Introduction♡

> *This report explores the no-show appointments dataset, which collects information from over 100k medical appointments in Brazil. The report's goal is to predict who will not show up for an appointment based on a number of patient attributes.*
>
> ## In this analysis you will find answers to these questions:

1. How many appointments are showing up compared to no-shows?
2. How does the waiting time between booking and attending the appointment influence attendance?
3. Is reciveing SMS will affect the attendenc show up rate ?

In [1]:
```
# Cell all packages that i will use

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Data Wrangling

> In this section of the report, I will load in the data, check for cleanliness, and then trim and clean your dataset for analysis.

General Properties

In [2]:
```
# Load your data
df= pd.read_csv('noshowappointments-kagglev2-may-2016.csv')
# Showing the 5 rows of data
df.head()
```

Out[2]:

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

In [3]:
```
#Checking for the data structure
df.shape
```

```
(110527, 14)
```

Out[3]:

In [4]:
```
#Exploring general properties about the data
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
```

What we can get :

1. Comparing the numbers of rows with counts for each column , we can see there is no null value!
2. There is a typo in the (Handicaps)
3. ScheduledDay - AppointmentDay are columns with the date data type, so we have to change their data type into date
   - To keep it more simple we may sprate the date from time in those coulmns
4. PatientId and AppointmentID may also need to change its data type becuse they are not having meaning as intger and to easliy use them , we will converted them to object
5. To be more consistent with other column's values we may change the No-show values into (0 = No ,1 = Yes)

In [5]:
```
#Checking for duplicated values
df.duplicated().sum()
```

Out[5]:
```
0
```

In [6]:
```
#Checking for null values - to make sure
df.isnull().values.any()
```

Out[6]:
```
False
```

In [7]:
```
#Checking for numbers of patients we have
df.PatientId.nunique()
```

Out[7]:
```
62299
```

In [8]:
```
#Checking for numbers of Appointments that we have
df.AppointmentID.nunique()
```

Out[8]:
```
110527
```

The number of patients is less than the number of appointments, which means there are duplicates or some patients have more than one appointment.

In [9]:
```
#Checking for all the types of Neighnourhood

df.Neighbourhood.unique()
```

Out[9]:
```
array(['JARDIM DA PENHA', 'MATA DA PRAIA', 'PONTAL DE CAMBURI',
       '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'],
      dtype=object)
```

In [10]:
```
#Checking for numbers of Nieghbouthood
df.Neighbourhood.duplicated().size
```

Out[10]:
```
110527
```

In comparison to the unique values, that means may we have a situation where many patients visit the same place

In [11]:
```
#Chacking for the max value
print('This is the most Neighbourhood visted and has many appointments','  /    ' ,df['Ne
print('This is the amount of appointments','    / ', df['Neighbourhood'].value_counts()['
```

```
This is the most Neighbourhood visted and has many appointments   /    0    JARDIM CAMBU
RI
Name: Neighbourhood, dtype: object
This is the amount of appointments    /  7717
```

In [12]:
```
#Showing the general description
df.describe()
```

Out[12]:

	PatientId	AppointmentID	Age	Scholarship	Hipertension	Diabetes	Alcoholism
count	1.105270e+05	1.105270e+05	110527.000000	110527.000000	110527.000000	110527.000000	110527.000000
mean	1.474963e+14	5.675305e+06	37.088874	0.098266	0.197246	0.071865	0.030400
std	2.560949e+14	7.129575e+04	23.110205	0.297675	0.397921	0.258265	0.171686
min	3.921784e+04	5.030230e+06	-1.000000	0.000000	0.000000	0.000000	0.000000
25%	4.172614e+12	5.640286e+06	18.000000	0.000000	0.000000	0.000000	0.000000
50%	3.173184e+13	5.680573e+06	37.000000	0.000000	0.000000	0.000000	0.000000
75%	9.439172e+13	5.725524e+06	55.000000	0.000000	0.000000	0.000000	0.000000
max	9.999816e+14	5.790484e+06	115.000000	1.000000	1.000000	1.000000	1.000000

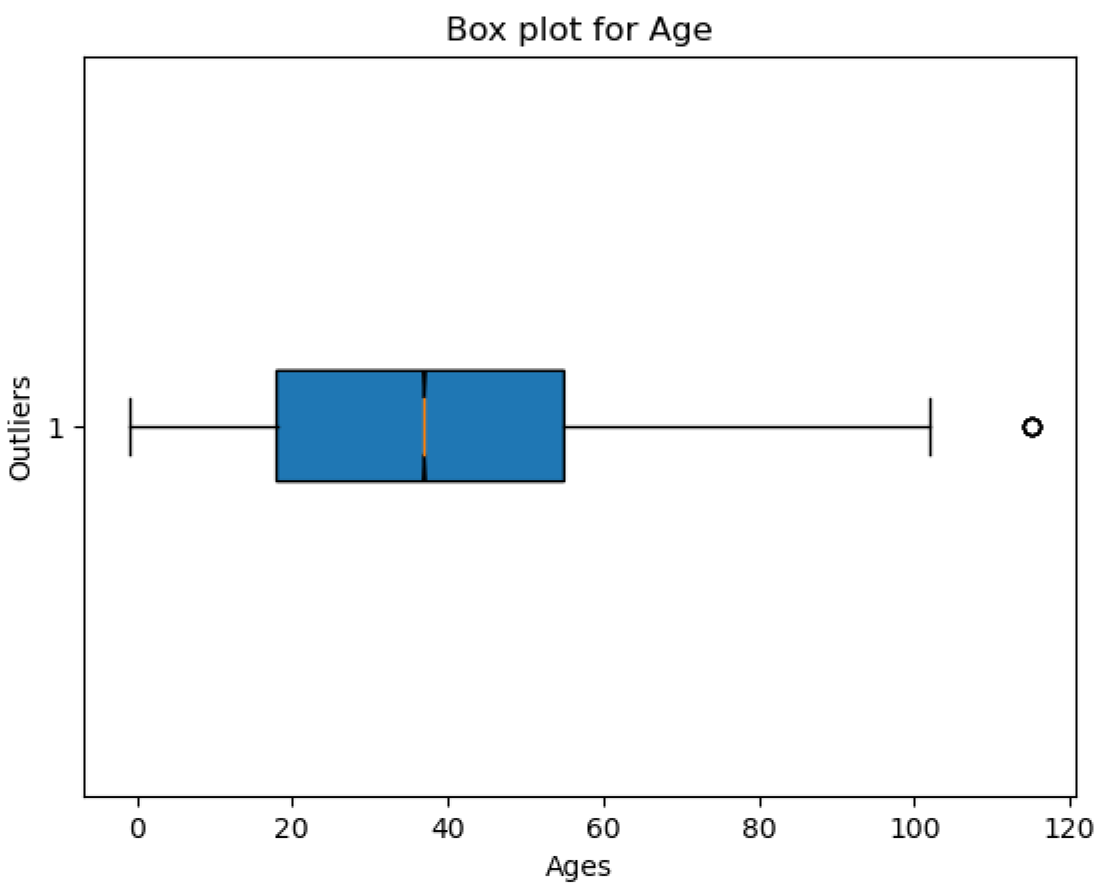
In [13]:
```
#Showing the general description for Neighbourhood because it did not appear above
df['Neighbourhood'].describe()
```

Out[13]:
```
count              110527
unique                 81
top         JARDIM CAMBURI
freq                 7717
Name: Neighbourhood, dtype: object
```

In [14]:
```
#Showing the general description for Gender because it did not appear above
df['Gender'].describe()
```

Out[14]:
```
count     110527
unique         2
top            F
freq       71840
Name: Gender, dtype: object
```

In [15]:
```
#Checking for the outliers again because we found in above there is Max value =115 , and
plt.boxplot(df['Age'],vert=False , patch_artist = True , notch= True)
# show plot
plt.title('Box plot for Age')
plt.xlabel('Ages')
plt.ylabel('Outliers')
plt.show()
```



In [16]:
```
#Checking for patients with less than 0 Age (Maybe 0 means there are newborn, so I will
df.loc[df['Age'] <0]
```

Out[16]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
99832	4.659432e+14	5775010	F	2016-06-06T08:58:13Z	2016-06-06T00:00:00Z	-1	ROMÃO	

What we can get :

- From the statistics descriptive we can summarize that:
  - Age has one or more negative values, so it must be removed because in the logic it is impossible to have Age with -1
  - Female was the top gender , but we need to convert the data to code (1= F, 0=M) to have more meaning by numbers
  - The mean age of the patients is 37, and most are between 37-55, which is reasonable because we are more likely to visit a doctor at this age.
