Project: Investigate a Dataset noshow_final_processed

1. Library Imports

In this section, we import the necessary Python libraries for data manipulation and numerical analysis. We use `pandas` for data handling and `numpy` for mathematical operations.

In [2]:
```
import pandas as pd
import numpy as np
```

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2. Data Loading

The dataset containing medical appointment no-show information is loaded into a pandas DataFrame from the CSV file.

In [3]:
```
df = pd.read_csv('noshowappointments-kagglev2-may-2016.csv')
df.head()
```

Out[3]:

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

Initial Data Inspection We display the first five rows of the dataset to understand the structure of the data, identify the column names, and verify that the file was loaded correctly.

Age Impact: Does a patient's age correlate with their likelihood of missing an appointment?

SMS Reminders: How effective are SMS notifications in reducing the number of missed appointments?

we will answer that question later

Convert ScheduledDay and AppointmentDay to datetime objects.

In [4]:
```
df['ScheduledDay'] = pd.to_datetime(df['ScheduledDay'])
df['AppointmentDay'] = pd.to_datetime(df['AppointmentDay'])

print(df[['ScheduledDay', 'AppointmentDay']].dtypes)
df[['ScheduledDay', 'AppointmentDay']].head()
```

```
ScheduledDay      datetime64[ns, UTC]
AppointmentDay    datetime64[ns, UTC]
dtype: object
```

Out[4]:

	ScheduledDay	AppointmentDay
0	2016-04-29 18:38:08+00:00	2016-04-29 00:00:00+00:00
1	2016-04-29 16:08:27+00:00	2016-04-29 00:00:00+00:00
2	2016-04-29 16:19:04+00:00	2016-04-29 00:00:00+00:00
3	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00
4	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00

The `ScheduledDay` and `AppointmentDay` columns are currently stored as strings. We convert them into datetime objects to facilitate time-based analysis.

Handle the erroneous -1 age value.

In [5]:
```
erroneous_age_count = df[df['Age'] < 0].shape[0]
print(f"Removing {erroneous_age_count} records with with age < 0.")

df = df[df['Age'] >= 0]

print(f"New minimum age: {df['Age'].min()}")
```

```
Removing 1 records with with age < 0.
New minimum age: 0
```

During data exploration, an invalid age value of -1 was identified. We remove these records to maintain data integrity and verify the new minimum age.

Standardize column names

In [6]:
```
def standardize_columns(dataframe):
    rename_map = {
        'Hipertension': 'hypertension',
        'Handcap': 'handicap',
        'No-show': 'no_show',
        'PatientId': 'patient_id',
        'AppointmentID': 'appointment_id'
```

```
    }
    df.rename(columns=rename_map, inplace=True)
    df.columns = df.columns.str.lower()
    return df

df = standardize_columns(df)
print(df.columns)
```

```
Index(['patient_id', 'appointment_id', 'gender', 'scheduledday',
       'appointmentday', 'age', 'neighbourhood', 'scholarship', 'hypertension',
       'diabetes', 'alcoholism', 'handicap', 'sms_received', 'no_show'],
      dtype='object')
```

To improve consistency and accessibility, we correct typos in column names (e.g., 'Hipertension' to 'Hypertension') and convert all column headers to lowercase.

Calculate the Waiting Time (days between booking and appointment)

In [7]:
```
df['waiting_days'] = (df['appointmentday'].dt.normalize() - df['scheduledday'].dt.normalize()).dt.days
df = df[df['waiting_days'] >= 0]

df['day_of_week'] = df['appointmentday'].dt.day_name()
df.head()
```

Out[7]:

	patient_id	appointment_id	gender	scheduledday	appointmentday	age	neighbourhood	scholarship	hypertension	dia
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	
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	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	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	0	
4	8.841186e+12	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	0	1	

We create a new feature, `waiting_days`, by calculating the difference between the appointment date and the scheduled date. We also extract the day of the week for further analysis.

.

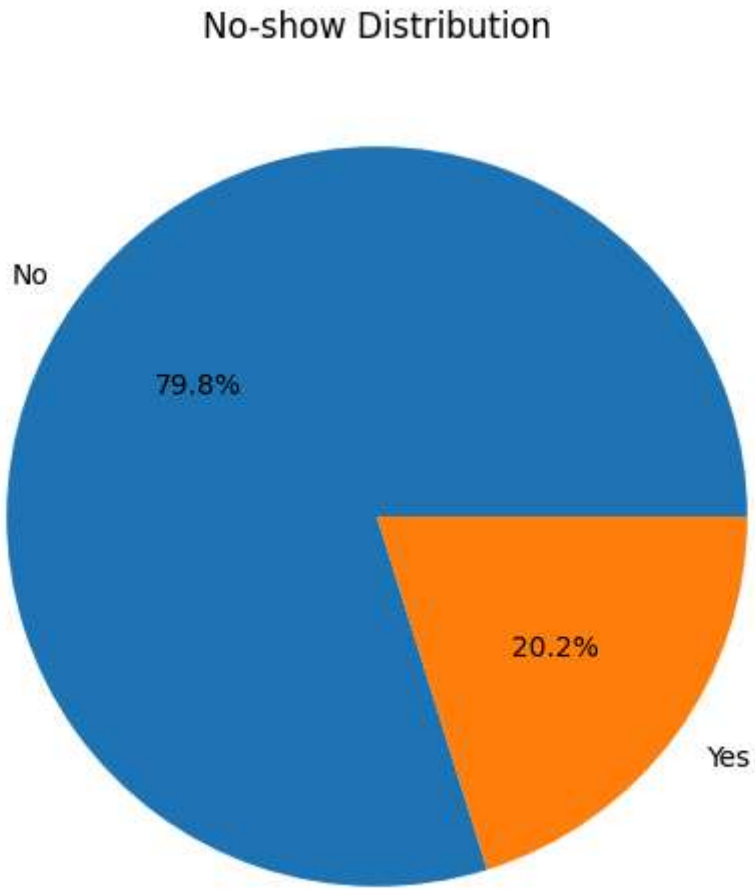
In [8]:
```
df['no_show_num'] = df['no_show'].apply(lambda x: 1 if x == 'Yes' else 0)
```

