
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
import os
print(os.listdir("../Project-1/Database_No_show_appointments/"))
```

```
['noshowappointments-kagglev2-may-2016.csv']
```

In [3]:
```
pd.read_csv('../Project-1/Database_No_show_appointments/noshowappointments-kagglev2-may-
```

Out[3]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarsl
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	

1.3. Questions for Analysis

From the dataset information and its attributes, the following questions can be formulated:

- **Regarding the no-showing appointents**:
  - Do the patients forget the appointment?
  - What is the average waiting time between the scheduling data and the appointment date?
- **Regarding the patient profile**:
  - Is there any common characteristics among those patients that miss appointments?
  - What is the *missing appointments per patient* relation in the dataset?
  - How many patients have missed an appointment at least once?
  - Patients suffering from serious illnesses show up more on the appointment date?
- **Regarding the health unite**:
  - What are the neighbourhoods with the highest no-showing rate?

- Considering there are common characteristics among those who do not attend the appointments, how these characteristics are geographically distributed?

- **Regarding the data**:
  - Is the data balanced in relation to the interest class (showing/no-showing to appointments)?
  - How is the data distributed in relation to the location(neighborhood)?
  - Does patients who wait less for their appointments show up to their appointments more?
  - Does age affect if the patient will show up for scheduled appointment?
  - Does being handicapped affect if the patient will show up for scheduled appointment?
  - What about other factors such as (scholarship, hypertension, diabetes, alcoholic, reminder SMS)

2. Data Wrangling

In this section the data will be loaded and some operations will be performed to inspect data types, to look for missing values or possibly errant data. Data cleaning operations will be executed in the same section where a specific attribute is being analyzed.

2.1. General Properties

Load Data

In [4]:
```
# Load the data
df = pd.read_csv('../Project-1/Database_No_show_appointments/noshowappointments-kagglev2
df.head()
```

Out[4]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarsl
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	

In [5]:
```
print("The shape of the DataFrame is => {}".format(df.shape))
```

```
The shape of the DataFrame is => (110527, 14)
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 110527 entries, 0 to 110526
Data columns (total 14 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   PatientId       110527 non-null  float64
```

```
 1   AppointmentID   110527 non-null  int64
 2   Gender          110527 non-null  object
 3   ScheduledDay    110527 non-null  object
 4   AppointmentDay  110527 non-null  object
 5   Age             110527 non-null  int64
 6   Neighbourhood   110527 non-null  object
 7   Scholarship     110527 non-null  int64
 8   Hipertension    110527 non-null  int64
 9   Diabetes        110527 non-null  int64
 10  Alcoholism      110527 non-null  int64
 11  Handcap         110527 non-null  int64
 12  SMS_received    110527 non-null  int64
 13  No-show         110527 non-null  object
dtypes: float64(1), int64(8), object(5)
memory usage: 11.8+ MB
```

- Column names inconsistent.
- Typos in column names.
- ScheduledDay and AppointmentDay should be Datetime format.

In [7]:
```python
# check unique
df.nunique()
```

Out[7]:
```
PatientId          62299
AppointmentID     110527
Gender                 2
ScheduledDay      103549
AppointmentDay        27
Age                  104
Neighbourhood         81
Scholarship            2
Hipertension           2
Diabetes               2
Alcoholism             2
Handcap                5
SMS_received           2
No-show                2
dtype: int64
```

- There are 110527 appointments but only 62299 patients -> some patients have multiple appointments.
- Age has 104 unique values -> something might be wrong

In [8]:
```python
# Check missing values
df.isnull().sum()
```

Out[8]:
```
PatientId         0
AppointmentID     0
Gender            0
ScheduledDay      0
AppointmentDay    0
Age               0
Neighbourhood     0
Scholarship       0
Hipertension      0
Diabetes          0
Alcoholism        0
Handcap           0
SMS_received      0
No-show           0
dtype: int64
```

- There's no missing value in the dataset

In [9]:
```
# Check duplicate rows
df.duplicated().sum()
```

Out[9]:
```
0
```

- There's no duplicate rows

Conclude the findings about the dataset

General:

1. Column names are inconsistent. (Upper & lowercase)
2. Some columns have typos. (ex: Hipertension -> Hypertension, Handcap -> Handicap)
3. Null values does not exists in this dataset.
4. No duplicated rows in the dataset.

Features:

1. PatientID and AppointmentID should be string type.
2. ScheduleDay and AppointmentDay are strings not datetime dtype.
3. AppointmentDay does not record the exact time, just date. change to YYYY-MM-DD.
4. PatientID is less than AppointmentID: Some patient may revisit several times.
5. Age has 104 unique values (-1~115).
6. Handcap values are (0,1,2,3,4) stands for different levels of being a Handicap.
7. No-show feature is string, change to (0, 1) where '1' for patients who did no show up and '0' for who showed up.

In [10]:
```
# Duplicate dataframe for modification
df_mod=df.copy()
df_mod.head()
```

Out[10]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarsl
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	

- We will use **df_mod** for any modifications to the dataset.

In [11]:
```
# Rename all variables to be in conventional naming
df_mod.rename(columns=lambda x:x.lower().replace('-','_'), inplace = True)
df_mod.columns
```

Out[11]:
```
Index(['patientid', 'appointmentid', 'gender', 'scheduledday',
       'appointmentday', 'age', 'neighbourhood', 'scholarship', 'hipertension',
       'diabetes', 'alcoholism', 'handcap', 'sms_received', 'no_show'],
      dtype='object')
```

In [12]:
```
# get rid of typos and rename columns to be lowercase and consistent
df_mod.rename(columns={'hipertension': 'hypertension', 'handcap':'handicap'}, inplace=Tr
df_mod.head()
```

Out[12]:

	patientid	appointmentid	gender	scheduledday	appointmentday	age	neighbourhood	scholarship
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	C
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	C
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	C
3	8.679512e+11	5642828	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	C
4	8.841186e+12	5642494	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	C

In [ ]:

2.2. Numerical attributes and outliers

In [13]:
```
df_mod.describe()
```

Out[13]:

	patientid	appointmentid	age	scholarship	hypertension	diabetes	alco
count	1.105270e+05	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.000000	110527.(
mean	1.474963e+14	5.675305e+06	37.088874	0.098266	0.197246	0.071865	0.(
std	2.560949e+14	7.129575e+04	23.110205	0.297675	0.397921	0.258265	0
min	3.921784e+04	5.030230e+06	-1.000000	0.000000	0.000000	0.000000	0.(
25%	4.172614e+12	5.640286e+06	18.000000	0.000000	0.000000	0.000000	0.(
50%	3.173184e+13	5.680573e+06	37.000000	0.000000	0.000000	0.000000	0.(
75%	9.439172e+13	5.725524e+06	55.000000	0.000000	0.000000	0.000000	0.(
max	9.999816e+14	5.790484e+06	115.000000	1.000000	1.000000	1.000000	1.(

Numerical attributes: ['patientid', 'appointmentid', 'age', 'scholarship', 'hypentension', 'diabetes', 'alcoholism','handicap', 'sms_received']

2.2.1 PatientID:

- PatientID represents the patient identification, any numerical operations should not be applied to it and therefore it will be transformed into a string type

In [14]:
```
# Converting the values to int type and then to str type:
df_mod['patientid'] = df_mod['patientid'].apply(lambda x: str(int(x)));
df_mod['patientid'].dtypes
```

```
dtype('O')
```

Out[14]:

In [15]:
```
# Counting how many unique patients are in the dataset:
print("The number of unique patients => {}".format(len(df_mod['patientid'].unique())))
```

```
The number of unique patients => 62299
```

2.2.2 AppointmentID:

- AppointmentID represents the appointment identification, any numerical operations should not be applied to it and therefore it will be transformed into a string type

In [16]:
```
## Converting the values to int type and then to str type:
df_mod['appointmentid'] = df_mod['appointmentid'].apply(lambda x: str(int(x)));
```

In [17]:
```
# Counting how many unique appointments are in the dataset:
print("The number of unique appointments => {}".format(len(df_mod['appointmentid'].uniqu
```

```
The number of unique appointments => 110527
```

This attribute seems to be consistent: there are 110,527 instances in the dataset, as well as 110,527 unique values for the appointmentIDs. For last, since each instance corresponds to an appointment register, we will redefine the dataset index to the appointment IDs.

In [18]:
```
df_mod.set_index('appointmentid', drop=True, inplace=True)
df_mod.head()
```

Out[18]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarshi
appointmentid							
5642903	29872499824296	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	
5642503	558997776694438	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	
5642549	4262962299951	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	
5642828	867951213174	F	2016-04-29T17:29:31Z	2016-04-29T00:00:00Z	8	PONTAL DE CAMBURI	
5642494	8841186448183	F	2016-04-29T16:07:23Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	

2.2.3 Age attribute:

In [19]:
```
# Print Unique Values for 'Age'
print("Unique Values in 'Age' => {}".format(np.sort(df_mod.age.unique())))
```