  - If we change the type of data to - No show columns - we may be able to investigate further statisticly
  - Approximately 75% of patients received SMS (SMS = 1), so we need to see how this affects attendance.
  - There is one place that is the most visited, so we need to find out why

> **What coming in the cleaning :**
>
> 1. Change some data type
> 2. Correct the typo
> 3. Change some value type
> 4. Delete the outliers
> 5. Separate columns
> 6. Create a helper column

Data Cleaning and deep exploring

In [17]:
```
# rename typo columns
df.rename(columns={'Handcap': 'Handicap', 'SMS_received': 'SMSReceived', 'No-show': 'Att
          inplace=True)
# confirm changes
df.head(3)
```

Out[17]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	H
0	2.987250e+13	5642903	F	2016-04-29T18:38:08Z	2016-04-29T00:00:00Z	62	JARDIM DA PENHA	0	
1	5.589978e+14	5642503	M	2016-04-29T16:08:27Z	2016-04-29T00:00:00Z	56	JARDIM DA PENHA	0	
2	4.262962e+12	5642549	F	2016-04-29T16:19:04Z	2016-04-29T00:00:00Z	62	MATA DA PRAIA	0	

In [18]:
```
# Will convert ScheduledDay, AppointmentDay  data type so i can extract the date
for x in ['ScheduledDay', 'AppointmentDay']:
    df[x]= pd.to_datetime(df[x])
```

In [19]:
```
# Confiem the change
df.head(4)
```

Out[19]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	H
0	2.987250e+13	5642903	F	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00	62	JARDIM DA PENHA	0	

1	5.589978e+14	5642503	M	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	0
2	4.262962e+12	5642549	F	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00	62	MATA DA PRAIA	0
3	8.679512e+11	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL DE CAMBURI	0

In [20]:
```
# Will extract date to help in further investigation if need it
for d in ['ScheduledDay', 'AppointmentDay']:

   df['Scheduled']= df[d].dt.date
   df['Appointment']= df[d].dt.date
```

Since we have almost all appointments at the same time as shown in the Appointment Date column, I decided to create new columns for a date only and keep the original in case we need the time.

In [21]:
```
# Will convert Attending values to 1 and 0
df['Attending'].replace({'No': 0, 'Yes': 1}, inplace=True)
```

In [22]:
```
# Will convert Attending data type
df['Attending']=df['Attending'].astype(int)
```

The conversion of the values to (0, 1) and the type to an integer will assist in creating more charts and using them for statistical analysis

In [23]:
```
# Will convert PatientID data type
df['PatientId']=df['PatientId'].astype(int)
```

Changing the type to an integer will help in the future for instance to know how many appointments each patient has.

In [24]:
```
#Will drop the one row that has -1 Age
df_Age = df[df['Age'] <0].index # Filter the rows
df.drop(df_Age,inplace=True)
```

In [25]:
```
#Checking for Age change
df.loc[df['Age'] <0]
```

Out[25]:

PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship	Hiperte

In [26]:
```
#confirm changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110526 entries, 0 to 110526
Data columns (total 16 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   PatientId       110526 non-null  int32
 1   AppointmentID   110526 non-null  int64
 2   Gender          110526 non-null  object
 3   ScheduledDay    110526 non-null  datetime64[ns, UTC]
 4   AppointmentDay  110526 non-null  datetime64[ns, UTC]
 5   Age             110526 non-null  int64
 6   Neighbourhood   110526 non-null  object
 7   Scholarship     110526 non-null  int64
 8   Hipertension    110526 non-null  int64
```

```
 9   Diabetes        110526 non-null  int64
 10  Alcoholism      110526 non-null  int64
 11  Handicap        110526 non-null  int64
 12  SMSReceived     110526 non-null  int64
 13  Attending       110526 non-null  int32
 14  Scheduled       110526 non-null  object
 15  Appointment     110526 non-null  object
dtypes: datetime64[ns, UTC](2), int32(2), int64(8), object(4)
memory usage: 13.5+ MB
```

In [27]:
```
#Creating a new column and extract its days only through using  dt
df['gap_days'] = (df['AppointmentDay']-df['ScheduledDay']).dt.days
```

To see if the timing difference between a scheduled appointment and the actual appointment affects attendance

In [28]:
```
#Confirm changes
df.loc[df['gap_days']>1]
```

Out[28]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarshi
11	-2147483648	5620163	M	2016-04-26 08:44:12+00:00	2016-04-29 00:00:00+00:00	29	NOVA PALESTINA	
15	-2147483648	5620206	F	2016-04-26 08:47:27+00:00	2016-04-29 00:00:00+00:00	15	NOVA PALESTINA	
18	-2147483648	5621836	F	2016-04-26 10:54:18+00:00	2016-04-29 00:00:00+00:00	30	NOVA PALESTINA	
22	-2147483648	5616091	M	2016-04-25 13:29:16+00:00	2016-04-29 00:00:00+00:00	13	CONQUISTA	
25	-2147483648	5624020	M	2016-04-26 15:04:17+00:00	2016-04-29 00:00:00+00:00	46	CONQUISTA	
...	...	...	...	...	...	...	...	