Transform the categorical no_show column into a binary numeric format (1 for Yes, 0 for No) for analysis.

In [9]:
```
import matplotlib.pyplot as plt

def apply_plot_labels(title, xlabel, ylabel):
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
```

this function added tittle and labels it can be used with each plot in the notebook

In [10]:
```
ax1 = df['no_show'].value_counts().plot(
    kind='pie',
    autopct='%1.1f%%',
    figsize=(6, 6)
)
apply_plot_labels('No-show Distribution', '', '')
```

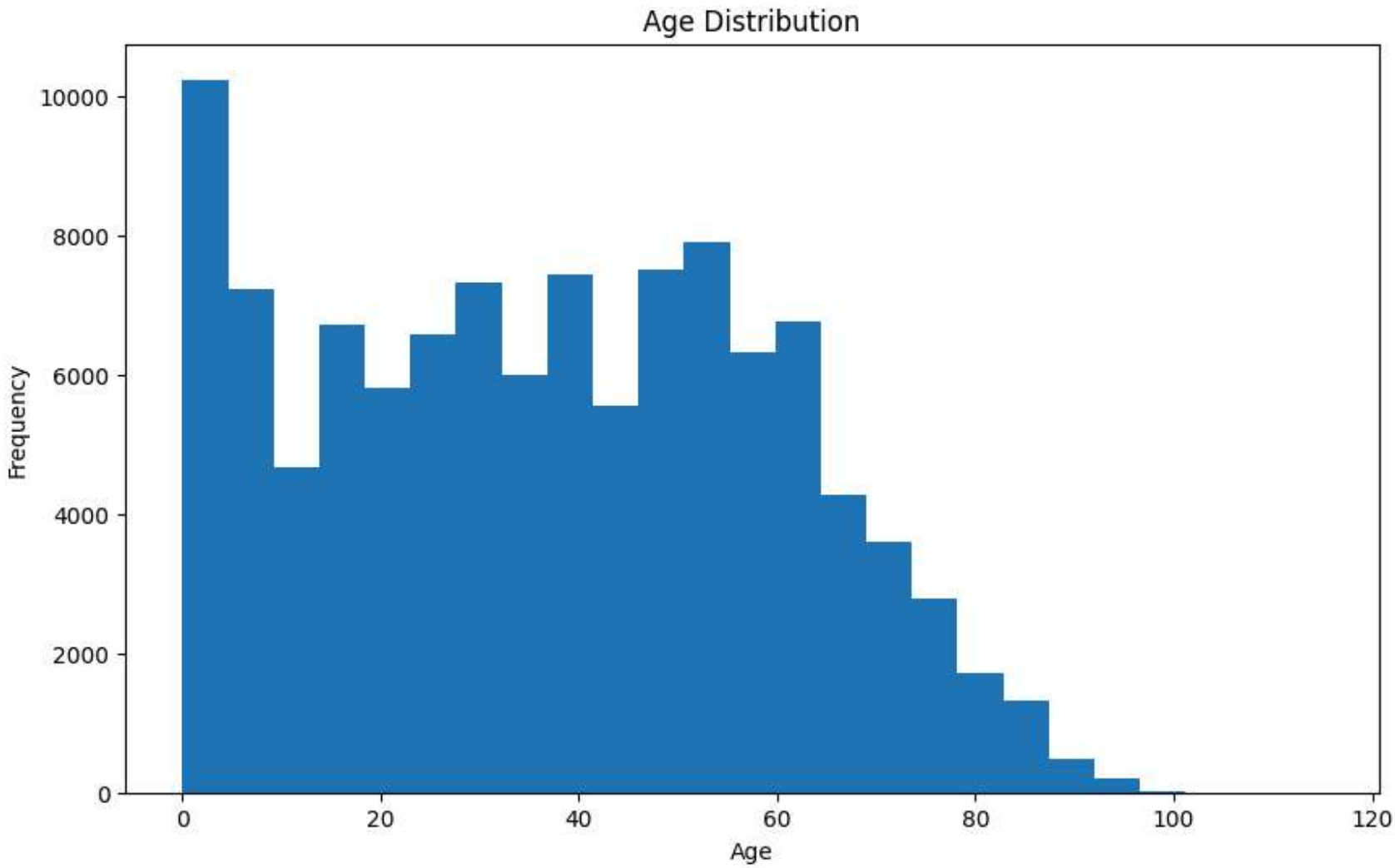


the code is analyzing the distribution of a categorical variable named no_show and rendering it as a pie chart.