```
Unique Values in 'Age' => [ -1   0   1   2   3   4   5   6   7   8   9  10  11  12  13
14  15  16
  17  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34
  35  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52
  53  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70
  71  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88
  89  90  91  92  93  94  95  96  97  98  99 100 102 115]
```

It is not possible to be aged -1, as well as older than 100 years are suspicious. Patients aged 0 are supposed to be infants. The former will be analyzed appropriately at the exploratory data analysis section, but age value under zero are definitely a mistake. In this case, we will first check how many instances correspond to this before treat them.

In [20]:
```
# Find the appointment that age < 0
df_mod[df_mod.age<0]
```

Out[20]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarshi
appointmentid							
5775010	465943158731293	F	2016-06-06T08:58:13Z	2016-06-06T00:00:00Z	-1	ROMÃO	

In [21]:
```
# Check the PatientID to see if the patient has other records
df_mod[df_mod.patientid=='465943158731293']
```

Out[21]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarshi
appointmentid							
5775010	465943158731293	F	2016-06-06T08:58:13Z	2016-06-06T00:00:00Z	-1	ROMÃO	

Since there is only one occurrence and cannot find other information through PatientID, I will remove the data from dataset.

In [22]:
```
# drop the appointment with age < 0
df_mod.drop('5775010', inplace= True)
```

2.2.4 Handcap attribute:

- In the dataset description, it is said that the handcap attribute should cointain a boolean value. However, as seen above, this attribute assumes values from 0 to 4, probably indicating the handicap number for each patient. In this analysis, I will create another attribute **'Degree_Handicap'** to keep it and map the **'Handcap'** to 1 any value higher than 0.
- There is a typo in the attribute name.

In [23]:
```
df_mod['degree_handicap'] = df_mod['handicap']
df_mod['handicap'] = np.where(df_mod['handicap']>0, 1, 0)
```

In [24]:
```
df_mod['handicap'].unique()
```

Out[24]:
```
array([0, 1])
```

In [25]:
```
df_mod['degree_handicap'].unique()
```

Out[25]:
```
array([0, 1, 2, 3, 4])
```

2.2.5 Rest of the Numerical attribute:

In [26]:
```
# Print Unique Values
print("Unique Values in 'scholar' => {}".format(df_mod.scholarship.unique()))
print("Unique Values in 'hypertension' => {}".format(df_mod.hypertension.unique()))
print("Unique Values in 'diabetes' => {}".format(df_mod.diabetes.unique()))
print("Unique Values in 'alcoholism' => {}".format(df_mod.alcoholism.unique()))
```

```
print("Unique Values in 'handicap' => {}".format(df_mod.handicap.unique()))
print("Unique Values in 'sms_received' => {}".format(df_mod.sms_received.unique()))
```

```
Unique Values in 'scholar' => [0 1]
Unique Values in 'hypertension' => [1 0]
Unique Values in 'diabetes' => [0 1]
Unique Values in 'alcoholism' => [0 1]
Unique Values in 'handicap' => [0 1]
Unique Values in 'sms_received' => [0 1]
```

In [ ]:

2.3. Categorical attributes

2.3.1. *Gender* attribute:

Only two values are expected from this attribute. In order to check its consistency, the sum for both **Male** and **Female** classes must equal the total number of instances.

In [27]:

```
## Counting gender classes
df_mod.gender.value_counts()
```

Out[27]:

```
F    71839
M    38687
Name: gender, dtype: int64
```

unbalanced for gender

2.3.2. Schedule and Appoingment attribute:

AppointmentDay and ScheduledDay should be datetime format. AppointmentDay only has date information while the ScheduledDay has both date and time information. Here I choose to count only date and use these feature to find out the waiting days.

In [28]:

```
df_mod['scheduledday'] = pd.to_datetime(df_mod.scheduledday).dt.date.astype('datetime64[
df_mod['appointmentday'] = pd.to_datetime(df_mod.appointmentday).dt.date.astype('datetim
```

In [29]:

```
df_mod.dtypes
```

Out[29]:

```
patientid                 object
gender                    object
scheduledday      datetime64[ns]
appointmentday    datetime64[ns]
age                        int64
neighbourhood             object
scholarship                int64
hypertension               int64
diabetes                   int64
alcoholism                 int64
handicap                   int64
sms_received               int64
no_show                   object
degree_handicap            int64
dtype: object
```

In [30]:

```
df_mod.head()
```

Out[30]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarshi

appointmentid						
5642903	29872499824296	F	2016-04-29	2016-04-29	62	JARDIM DA PENHA
5642503	558997776694438	M	2016-04-29	2016-04-29	56	JARDIM DA PENHA
5642549	4262962299951	F	2016-04-29	2016-04-29	62	MATA DA PRAIA
5642828	867951213174	F	2016-04-29	2016-04-29	8	PONTAL DE CAMBURI
5642494	8841186448183	F	2016-04-29	2016-04-29	56	JARDIM DA PENHA

2.3.3. Day of Week (DOW) & Waiting days:

Relevant informations for this analysis are the the Day-of-Week (DOW) and Waiting time, in days, between the scheduling date and the appointment date.

In [31]:
```
df_mod['waitingdays']=df_mod['appointmentday']-df_mod['scheduledday']
```

- Add ***Day of Week (DOW)*** information for scheduledday and appointmentda

In [32]:
```
df_mod['scheduledday_DOW'] = df_mod['scheduledday'].dt.day_name()
df_mod['appointmentday_DOW'] = df_mod['appointmentday'].dt.day_name()
```

- Add ***Waiting time*** information

In [33]:
```
df_mod['waitingdays']=df_mod['appointmentday']-df_mod['scheduledday']
```

In [34]:
```
int(str(df_mod.waitingdays[0])[:2])
df_mod.waitingdays=df_mod.waitingdays.apply(lambda x: int(str(x)[:2]))
```

In [35]:
```
# Print Unique Values for 'waitingdays'
print("Unique Values in 'waitingdays' => {}".format(np.sort(df_mod.waitingdays.unique()))
```

```
Unique Values in 'waitingdays' => [-6 -1  0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15
16 17 18 19 20 21
 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45
 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69
 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93
 94 95 96 97 98]
```

- waitingdays < 0 does not make sense. I will drop these rows.

In [36]:
```
# Drop case of waitingdays = -6
df_mod[df_mod.waitingdays == -6]
```

Out[36]:

	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarship
appointmentid							
5686628	998231581612122	F	2016-05-11	2016-05-05	81	SANTO ANTÔNIO	(

In [37]:
```
df_mod.drop('5686628', inplace=True)
```

In [38]:
```
# Cases of waitingdays = -1
df_mod[df_mod.waitingdays == -1]
```

Out[38]:

appointmentid	patientid	gender	scheduledday	appointmentday	age	neighbourhood	scholarship
5679978	7839272661752	M	2016-05-10	2016-05-09	38	RESISTÊNCIA	C
5715660	7896293967868	F	2016-05-18	2016-05-17	19	SANTO ANTÔNIO	C
5664962	24252258389979	F	2016-05-05	2016-05-04	22	CONSOLAÇÃO	C
5655637	3787481966821	M	2016-05-04	2016-05-03	7	TABUAZEIRO	C

In [39]:
```
df_mod.drop('5679978', inplace=True)
df_mod.drop('5715660', inplace=True)
df_mod.drop('5664962', inplace=True)
df_mod.drop('5655637', inplace=True)
```

In [ ]:

2.3.4. *Neighborhood* names

Accordingly to the dataset description, this attributes refers to the neighborhoods the health units are located in the city of *Vitória*, in the State of *Espírito Santo*, Brazil.

In [40]:
```
# Print Unique Values for 'neighbourhood'
print("Unique Values in 'neighbourhood' => {}".format(df_mod.neighbourhood.unique()))
```