110522	-2147483648	5651768	F	2016-05-03 09:15:35+00:00	2016-06-07 00:00:00+00:00	56	MARIA ORTIZ	
110523	-2147483648	5650093	F	2016-05-03 07:27:33+00:00	2016-06-07 00:00:00+00:00	51	MARIA ORTIZ	
110524	-2147483648	5630692	F	2016-04-27 16:03:52+00:00	2016-06-07 00:00:00+00:00	21	MARIA ORTIZ	
110525	-2147483648	5630323	F	2016-04-27 15:09:23+00:00	2016-06-07 00:00:00+00:00	38	MARIA ORTIZ	
110526	-2147483648	5629448	F	2016-04-27 13:30:56+00:00	2016-06-07 00:00:00+00:00	54	MARIA ORTIZ	

60021 rows × 17 columns

In [29]:
```
#confirm changes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110526 entries, 0 to 110526
Data columns (total 17 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   PatientId       110526 non-null  int32
 1   AppointmentID   110526 non-null  int64
 2   Gender          110526 non-null  object
```

```
 3   ScheduledDay    110526 non-null  datetime64[ns, UTC]
 4   AppointmentDay  110526 non-null  datetime64[ns, UTC]
 5   Age             110526 non-null  int64
 6   Neighbourhood   110526 non-null  object
 7   Scholarship     110526 non-null  int64
 8   Hipertension    110526 non-null  int64
 9   Diabetes        110526 non-null  int64
 10  Alcoholism      110526 non-null  int64
 11  Handicap        110526 non-null  int64
 12  SMSReceived     110526 non-null  int64
 13  Attending       110526 non-null  int32
 14  Scheduled       110526 non-null  object
 15  Appointment     110526 non-null  object
 16  gap_days        110526 non-null  int64
dtypes: datetime64[ns, UTC](2), int32(2), int64(9), object(4)
memory usage: 14.3+ MB
```

In [30]:
```
# Checking the helper column
df.query('gap_days < -1').head()
```

Out[30]:

	PatientId	AppointmentID	Gender	ScheduledDay	AppointmentDay	Age	Neighbourhood	Scholarship
27033	-2147483648	5679978	M	2016-05-10 10:51:53+00:00	2016-05-09 00:00:00+00:00	38	RESISTÊNCIA	(
55226	-2147483648	5715660	F	2016-05-18 14:50:41+00:00	2016-05-17 00:00:00+00:00	19	SANTO ANTÔNIO	(
64175	-2147483648	5664962	F	2016-05-05 13:43:58+00:00	2016-05-04 00:00:00+00:00	22	CONSOLAÇÃO	(
71533	-2147483648	5686628	F	2016-05-11 13:49:20+00:00	2016-05-05 00:00:00+00:00	81	SANTO ANTÔNIO	(
72362	-2147483648	5655637	M	2016-05-04 06:50:57+00:00	2016-05-03 00:00:00+00:00	7	TABUAZEIRO	(

It turns out that we have unreasonable values! There can be no less than one day between the appointment and the scheduled for. Assuming that the -1 represents some hours between them, this would make sense, but the data indicates that we have -2 and more. let us see what this means

Exploratory Data Analysis

> **Note** :Initially, I will try to answer the questions that have already been raised, and we may move into other areas of data analysis.

In [31]:
```
# To filter the data more esiry i creted a mask for the attending column
showed = df['Attending'] == 1
not_showed = df['Attending'] == 0
df['showed'] = showed
df['not_showed'] = not_showed
```

In order to filter the data more easily, I created a mask for the attending column.

- Since the main goal of this data set is to explore the pattern and reasons behind the (N0-Show) attitude

Question 1

How many appointments are showing up compared to no-shows?

In [32]:
```
#Check the rate of  the Not_showed
df['not_showed'].value_counts(normalize=True).mul(100).round().astype(str)+ '%'
```

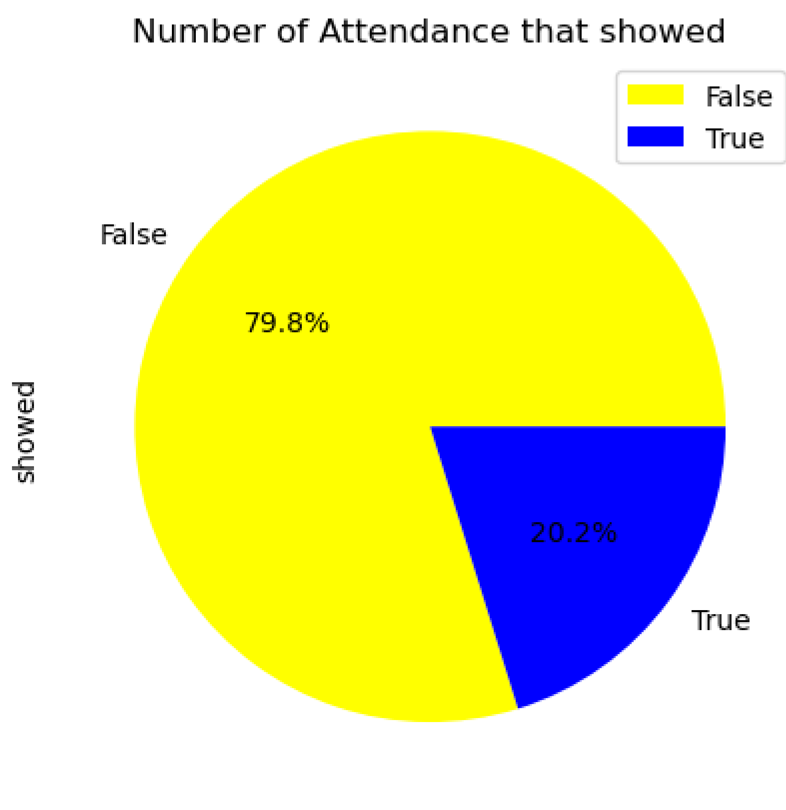
Out[32]:
```
True      80.0%
False     20.0%
Name: not_showed, dtype: object
```

In [33]:
```
#Check the rate of  the Not_showed
df['showed'].value_counts(normalize=True).mul(100).round().astype(str)+ '%'
```

Out[33]:
```
False     80.0%
True      20.0%
Name: showed, dtype: object
```

First, check the filter. I counted their rate and rounded it and change the type of result to string to write in them % and make it more obvious for the reader.

In [34]:
```
y = df['showed'].value_counts()
colors=['yellow','blue']
y.plot.pie(autopct='%1.1f%%' , colors=colors)
plt.title("Number of Attendance that showed")
plt.legend();
plt.show()
```



Approximately 20% of the total attendees show up for their appointments. Meanwhile, 80% of people fail to show up for appointments

Let's see if the attendance is affacting by the Age or Gender

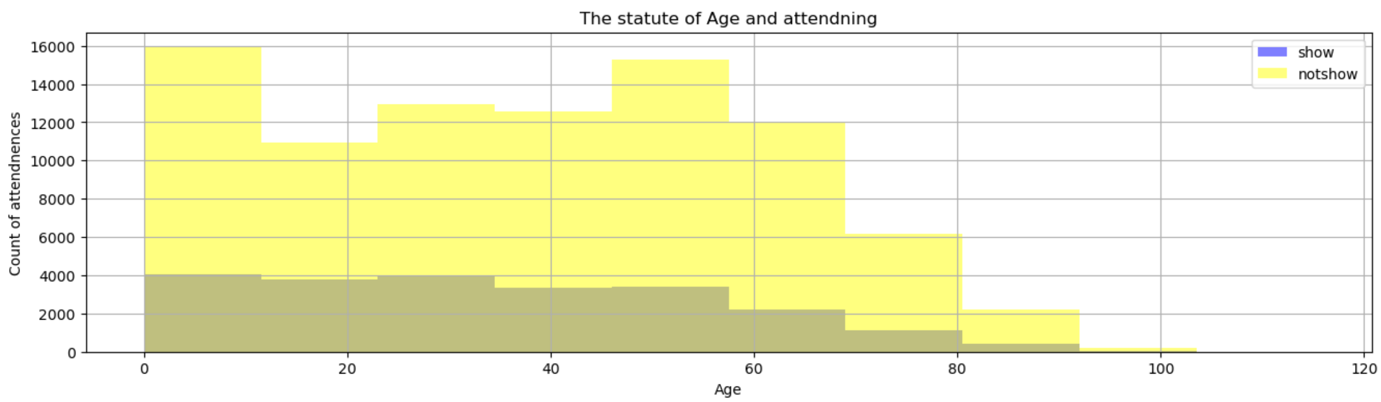
In [35]:
```
# The mean Age of the show up vs not
pd.pivot_table(data = df, index = ["Attending"], values = "Age")
```

Out[35]:

Age

Attending	
0	37.790504
1	34.317667

In [36]:
```
# Visualizing the Age distribution
def attending_hist(df,col,t,x):
    plt.figure(figsize=[16,4])
    df[col][showed].hist(alpha=.5,bins=10,color='blue',label='show')
    df[col][not_showed].hist(alpha=.5,bins=10,color='yellow',label='notshow')
    plt.legend()
    plt.title(t)
    plt.xlabel(x)
    plt.ylabel('Count of attendnences');
attending_hist(df, 'Age',  'The statute of Age and attendning' ,'Age')
```

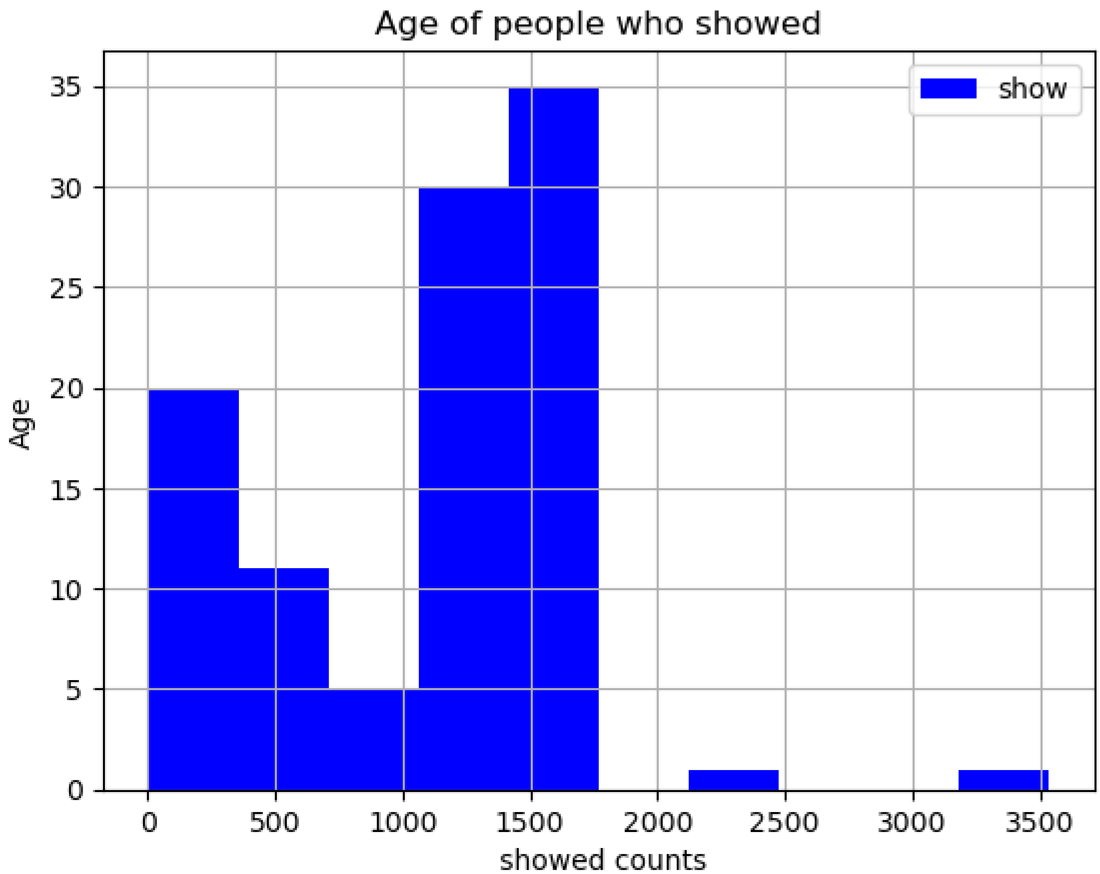


Most patients between 0 and 60 are showing for their appointments , whereas those not showing appear more at 0 Aged ,and the whole distribution are fluctuate not in a stable manner. However, I believe the number of the group is affected by the sum of the no shown and shown attendees, as well as the number of 0-60 age's attendees, so it will not well impact the attendance or provide a reliable result.

In [37]:
```
# Counting the number of patients to check the top ages
df['Age'].value_counts()
```

Out[37]:
```
0      3539
1      2273
52     1746
49     1652
53     1651
       ...
98        6
115       5
100       4
102       2
99        1
Name: Age, Length: 103, dtype: int64
```

In [38]:
```
# Checking is true the mean Age of showen up is between 39 >
df.groupby('Age')['showed'].count().hist(bins=10,label='show' , color= 'blue')
plt.xlabel(" showed counts")
plt.ylabel("Age")
plt.title("Age of people who showed")
plt.legend();
```



Even though older people need more hospital care, the smaller age group seems to care and show up more often

#Find the Gender relation

In [39]:
```
# Show the mean Age of female
df.Age[df['Gender']=='F'].mean()
```

Out[39]:
```
38.894541961887
```

In [40]:
```
# Show the mean Age of male
df.Age[df['Gender']=='M'].mean()
```

Out[40]:
```
33.73686251195492
```

In [41]:
```
# Getting the mean age of the genders who show up for their appointments
G_showed = pd.pivot_table(data = df, index = ["Gender"], values = 'showed',aggfunc = np.