```
Unique Values in 'neighbourhood' => ['JARDIM DA PENHA' 'MATA DA PRAIA' 'PONTAL DE CAMBUR
I' 'REPÚBLICA'
 'GOIABEIRAS' 'ANDORINHAS' 'CONQUISTA' 'NOVA PALESTINA' 'DA PENHA'
 'TABUAZEIRO' 'BENTO FERREIRA' 'SÃO PEDRO' 'SANTA MARTHA' 'SÃO CRISTÓVÃO'
 'MARUÍPE' 'GRANDE VITÓRIA' 'SÃO BENEDITO' 'ILHA DAS CAIEIRAS'
 'SANTO ANDRÉ' 'SOLON BORGES' 'BONFIM' 'JARDIM CAMBURI' 'MARIA ORTIZ'
 'JABOUR' 'ANTÔNIO HONÓRIO' 'RESISTÊNCIA' 'ILHA DE SANTA MARIA'
 'JUCUTUQUARA' 'MONTE BELO' 'MÁRIO CYPRESTE' 'SANTO ANTÔNIO' 'BELA VISTA'
 'PRAIA DO SUÁ' 'SANTA HELENA' 'ITARARÉ' 'INHANGUETÁ' 'UNIVERSITÁRIO'
 'SÃO JOSÉ' 'REDENÇÃO' 'SANTA CLARA' 'CENTRO' 'PARQUE MOSCOSO'
 'DO MOSCOSO' 'SANTOS DUMONT' 'CARATOÍRA' 'ARIOVALDO FAVALESSA'
 'ILHA DO FRADE' 'GURIGICA' 'JOANA D´ARC' 'CONSOLAÇÃO' 'PRAIA DO CANTO'
 'BOA VISTA' 'MORADA DE CAMBURI' 'SANTA LUÍZA' 'SANTA LÚCIA'
 'BARRO VERMELHO' 'ESTRELINHA' 'FORTE SÃO JOÃO' 'FONTE GRANDE'
 'ENSEADA DO SUÁ' 'SANTOS REIS' 'PIEDADE' 'JESUS DE NAZARETH'
 'SANTA TEREZA' 'CRUZAMENTO' 'ILHA DO PRÍNCIPE' 'ROMÃO' 'COMDUSA'
 'SANTA CECÍLIA' 'VILA RUBIM' 'DE LOURDES' 'DO QUADRO' 'DO CABRAL' 'HORTO'
 'SEGURANÇA DO LAR' 'ILHA DO BOI' 'FRADINHOS' 'NAZARETH' 'AEROPORTO'
 'ILHAS OCEÂNICAS DE TRINDADE' 'PARQUE INDUSTRIAL']
```

In [41]:
```
## Counting again the neighborhood number:
len(df_mod.neighbourhood.unique())
```

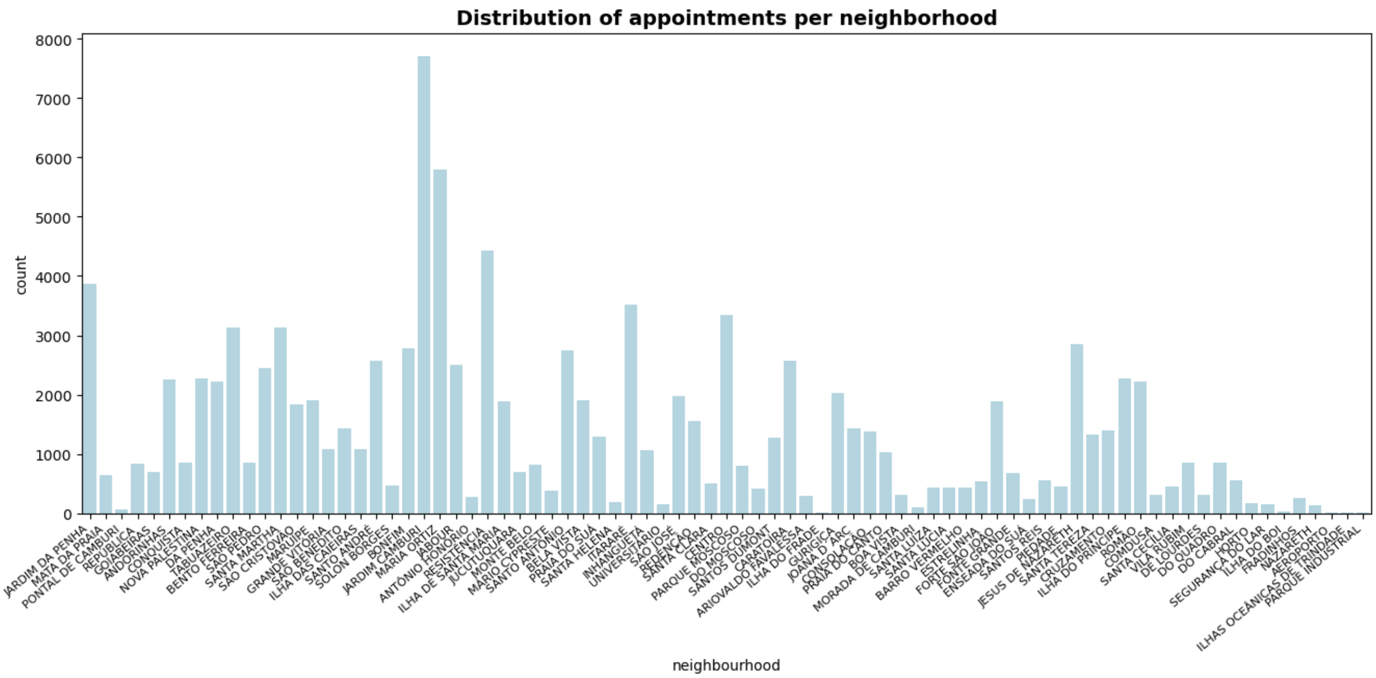
Out[41]:
```
81
```

In [42]:
```
df_mod.neighbourhood
```

Out[42]:
```
appointmentid
5642903      JARDIM DA PENHA
5642503      JARDIM DA PENHA
5642549        MATA DA PRAIA
5642828    PONTAL DE CAMBURI
```