round(G_showed * 100, 2)
```

Out[41]:

	showed
Gender	
F	20.31
M	19.97

In [42]:
```
# Getting the mean age of the genders who  don't show up for their appointments
G_not_showed = pd.pivot_table(data = df, index = ["Gender"], values = "not_showed",aggfu
round(G_not_showed  * 100, 2)
```

Out[42]:

not_showed

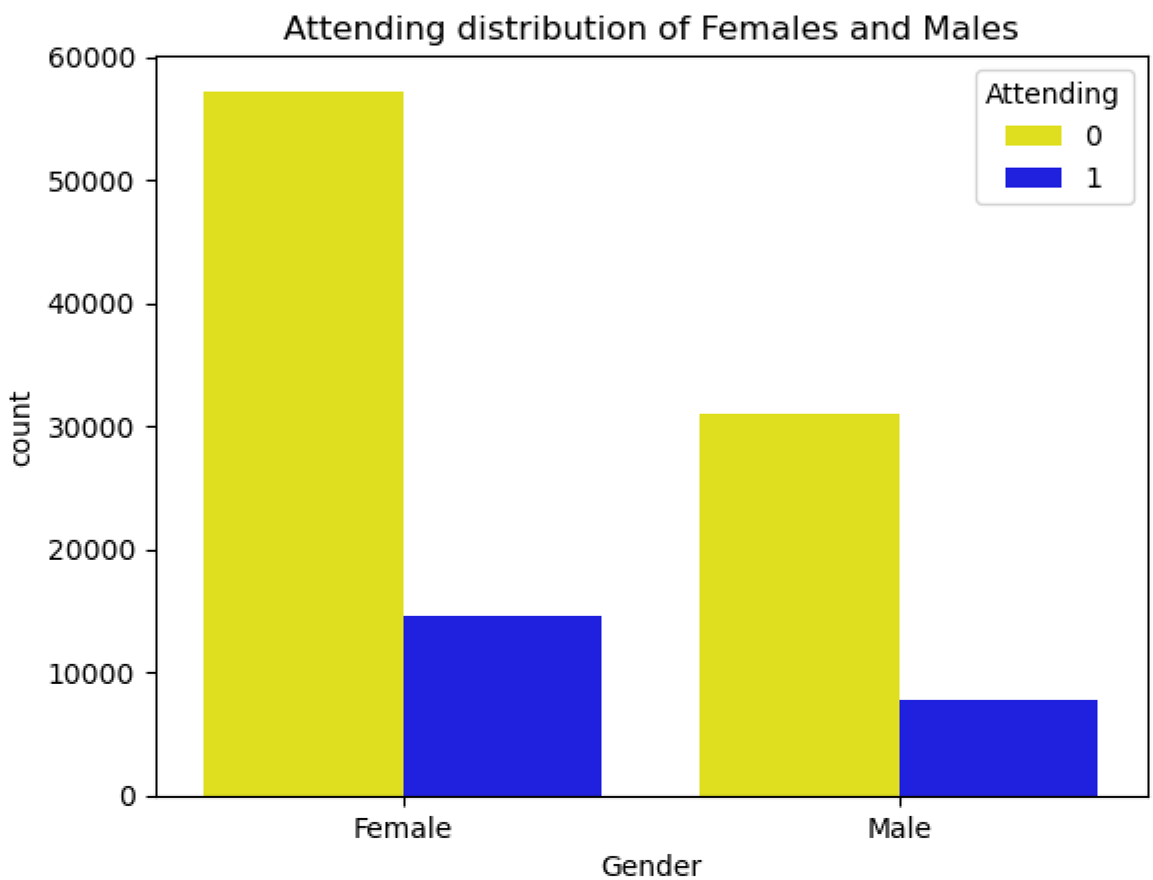
Gender	
F	79.69
M	80.03

Note:I used the pivot because I wanted to summarize one numerical data based on a categorical/object data type

In general, males seems to show up less than females with a smelest diffrence between them. I don't think Gender has a relation with attending the appontnments . Even though i was expacting Females to show more than males.

- Considering that males have a lower mean age than females, they should be showing up to appointments less than females, since the older we get, the more appointments we have

In [43]:
```
# Used seaborn library because it more appropriate to represent the categorical/object d
Att = sns.countplot(x=df.Gender, hue=df.Attending,data=df, palette=['yellow',"blue"])
Att.set_title("Attending distribution of Females and Males")
x_ticks_labels=['Female', 'Male']
Att.set_xticklabels(x_ticks_labels)
plt.show()
```



Despite the fact that the mean age of females is more than the mean age of males, the females are less likely to attend than the males. There is a possibility that this affected by the total number of females compared to males

In [44]:
```
#Checking the total numbers of Gender
df.Gender.value_counts()
```

Out[44]:
```
F     71839
M     38687
```

```
Name: Gender, dtype: int64
```

> **The answer:**

Nearly 79.8% of patients who schedule appointments do not show up, regardless of their age or gender. The only problem is that it seems there are a number of females with negative attitudes toward attending, despite the fact that they have an average age of 38, so they should attend more, but for some reason they don't, possibly due to family commitments.

Question 2

> **How does the waiting time between booking and attending the appointment influence attendance?**

Note : Before answering the question, I created bins and divided the gap days into subgroups. In order to make it easier to visualize

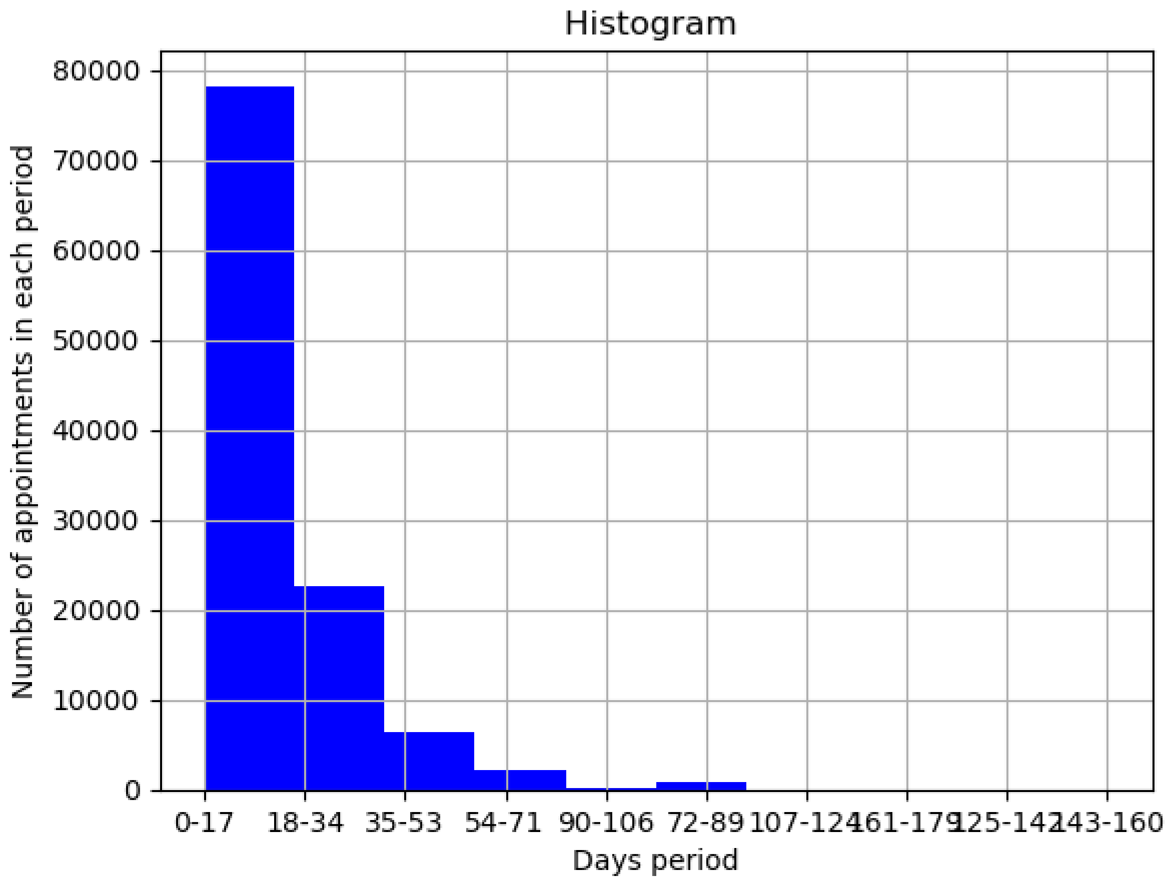
In [45]:
```
df["gap_days"] = pd.cut(df["gap_days"], 10, labels = ["0-17", "18-34", "35-53", "54-71",
```

In [46]:
```
# Check the change
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 110526 entries, 0 to 110526
Data columns (total 19 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   PatientId       110526 non-null  int32
 1   AppointmentID   110526 non-null  int64
 2   Gender          110526 non-null  object
 3   ScheduledDay    110526 non-null  datetime64[ns, UTC]
 4   AppointmentDay  110526 non-null  datetime64[ns, UTC]
 5   Age             110526 non-null  int64
 6   Neighbourhood   110526 non-null  object
 7   Scholarship     110526 non-null  int64
 8   Hipertension    110526 non-null  int64
 9   Diabetes        110526 non-null  int64
 10  Alcoholism      110526 non-null  int64
 11  Handicap        110526 non-null  int64
 12  SMSReceived     110526 non-null  int64
 13  Attending       110526 non-null  int32
 14  Scheduled       110526 non-null  object
 15  Appointment     110526 non-null  object
 16  gap_days        110526 non-null  category
 17  showed          110526 non-null  bool
 18  not_showed      110526 non-null  bool
dtypes: bool(2), category(1), datetime64[ns, UTC](2), int32(2), int64(8), object(4)
memory usage: 13.8+ MB
```

In [47]:
```
# Creating hist to definded the frequency of days between them
df['gap_days'].hist(color='blue')
plt.xlabel('Days period')
plt.ylabel('Number of appointments in each period')
plt.title('Histogram ')
```

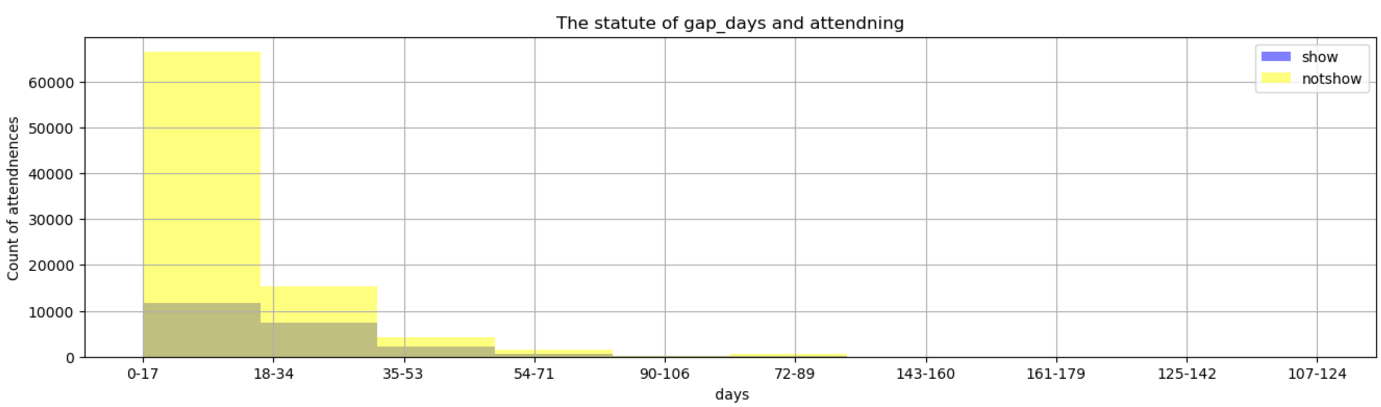
Out[47]:
```
Text(0.5, 1.0, 'Histogram ')
```



The distribution is right-skewed and most appointments occur within the 53 days. Let's see how this affects attendance.

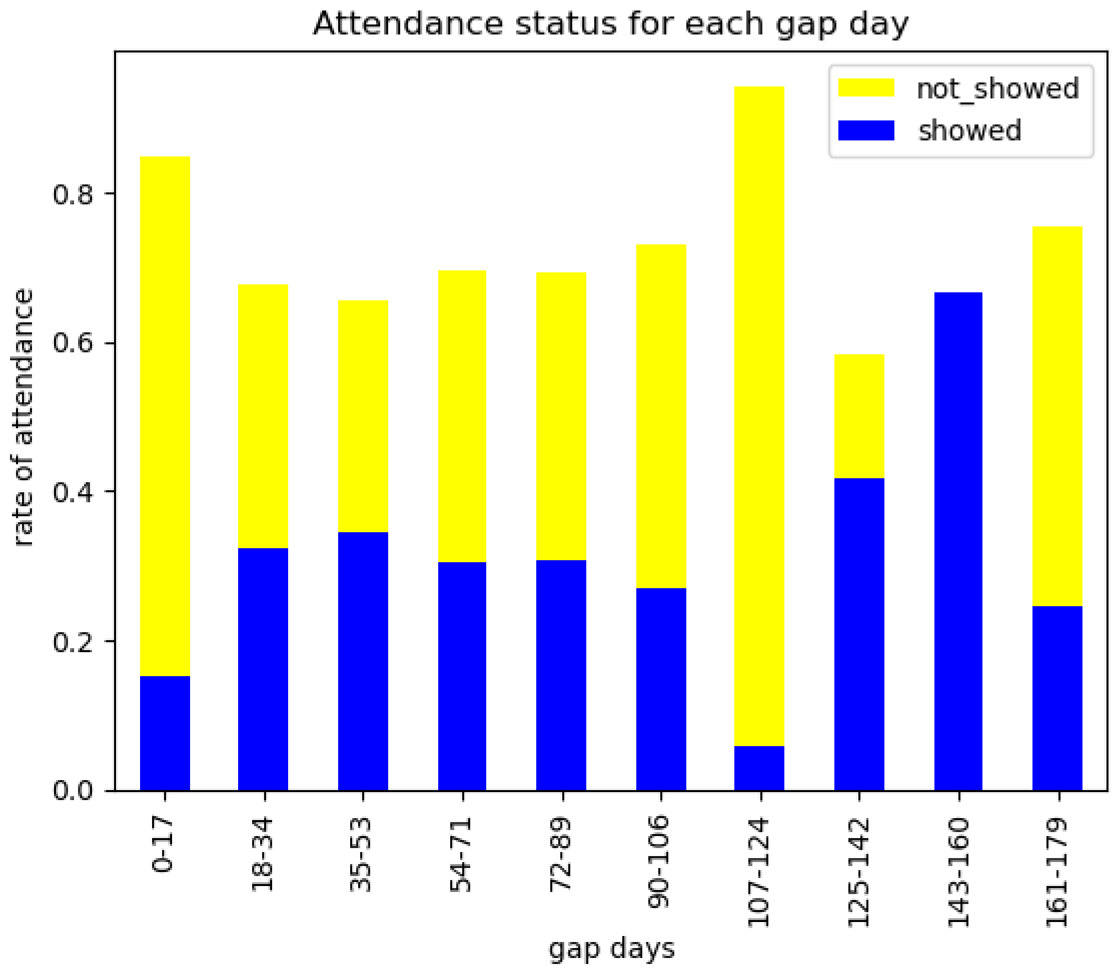
- What is the tendency of people showing up for appointments during that period?

In [48]:
```
#Createing a hist to show the affects on attendance
attending_hist(df, 'gap_days','The statute of gap_days and attendning' ,' days')
```



Unfortunately, most of them did not attend the appointment!