```
5642494       JARDIM DA PENHA
                     ...
5651768          MARIA ORTIZ
5650093          MARIA ORTIZ
5630692          MARIA ORTIZ
5630323          MARIA ORTIZ
5629448          MARIA ORTIZ
Name: neighbourhood, Length: 110521, dtype: object
```

In [43]:
```
## Plotting an histogram with the neighborhoods sorted alphabetically.
plt.figure(figsize=(16,6))
ax = sns.countplot(x='neighbourhood', data=df_mod, color = "lightblue")
ax.set_xticklabels(ax.get_xticklabels(), rotation=40, ha="right", fontsize=8)
plt.title('Distribution of appointments per neighborhood', fontsize=14, fontweight='bold
plt.show()
```



Among the 81 different neighborhoods, 8 of them register more than 3k appointments. It is mentioned there are 45 health units, which leads us to consider the neighborhood as where the patient lives.

2.3.5. *No-show* class

In [44]:
```
## Counting gender classes
df_mod['no_show'].value_counts()
```

Out[44]:
```
No     88207
Yes    22314
Name: no_show, dtype: int64
```

In [45]:
```
df_mod[df_mod['no_show']=='Yes']['no_show'].count()/df_mod['no_show'].count()
```

Out[45]:
```
0.2018982817745044
```

From the above information we can see that there is clearly a class imbalance. Around 80% of the patients are coming for the visit after an appointment and around 20% are skipping their appointments.

In [46]:
```
# Change values of no_show column to be (0: show up, 1: no show)
df_mod['no_show'] =  df_mod['no_show'].apply(lambda x: 0 if x == 'No' else 1)
df_mod['no_show']=df_mod['no_show'].astype('object')
df_mod['no_show'].dtypes
```

Out[46]: dtype('O')

2.4. Data wrangling overview

Just in order to help its reading, the dataset attributes will be rearranged to put all the date and time information together, as well as correcting the typos in the attribute names:

In [47]:
```
## Reading the dataset attributes (columns):
df_mod.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 110521 entries, 5642903 to 5629448
Data columns (total 17 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   patientid           110521 non-null  object
 1   gender              110521 non-null  object
 2   scheduledday        110521 non-null  datetime64[ns]
 3   appointmentday      110521 non-null  datetime64[ns]
 4   age                 110521 non-null  int64
 5   neighbourhood       110521 non-null  object
 6   scholarship         110521 non-null  int64
 7   hypertension        110521 non-null  int64
 8   diabetes            110521 non-null  int64
 9   alcoholism          110521 non-null  int64
 10  handicap            110521 non-null  int64
 11  sms_received        110521 non-null  int64
 12  no_show             110521 non-null  object
 13  degree_handicap     110521 non-null  int64
 14  waitingdays         110521 non-null  int64
 15  scheduledday_DOW    110521 non-null  object
 16  appointmentday_DOW  110521 non-null  object
dtypes: datetime64[ns](2), int64(9), object(6)
memory usage: 19.2+ MB
```

In [48]:
```
df_mod = df_mod.reindex(columns=['patientid', 'gender', 'neighbourhood', 'age',
                         'scholarship', 'hypertension', 'diabetes','alcoholism', 'handic
                         'scheduledday', 'appointmentday', 'scheduledday_DOW', 'appointm
```

In [49]:
```
## Reading the dataset attributes (columns):
df_mod.head()
```

Out[49]:

	patientid	gender	neighbourhood	age	scholarship	hypertension	diabetes	alcol
appointmentid								
5642903	29872499824296	F	JARDIM DA PENHA	62	0	1	0	
5642503	558997776694438	M	JARDIM DA PENHA	56	0	0	0	
5642549	4262962299951	F	MATA DA PRAIA	62	0	0	0	
5642828	867951213174	F	PONTAL DE CAMBURI	8	0	0	0	
5642494	8841186448183	F	JARDIM DA PENHA	56	0	1	1	

We then conclude this data wrangling step by showing an overview of the pre-processed data, i.e. the data after the wrangling and cleansing process.

In [50]:
```
## Checking again the dataset information (for numerical attributes) and description (fo
print(df_mod.info())
df_mod.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 110521 entries, 5642903 to 5629448
Data columns (total 17 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   patientid           110521 non-null  object
 1   gender              110521 non-null  object
 2   neighbourhood       110521 non-null  object
 3   age                 110521 non-null  int64
 4   scholarship         110521 non-null  int64
 5   hypertension        110521 non-null  int64
 6   diabetes            110521 non-null  int64
 7   alcoholism          110521 non-null  int64
 8   handicap            110521 non-null  int64
 9   degree_handicap     110521 non-null  int64
 10  sms_received        110521 non-null  int64
 11  scheduledday        110521 non-null  datetime64[ns]
 12  appointmentday      110521 non-null  datetime64[ns]
 13  scheduledday_DOW    110521 non-null  object
 14  appointmentday_DOW  110521 non-null  object
 15  waitingdays         110521 non-null  int64
 16  no_show             110521 non-null  object
dtypes: datetime64[ns](2), int64(9), object(6)
memory usage: 19.2+ MB
None
```

Out[50]:

	age	scholarship	hypertension	diabetes	alcoholism	handicap	degree
count	110521.000000	110521.000000	110521.000000	110521.000000	110521.000000	110521.000000	1105
mean	37.089386	0.098271	0.197257	0.071869	0.030401	0.020259	
std	23.109885	0.297682	0.397929	0.258272	0.171690	0.140884	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	18.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	37.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	55.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
max	115.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

In [ ]:
```

```

3. Exploratory Data Analysis

Once the data were trimmed and cleaned, we will move on to explore the questions posed on Section 1.3. Given the dataset limitations, this analysis will address the first two questions, as organized in the following topics::

- **3.1. Exploring no-showing appointments**
- **3.2. Exploring the patient profiles**

3.1. Exploring the *no-showing appointments*

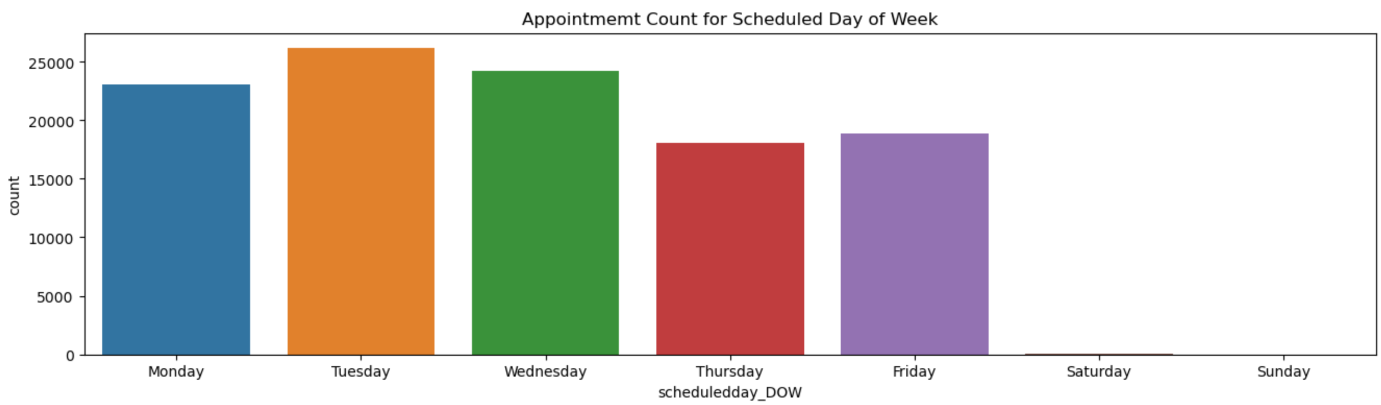
In this section we will seek to answer the following questions based on the available data:

- Does DOW of the scheduled day and appointment day affect the no-showing rate?
- What is the average waiting time between the scheduling date and the appointment date?
- Is there any relation between the waiting time and the no-showing appointments?

3.1.1. Day of Week (DOW)

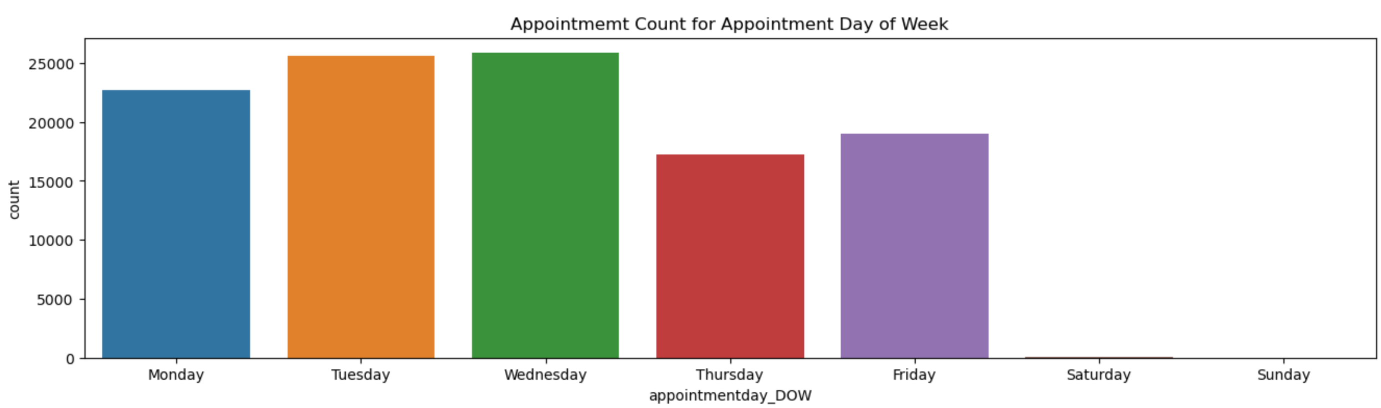
scheduled_DOW

In [51]:
```
plt.figure(figsize=(16,4))
order=['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday']
ax = sns.countplot(x=df_mod.scheduledday_DOW, order=order)
ax.set_title('Appointmemt Count for Scheduled Day of Week')
plt.show()
```

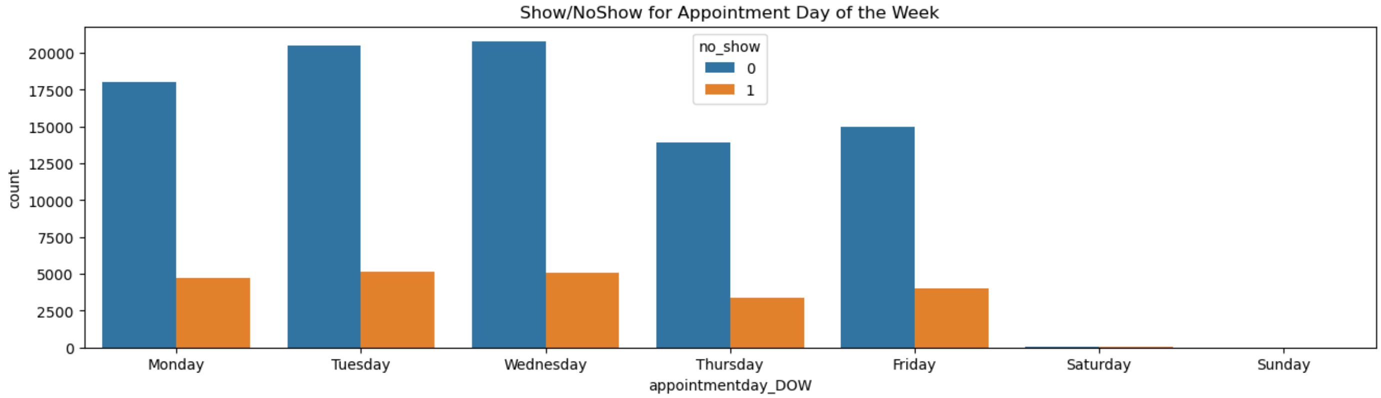


appointment_DOW

In [52]:
```
plt.figure(figsize=(16,4))
ax = sns.countplot(x=df_mod.appointmentday_DOW, order=order)
ax.set_title('Appointmemt Count for Appointment Day of Week')
plt.show()
```



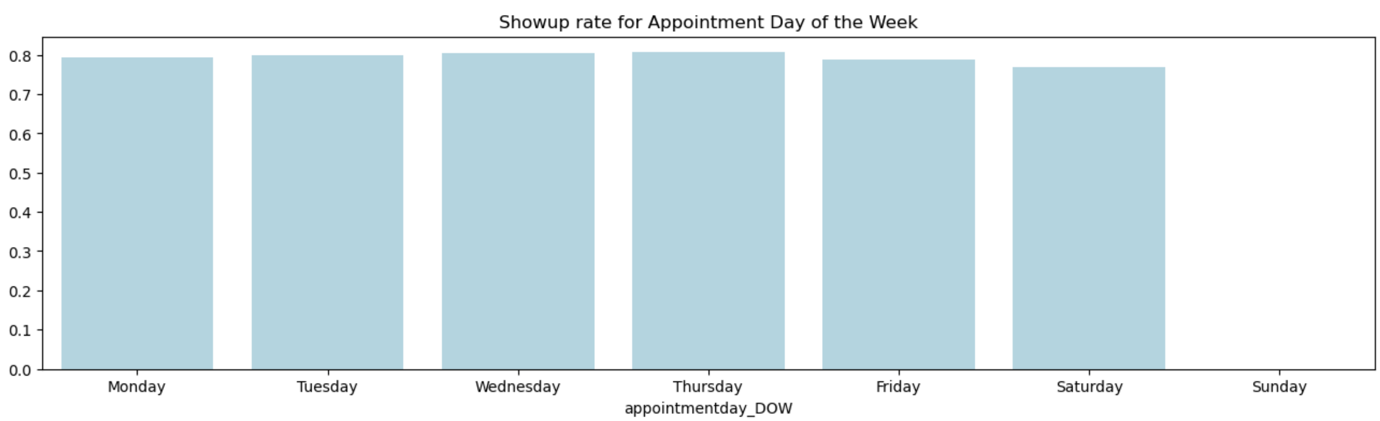
In [53]:
```
plt.figure(figsize=(16,4))
ax = sns.countplot(x=df_mod.appointmentday_DOW, hue=df_mod.no_show, order=order)
ax.set_title("Show/NoShow for Appointment Day of the Week")
plt.show()

# Counts of No-show versus DOW
print(df_mod[df_mod.no_show == 1].groupby(['appointmentday_DOW']).size())
```




```
appointmentday_DOW
Friday       4037
Monday       4689
Saturday        9
Thursday     3337
Tuesday      5150
Wednesday    5092
dtype: int64
```

In [54]:

```python
# Show up rate versus DOW
df_a_dow_ratio = df_mod[df_mod.no_show == 0].groupby(['appointmentday_DOW']).size()/df_m
plt.figure(figsize=(16,4))
ax = sns.barplot(x=df_a_dow_ratio.index, y=df_a_dow_ratio, order=order, color='lightblue
ax.set_title("Showup rate for Appointment Day of the Week")
plt.show()

print(df_a_dow_ratio)
```



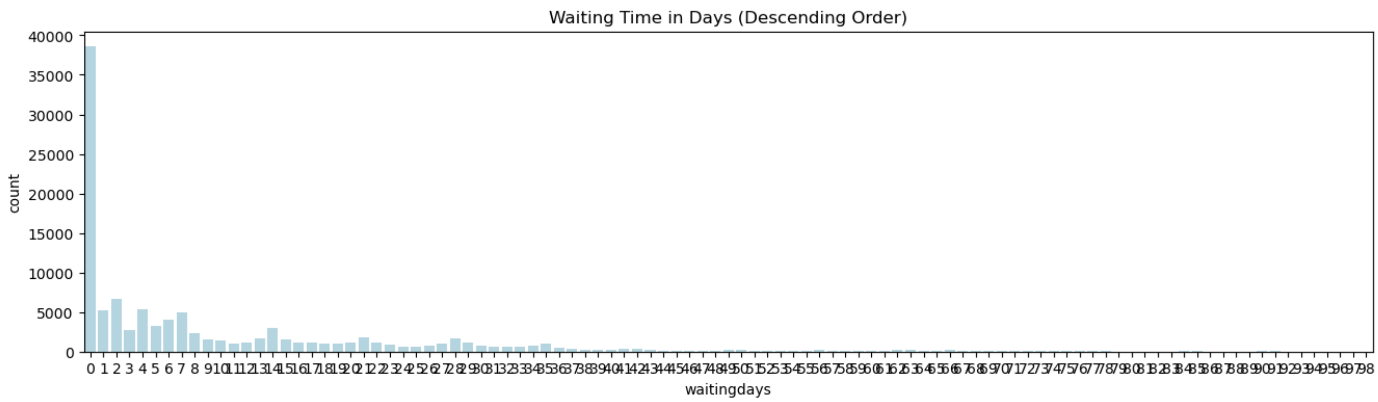

```
appointmentday_DOW
Friday       0.787739
Monday       0.793554
Saturday     0.769231
Thursday     0.806506
Tuesday      0.799126
Wednesday    0.803139
dtype: float64
```

Conclusion on Day of Week (DOW)

- Little or No appointments taken on Saturday and Sunday.
- The show-up rate for appointment days are arounod 76.9% to 80.7 % across the weekdays.
- AppointmentDay_DOW could help in determining if a patient visits the hospital after taking an appointment.

3.1.2. Waiting time between the scheduling and the appointment date

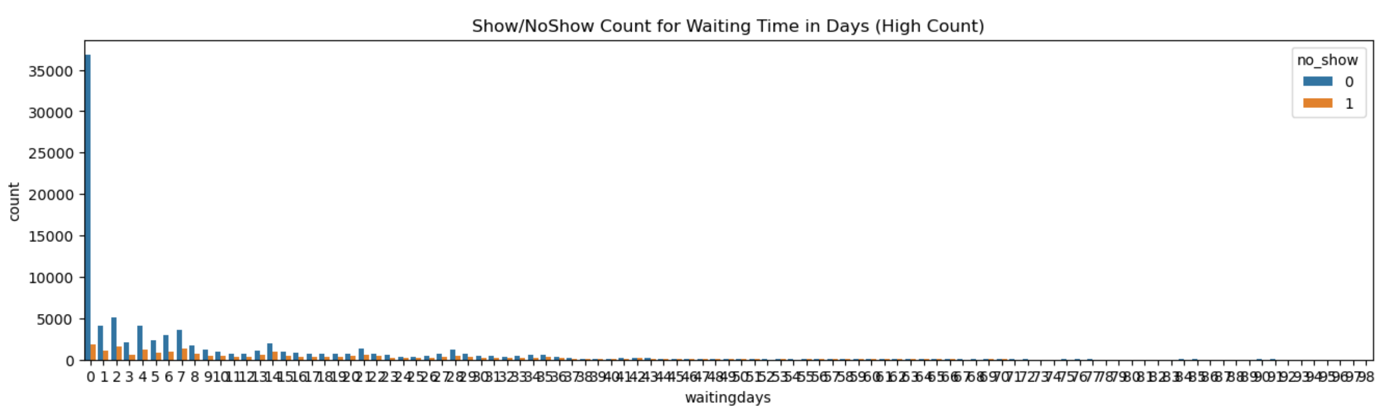
In [55]:
```python
plt.figure(figsize=(16,4))
ax = sns.countplot(x=df_mod.waitingdays, order=np.sort(df_mod.waitingdays.unique()), col
ax.set_title("Waiting Time in Days (Descending Order)")
plt.show()

total = df_mod.waitingdays.values
print('Mean:', np.mean(total))
print('Standard deviation:', np.std(total))
print('Minimum:', np.min(total))
print('Maximum:', np.max(total))
print('Median:', np.median(total))
```



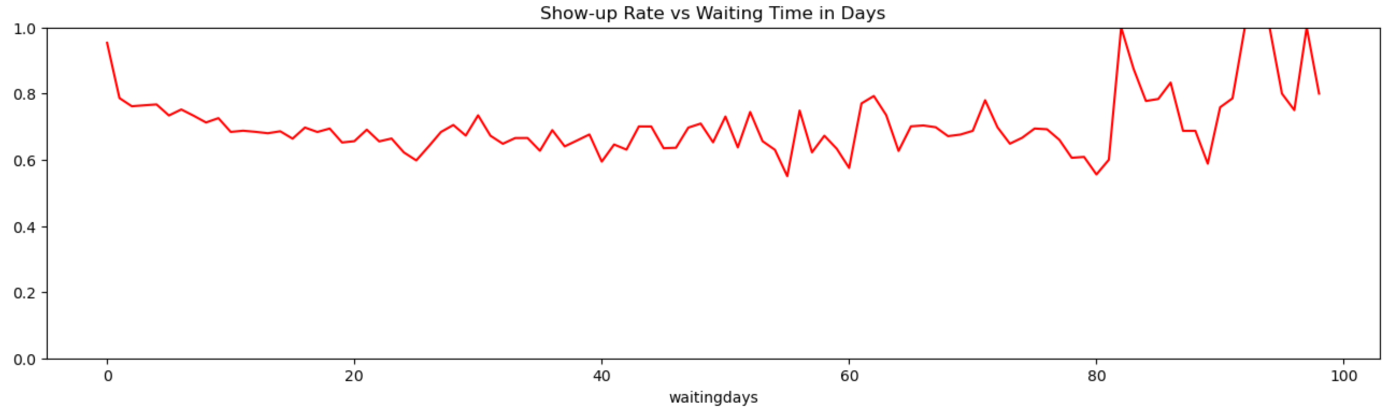