In [49]:
```
#Create a bar chart to see when they usually attend and not? If they schedule it before
def bar_plot(col, Tit,X,Y):
    df.groupby(col).not_showed.mean().plot(kind='bar',color='yellow' ,stacked=True)
    df.groupby(col).showed.mean().plot(kind='bar',color='blue',stacked=True)
    plt.legend()
    plt.title(Tit)
    plt.xlabel(X)
    plt.ylabel(Y)
    plt.show();
bar_plot('gap_days'," Attendance status for each gap day ", 'gap days', ' rate of attend
```



We can find that if they scheduled the appointment before hours or 17 days they mostly will not show up , on other hand if they scheduler before 143-160 days they mostly will show up

In [50]:
```
# Checking the totall numbers of each gap period and group( who show up , do not)
df.groupby(df['Attending'],as_index=False)['gap_days'].value_counts()
```

Out[50]:

	Attending	gap_days	count
0	0	0-17	66398
1	0	18-34	15308
2	0	35-53	4189
3	0	54-71	1537
4	0	72-89	538
5	0	90-106	152
6	0	161-179	34
7	0	107-124	33
8	0	125-142	14
9	0	143-160	4
10	1	0-17	11784
11	1	18-34	7330
12	1	35-53	2207
13	1	54-71	673

14	1	72-89	238
15	1	90-106	56
16	1	161-179	11
17	1	125-142	10
18	1	143-160	8
19	1	107-124	2

In [51]:
```
df.groupby("gap_days").mean()['showed']
```

Out[51]:
```
gap_days
0-17       0.150725
18-34      0.323792
35-53      0.345059
54-71      0.304525
72-89      0.306701
90-106     0.269231
107-124    0.057143
125-142    0.416667
143-160    0.666667
161-179    0.244444
Name: showed, dtype: float64
```

In [52]:
```
df.groupby("gap_days").mean()['not_showed']
```

Out[52]:
```
gap_days
0-17       0.849275
18-34      0.676208
35-53      0.654941
54-71      0.695475
72-89      0.693299
90-106     0.730769
107-124    0.942857
125-142    0.583333
143-160    0.333333
161-179    0.755556
Name: not_showed, dtype: float64
```

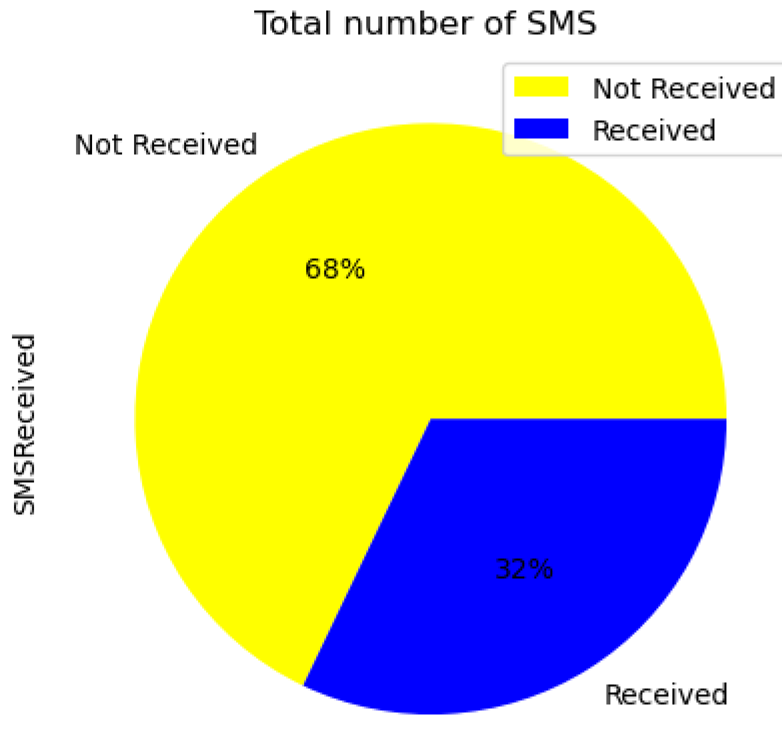
> **The answer:**

I think the pattern are not stable because we have some of them attended and take more than 100 days between the scheduled and appointment , and other are take only some of days and still can not make it.

Question 3

> **Is reciveing SMS will affect the attendenc show up rate ?**

In [53]:
```
# Visualizing the total number of SMS receiving
df['SMSReceived'].value_counts().plot(kind="pie",labels=["Not Received","Received"],auto
plt.title("Total number of SMS ")
plt.legend();
```



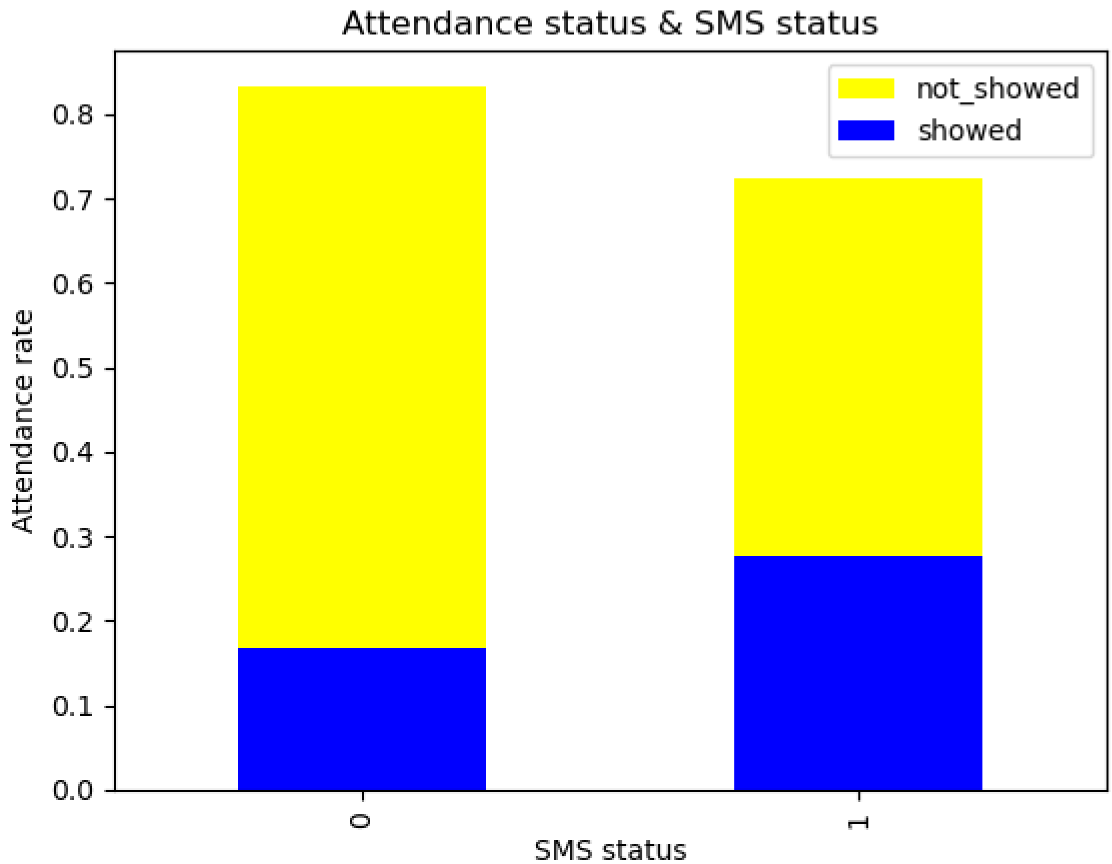
As we can see the majority is not receiving any SMS which is not a good sign for the organization's operation. Will this affect the percentage of attending patients?

In [54]:
```
#Calculating the count for each patient who is showing up (1)or not showing up for their
df.groupby("SMSReceived",as_index=False)['Attending'].value_counts()
```

Out[54]:

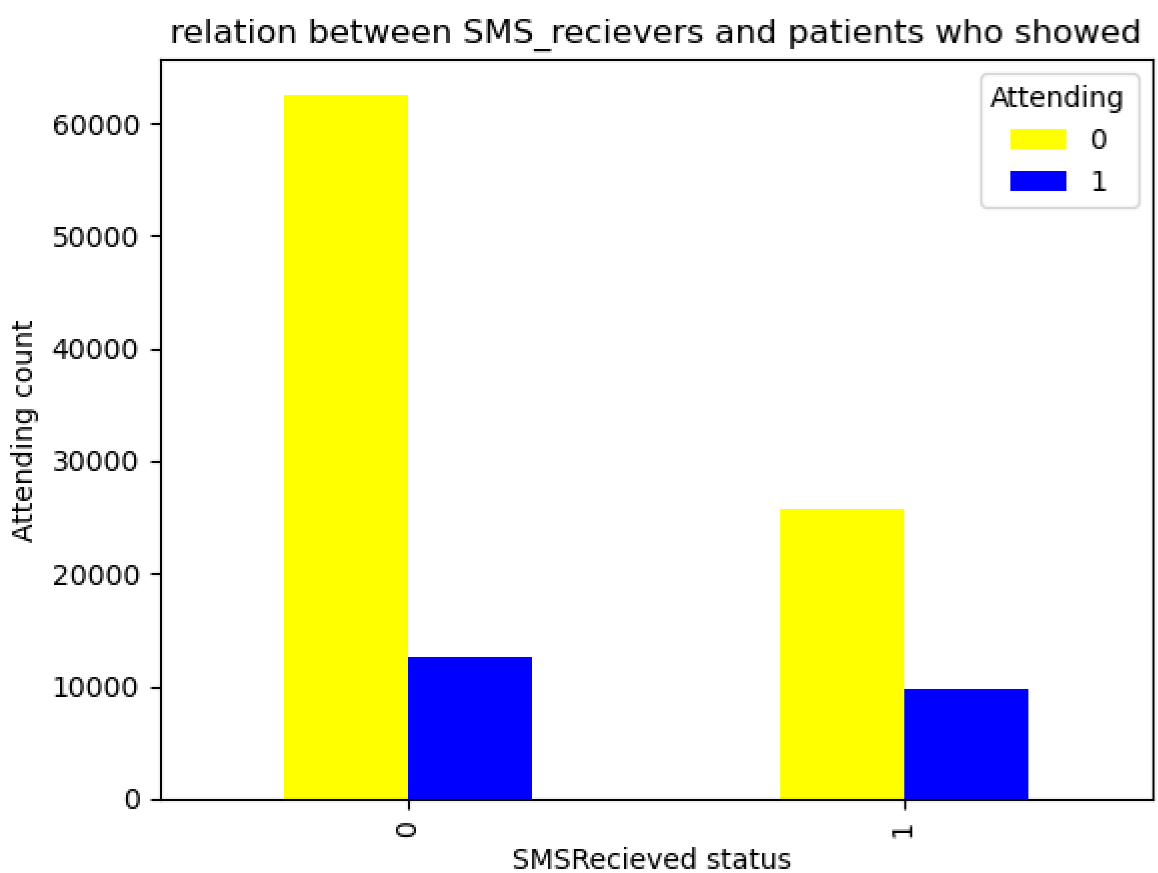
	SMSReceived	Attending	count
0	0	0	62509
1	0	1	12535
2	1	0	25698
3	1	1	9784

In [55]:
```
# Creating a bar chart to see the relation between SMS sending and attending
bar_plot('SMSReceived', 'Attendance status & SMS status','SMS status', 'Attendance rate'
```



In [56]:
```
#This other way to show the relation
df['Attending'].groupby(df['SMSReceived']).value_counts().unstack().plot( kind='bar', st
plt.ylabel("Attending count")
plt.xlabel("SMSRecieved status ")
plt.title("relation between SMS_recievers and patients who showed")
```

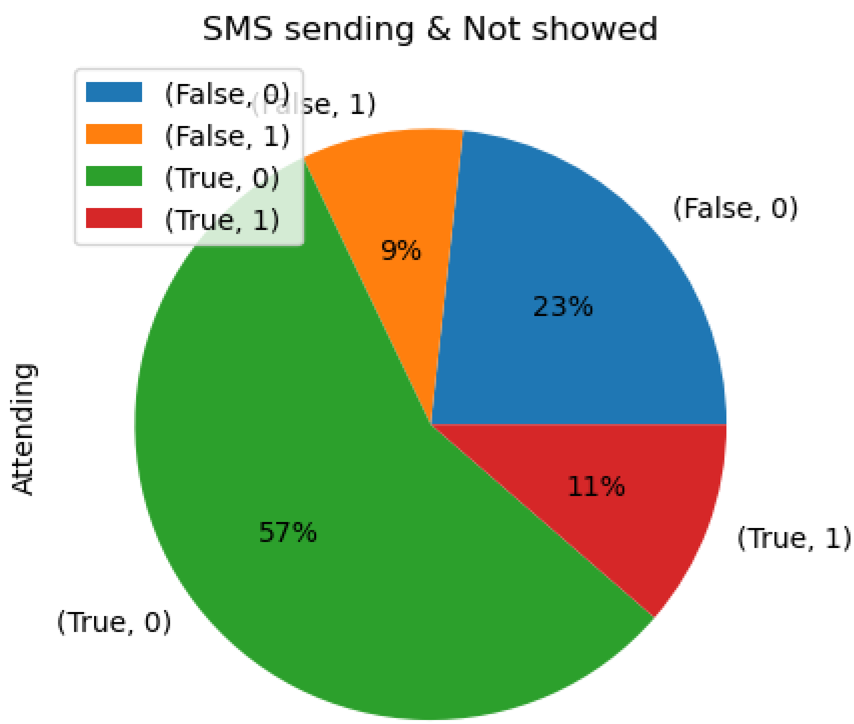
Out[56]:
```
Text(0.5, 1.0, 'relation between SMS_recievers and patients who showed')
```



We can find out there is no difference between sending SMS or not. Only when we take the sum of who received SMS into consideration, we will find that most patients who received an SMS made it to the appointment

In [57]:
```
#This is only to confirm the impact of SMS sending on showing up for their appointments

df['Attending'].groupby(df['SMSReceived']==0).value_counts().plot(kind="pie", autopct='%
plt.title("SMS sending & Not showed")
plt.legend();
```



Almost 57% out of 68% them don't receive any SMS and still not attending

> **The answer:**

On the whole, the data isn't providing us with enough information to decide, but if we compare the sending rate with itself, we will find that most of them attended.

Conclusions

1. Nearly 80% of patients do not attend their appointments
   - The mean Age of those who showed is 34.317667
2. Younger patients are more likely to commit on attending appointments
   - Males in the dataset have a mean age of 34, which is younger than females.
   - Almost from 15 to mid-30s are more likely to show up to their appointments.
3. The dataset contains a higher percentage of females, and females are more likely to commit to the appointment than males
4. There is no correlation between gender / Age alone and missing the appointment.

5. Most of the patients scheduled their appointment within 0-17 days of their actual appointments. Many of them failed to show up.
6. Attendings show inconsistent responses to the gap between the actual appointment and the schedule appointment..
7. Receiving an SMS did not increase the chance that the patient would show up to their appointment. However, if we look at the total number of SMS sent to patients , it seems most of them show up for their appointments

Limitations

- There are some mistakes for instance the time of the appointment shows for all 00
- The dataset covers a short period so it will affect finding pattern
- The dataset didn't provide many complementary features
- **Such as** :
- The time of sending SMS, may it will affect the attendees
- The reasons for the appointments
- The medical history to see its correlation with Age and attending

In [ ]:
```

```