```
Mean: 10.028555659105509
Standard deviation: 14.536662426569231
Minimum: 0
Maximum: 98
Median: 4.0
```

- From the plot, we can notice that **most of the patients are booking their appointments on the same day**. The next highest waiting times are **2 days, 4 days, and 1 days**.
- The **average waiting is about 10 days**, with a standard deviation of approximately 15 days.

In [56]:
```python
plt.figure(figsize=(16,4))
ax = sns.countplot(x=df_mod.waitingdays, hue=df_mod.no_show, order= np.sort(df_mod.waiti
ax.set_title("Show/NoShow Count for Waiting Time in Days (High Count)")
plt.show()
```



In [57]:
```python
showup_time=df_mod[df_mod.no_show == 0].groupby(['waitingdays']).size()/df_mod.groupby([

plt.figure(figsize=(16,4))
ax = sns.lineplot(x=showup_time.index, y=showup_time, color='red')
ax.set_title("Show-up Rate vs Waiting Time in Days")
ax.axes.set_ylim(0,1)
plt.show()
```



From the above visualization we can see that around 95% of the patients who have booked their appointments on the same day and visiting the hospital without fail. Also close to 80% of the patients are visiting the hospital if they had booked their appointments just before 4 days. The following concludes our observations:

- Through the chart above, it is noticed that the **show-up rate decreases as the waiting gets longer**.
- It reaches the higher rates when the attendance occurs in the same day it waas scheduled.
- Surprisingly, the **show-up rate increases after 90 days (quarter) waiting** and even reach to 100% in some days. This part will be further investigated in the later discussion.

In [58]:
```
# Get data for waitingdays = 0
wait0 = df_mod[df_mod['waitingdays']==0]
print('Number of Appointments for Waitingdays = 0 days: {} Appointments'.format(wait0.pa
x1 = wait0.mean(numeric_only=True)
```

```
Number of Appointments for Waitingdays = 0 days: 38562 Appointments
```

In [59]:
```
# Get data for waitingdays > 90
wait90 = df_mod[df_mod['waitingdays']>90]
print('Number of Appointments for Waitingdays > 90 days: {} Appointments'.format(wait90.
x2= wait90.mean(numeric_only=True)
```

```
Number of Appointments for Waitingdays > 90 days: 79 Appointments
```

In [60]:
```
df1=pd.DataFrame(x1)
df2=pd.DataFrame(x2)
df_compare = pd.concat([df1,df2], axis=1, ignore_index=True)
df_compare.columns=['waiting=0','waiting=90']
df_compare
```

Out[60]:

	waiting=0	waiting=90
age	34.452311	65.063291
scholarship	0.108656	0.050633
hypertension	0.175536	0.430380
diabetes	0.066542	0.101266
alcoholism	0.039884	0.000000
handicap	0.024169	0.063291
degree_handicap	0.026347	0.063291
sms_received	0.000000	0.645570
waitingdays	0.000000	92.265823

Same day appointment (N=38562):

- Average age: 34.5 yrs old
- Scholarship: **10% receives scholarship**
- Hypertension: 17.5% of the group individuals
- Diabetes: 6.6% of the group individuals
- Alcoholism: **3.9% of the group individuals**
- Handicap: 2.4% of the group individuals

Waitingdays > 90 (quarter) (N=79):

- Average age: **65.1 yrs old (senior)**
- Scholarship: 5.1% receives scholarship
- Hypertension: **43.0% of the group individuals**
- Diabetes: **10.1% of the group individuals**
- Alcoholism: 0.0% of the group individuals
- Handicap: **6.3% of the group individuals**

Conclusion on Waiting Days

While the number of appointments for the 2 compared groups (Sameday appointments/ Waitingdays > 90) have huge differences (N=38562 vs N=79)

We find the population with waiting period > 90 days (quarter) are mostly elderly people. Therefore, one hypothesis to explain for the show-up rate increase for waiting periods > 90 days (quarter) can be assigned to the patient profile:

Elderly people as well as those with chronic diseases who require regular medical follow-up tend to schedule long-term appointments and attend to them.

3.1.3. Neiborhood Analysis

This analysis seeks to find out how the no-showing appointments are distributed. In other words, how many appointments are registered to each health unit and if they were attended to or not. To find this out, we will carry two slightly distinct analysis based on the neighborhood attribute:

(i) How the absence number is distributed along the neighborhoods?

(ii) We have already seen that the no-showing rate increases as the waiting gets longer. Is the validity of this statement indifferent to geographical location?

To find this out, we will first group the dataset by the neighborhood names, followed by some data manipulation to gather the desired information for each question.

(i) No-showing rate by neighborhood

In this analysis we will show the absence number distribution into two ways: first in absolute numbers, to get not only the information of which health unit presents more absence, but to know which one has the highest number of attendments. Second, it is interesting to compare the normalized data, i.e. how much the absence of each health unit represents the total of its attendments.

In [61]:
```
## Using the pandas.groupby() method to generate a pivot table:
neighbors_I = df_mod.groupby(by='neighbourhood').no_show.value_counts().sort_index()
```

In [62]:
```
## Manipulating the data:
neighbors_I = neighbors_I.unstack()  #Converting the groupby object into a dataset
neighbors_I.isna().sum()
neighbors_I.fillna(value=0, inplace=True)  #Replacing NaN values by zero
neighbors_I.head()
```

Out[62]:

no_show neighbourhood	0	1
AEROPORTO	7.0	1.0
ANDORINHAS	1741.0	521.0
ANTÔNIO HONÓRIO	221.0	50.0
ARIOVALDO FAVALESSA	220.0	62.0
BARRO VERMELHO	332.0	91.0

In [63]:
```
def df_row_normalize(dataframe):
    '''Normalizes the values of a given pandas.Dataframe by the total sum of each line.
    Algorithm based on https://stackoverflow.com/questions/26537878/pandas-sum-across-co
    return dataframe.div(dataframe.sum(axis=1), axis=0)


## Normalizing the data using a predefined function:
normalNeighbor = df_row_normalize(neighbors_I)
print(normalNeighbor.head())
```

```
no_show                     0         1
neighbourhood
AEROPORTO            0.875000  0.125000
ANDORINHAS           0.769673  0.230327
ANTÔNIO HONÓRIO      0.815498  0.184502
ARIOVALDO FAVALESSA  0.780142  0.219858
BARRO VERMELHO       0.784870  0.215130
```

In [64]:
```
## Getting the normalized data statistics:
normalNeighbor.describe()
```

Out[64]:

no_show	0	1
count	81.000000	81.000000
mean	0.794592	0.205408
std	0.097235	0.097235
min	0.000000	0.000000
25%	0.782546	0.179907
50%	0.802412	0.197588
75%	0.820093	0.217454
max	1.000000	1.000000

In [65]:
```
def get_total(dataframe):
    '''Return the total sum of each numerical attribute of a pandas.Dataframe.'''
    return dataframe.sum(axis=1)
```

```python
## Adding a total column:
neighbors_I['Total'] = get_total(neighbors_I)
normalNeighbor['Total'] = get_total(normalNeighbor)
```

In [66]:
```python
#Reseting the 'neighbourhood' index and making it as a column:
neighbors_I.reset_index(inplace=True)
normalNeighbor.reset_index(inplace=True)
```

In [67]:
```python
normalNeighbor
```

Out[67]:

no_show	neighbourhood	0	1	Total
0	AEROPORTO	0.875000	0.125000	1.0
1	ANDORINHAS	0.769673	0.230327	1.0
2	ANTÔNIO HONÓRIO	0.815498	0.184502	1.0
3	ARIOVALDO FAVALESSA	0.780142	0.219858	1.0
4	BARRO VERMELHO	0.784870	0.215130	1.0
...	...	...	...	...
76	SÃO JOSÉ	0.783510	0.216490	1.0
77	SÃO PEDRO	0.789624	0.210376	1.0
78	TABUAZEIRO	0.817311	0.182689	1.0
79	UNIVERSITÁRIO	0.789474	0.210526	1.0
80	VILA RUBIM	0.834313	0.165687	1.0

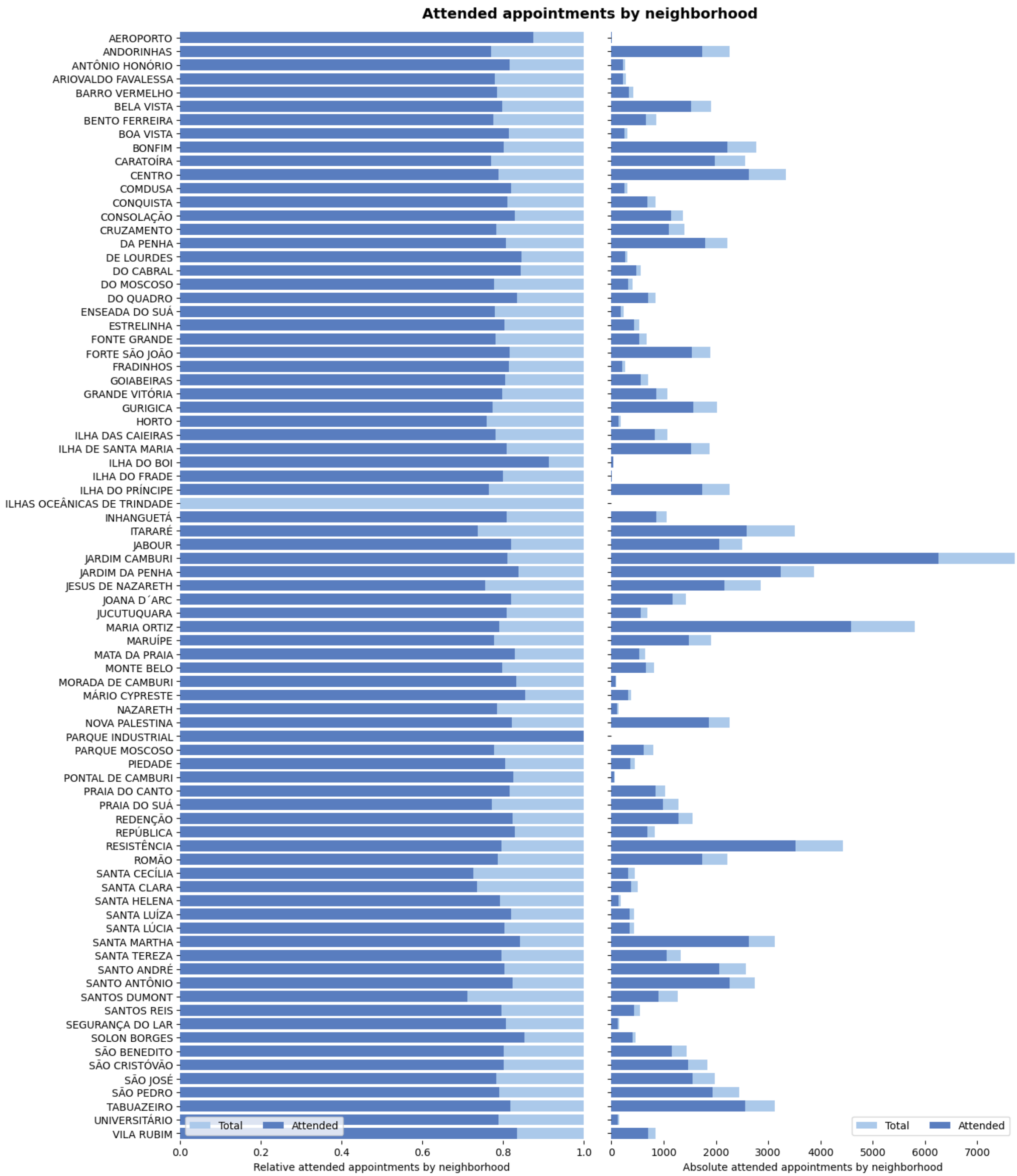
81 rows × 4 columns

In [68]:
```python
normalNeighbor.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 81 entries, 0 to 80
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   neighbourhood  81 non-null     object 
 1   0              81 non-null     float64
 2   1              81 non-null     float64
 3   Total          81 non-null     float64
dtypes: float64(3), object(1)
memory usage: 2.7+ KB
```

In [69]:
```python
## Initialize the matplotlib figure:
fig2, (ax1, ax2) = plt.subplots(1,2, figsize=(12,16), sharey=True)
fig2.tight_layout()
fig2.subplots_adjust(top=0.96)

## Plot the relative absence by neighborhood
#Total appointments
sns.set_color_codes("pastel")
sns.barplot(x="Total", y="neighbourhood", data=normalNeighbor, label="Total", color="b",
#Attended appointments
sns.set_color_codes("muted")
sns.barplot(x=0, y="neighbourhood", data=normalNeighbor, label="Attended", color="b", ax
## Add a legend and informative axis label
ax1.legend(ncol=2, loc="lower left", frameon=True)
ax1.set(xlim=(0, 1), ylabel="", xlabel="Relative attended appointments by neighborhood")
sns.despine(left=True, bottom=True,ax=ax1)
```

```
## Plot the absolute absence by neighborhood
#Total appointments
sns.set_color_codes("pastel")
sns.barplot(x="Total", y="neighbourhood", data=neighbors_I, label="Total", color="b",ax=
#Attended appointments
sns.set_color_codes("muted")
sns.barplot(x=0, y="neighbourhood", data=neighbors_I, label="Attended", color="b", ax=ax
## Add a legend and informative axis label
ax2.legend(ncol=2, loc="lower right", frameon=True)
ax2.set(xlim=(0, 7720), ylabel="", xlabel="Absolute attended appointments by neighborhoo
sns.despine(left=True, bottom=True, ax=ax2)

plt.suptitle('Attended appointments by neighborhood', fontsize=14, fontweight='bold')
plt.show()
```



In [70]:
```
df[df.Neighbourhood=='PARQUE INDUSTRIAL']
```

Out[70]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Sch
75199	8.255992e+12	5663947	F	2016-05-05T10:48:59Z	2016-05-05T00:00:00Z	17	PARQUE INDUSTRIAL	

In [71]:
```
df[df.Neighbourhood.str.contains('ILHAS')]
```

Out[71]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Sch
48754	5.349869e+11	5583947	F	2016-04-14T12:25:43Z	2016-05-13T00:00:00Z	51	ILHAS OCEÂNICAS DE TRINDADE	
48765	7.256430e+12	5583948	F	2016-04-14T12:26:13Z	2016-05-13T00:00:00Z	58	ILHAS OCEÂNICAS DE TRINDADE	

Conclusion on Neighbourhood

From the analyzed data we found out that 80% of the appointments are attended to, with a standard deviation of 9.7%. The distribution of this numbers are easily perceived on the charts above. The chart representing the absolute values (the right one) is important to avoid biased interpretations:

- **'PARQUE INDUSTRIAL'** had attended all its appointments but the same neighborhood carries only 1 appointment.
- **'ILHAS OCEÂNICAS DE TRINDADE'** had no show on all appointments but there are only 2 appointments.

3.2. Exploring the patient profiles

After understanding the characteristics of the missed appointments, we will now analyze the patient profiles driven by the following questions:

- How the no-shows are distributed among the patients?
- Is there any common characteristics among those patients that miss appointments?
- Patients suffering from serious illnesses are more assiduous?

Taking all waiting days into account will cause difficulties in visualization, therefore, we will make a **'WaitingCategories'** to categories waiting days into 7 categories

In [72]:
```
waitingdays = df_mod.groupby(by=['waitingdays','no_show'])
```

In [73]:
```
waitingdays = waitingdays.count()['patientid'].unstack()
```

In [74]:
```
waitingdays.fillna(value=0, inplace=True)
waitingdays.reset_index(drop=False, inplace=True)
waitingdays.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 99 entries, 0 to 98
```

```
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   waitingdays  99 non-null     int64  
 1   0            99 non-null     float64
 2   1            99 non-null     float64
dtypes: float64(2), int64(1)
memory usage: 2.4 KB
```

In [75]:
```
## Defining the categories label:
categories = pd.Series(['Same day: 0', 'Short: 1-3', 'Week: 4-7', 'Fortnight: 8-15', 'Mo
```

In [76]:
```
## Applying these categories both to the auxiliary and to the working datasets:
waitingdays['waitingdays'] = pd.cut(waitingdays.waitingdays, bins = [-1,0,3,7,15,30,90,1
df_mod['WaitingCategories'] = pd.cut(df_mod.waitingdays, bins = [-1,0,3,7,15,30,90,180],
```

In [77]:
```
waitingdays
```

Out[77]:

no_show	waitingdays	0	1
0	Same day: 0	36770.0	1792.0
1	Short: 1-3	4100.0	1113.0
2	Short: 1-3	5123.0	1602.0
3	Short: 1-3	2093.0	644.0
4	Week: 4-7	4059.0	1231.0
...	...	...	...
94	Semester: 91-180	2.0	0.0
95	Semester: 91-180	4.0	1.0
96	Semester: 91-180	3.0	1.0
97	Semester: 91-180	2.0	0.0
98	Semester: 91-180	4.0	1.0

99 rows × 3 columns

In [78]:
```
## Grouping the dataset by the waiting categories, returning the sum of all instances:
waitingdays = waitingdays.groupby('waitingdays').sum()
## Creating a new attribute, "No-showing rate", relating how many patients did not show
waitingdays['No-showing rate'] = (waitingdays[1] / waitingdays[0])*100
```

In [79]:
```
waitingdays
```

Out[79]:

no_show	0	1	No-showing rate
waitingdays			
Same day: 0	36770.0	1792.0	4.873538
Short: 1-3	11316.0	3359.0	29.683634
Week: 4-7	13097.0	4413.0	33.694739
Fortnight: 8-15	9425.0	4196.0	44.519894
Month: 16-30	10743.0	5170.0	48.124360
Quarter: 31-90	6792.0	3369.0	49.602473
Semester: 91-180	64.0	15.0	23.437500

Since we are now interested in the patients attribute that could characterize and differentiate those who attends to appointments from those who does not, we will first manipulate the dataset to show only the relevant information.

In [80]:
```
## Defining a new dataframe from the attributes of interest:
patients = df_mod[['gender','age','scholarship','hypertension','diabetes',
                    'alcoholism','handicap','WaitingCategories','sms_received','no_show'
```

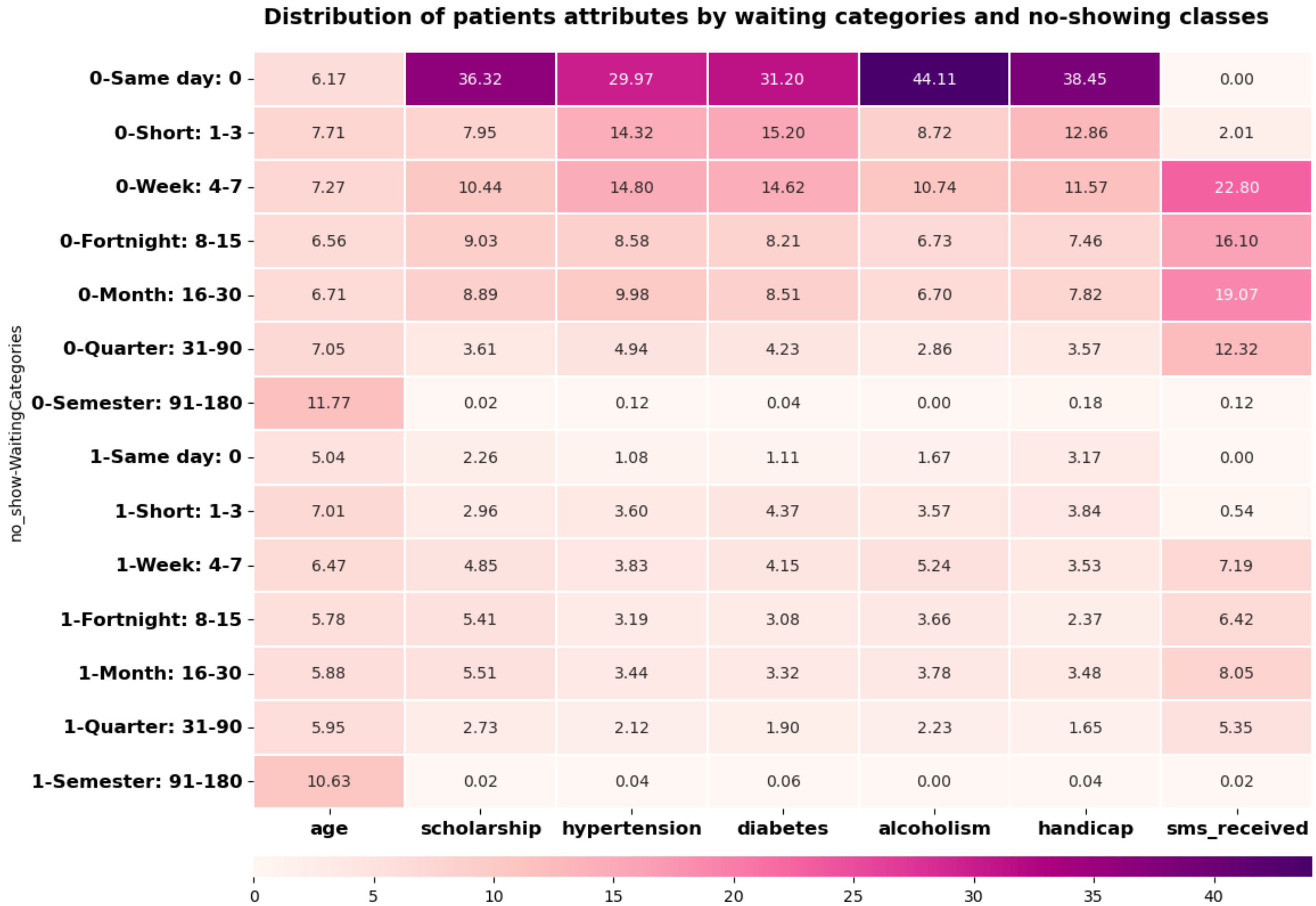
By using pandas.groupby() method we could extract the relation among waiting categories and the patient attributes like age, hipertension, diabetes and so forth, primarily separated among the No_show classes. This task is easily accomplished by the sum() method, except for the Age attribute which must be calculated by the mean() method.

In [81]:
```
## Grouping by classes and waiting categories and calculating the instances sum:
patients_sum = patients.groupby(by=['no_show','WaitingCategories']).sum()
## Grouping by classes and waiting categories and calculating the instances sum:
patients_mean = patients.groupby(by=['no_show','WaitingCategories']).mean()
```

In [82]:
```
## Adjusting the 'Age' attribute to have the mean instead of sum values:
patients = patients_sum.copy()
patients['age'] = patients_mean['age']
```

In [83]:
```
def df_column_normalize(dataframe, percent=False):
    '''Normalizes the values of a given pandas.Dataframe by the total sum of each column
    If percent=True, multiplies the final value by 100.
    Algorithm based on https://stackoverflow.com/questions/26537878/pandas-sum-across-co
    if percent:
        return dataframe.div(dataframe.sum(axis=0), axis=1)*100
    else:
        return dataframe.div(dataframe.sum(axis=0), axis=1)

## Normalizing data using the predefined function
patients = df_column_normalize(patients, percent=True)
```

In [84]:
```
# Drawing a heatmap with the numeric values in each cell
fig4, ax = plt.subplots(figsize=(12, 10))
fig4.subplots_adjust(top=.94)
plt.suptitle('Distribution of patients attributes by waiting categories and no-showing c

ax.set_yticklabels(ax.get_yticklabels(), ha="right", fontsize=12, weight='bold')
ax.set_xticklabels(ax.get_xticklabels(), fontsize=12, weight='bold')

cbar_kws = {'orientation':"horizontal", 'pad':0.05, 'aspect':50}
sns.heatmap(patients, annot=True, fmt='.2f', linewidths=.3, ax=ax, cmap='RdPu', cbar_kws
```



Conclusion on Patient profile

From the heatmap and descriptive statistics above the following conclusions can be drawn:

- The patients who attend to the appointments are in general older than those who don't.
- Most of the patients **who attend** the appointments scheduled in the **same day** receives scholarship and presents hipertension, diabetes, alcoholism, and handicap. These data may indicate these group of patients (i) may not have access to scheduling systems; or (ii) may need emergency care more often.
- Patients suffering from hypertension and diabetes are more assiduous in relation to medical appointments.
- Most **patients who have received SMS (70%) have attended to appointments scheduled from a week to a quarter.**

Conclusions

4.1. Limitation of Analysis

Regards to Data acquisition:

- There is no description on how the data were acquired.
- There is no description on how the patients ID were anonymized.
- It is not known if the health units share the same patient database. From this it follows that is not possible to know if the same patient receives different identification codes when he/she goes to a

different health unit.

Regards to Data quality:

- Few data need to be cleaned in the dataset (ex: negative age; scheduling date older than appointment date).

Regards to Data analysis:

- Given the above limitations, the present analysis was limited to categorizing the patient waiting time and exploring the associations of these categories with other attributes.

4.2. Summary of Conclusions

Regards to Day of Week (DOW) and length of Waiting days

- Little or No appointments taken on Saturday and Sunday.
- The show-up rate for appointment days are arounod 76.9% to 80.7 % across the weekdays.
- AppointmentDay_DOW could help in determining if a patient visits the hospital after taking an appointment.
- The no-showing rate increases as the waiting time gets longer.
- The no-showing rate reaches its lower value when the attendance occurs in the same day it was scheduled (This can be associated with emergency care).
- After 90 dyas waiting there is a slight return to the patient assiduity (no-show rate drops 49.6% to 23.4%)
- From the analysis, a possible hypothesis for the reduction of no-show rate in waiting days > 90 days can be assigned to the patient profile: **Elderly people as well as those with chronic diseases who require regular medical follow-up tend to schedule long-term appointments and attend to them.**

Regards to Neighbourhood

- From the analyzed data we found out that 80% of the appointments are attended to, with a standard deviation of 9.7%.
- **'PARQUE INDUSTRIAL'** had attended all its appointments but the same neighborhood carries only 1 appointment.
- **'ILHAS OCEÂNICAS DE TRINDADE'** had no show on all appointments but there are only 2 appointments.

Regards to Patient Profile

- The patients who attend to the appointments are in general older than those who don't.
- Most of the patients who attend the appointments scheduled in the same day receives scholarship and presents hipertension, diabetes, alcoholism, and handicap. These data may indicate these group of patients (i) may not have access to scheduling systems; or (ii) may need emergency care more often.
- Patients suffering from hypertension and diabetes are more assiduous in relation to medical appointments.
- Most patients who have received SMS (70%) have attended to appointments scheduled from a week to a quarter.

References

Applying heatmaps for categorical data analysis. (https://www.kaggle.com/code/tsilveira/applying-heatmaps-for-categorical-data-analysis)

```
In [ ]:
```