A pie chart clearly shows the ratio between two categories (No vs. Yes). Here it reveals that 79.8% of appointments had no-shows while only 20.2% did not, giving an immediate visual sense of the imbalance. When you have just two categorical values, a pie chart is effective for showing their relative proportions at a glance.

In [11]:
```
ax2 = df['age'].plot(
    kind='hist',
    bins=25,
    figsize=(10, 6)
```

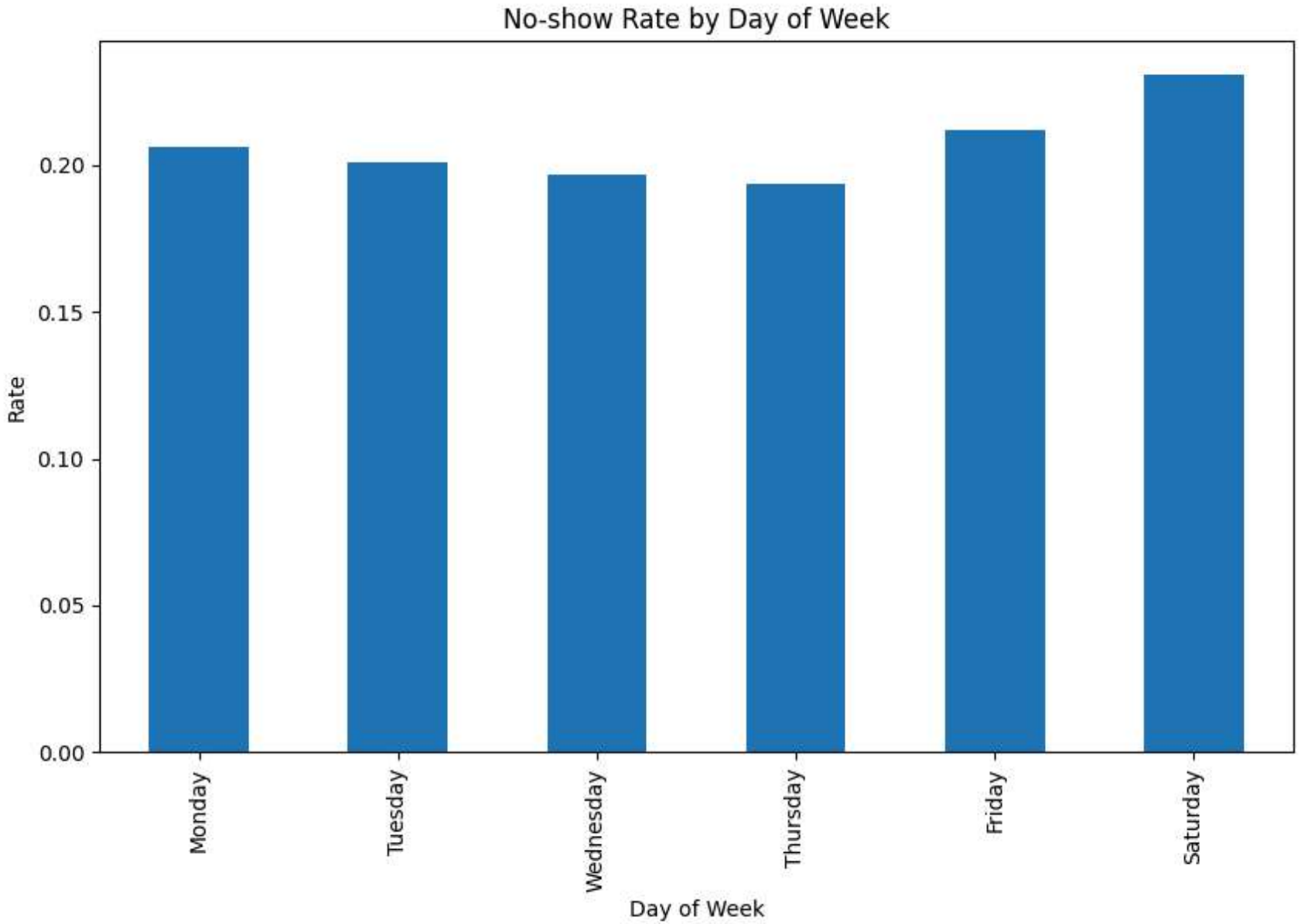
```
)

apply_plot_labels('Age Distribution', 'Age', 'Frequency')
```



the code generating a histogram to visualize the spread of ages in the dataset. A histogram was chosen because Age is a continuous numerical variable. This visualization allows us to see the shape of the distribution, identify the most common age groups, and spot any outliers

In [12]:

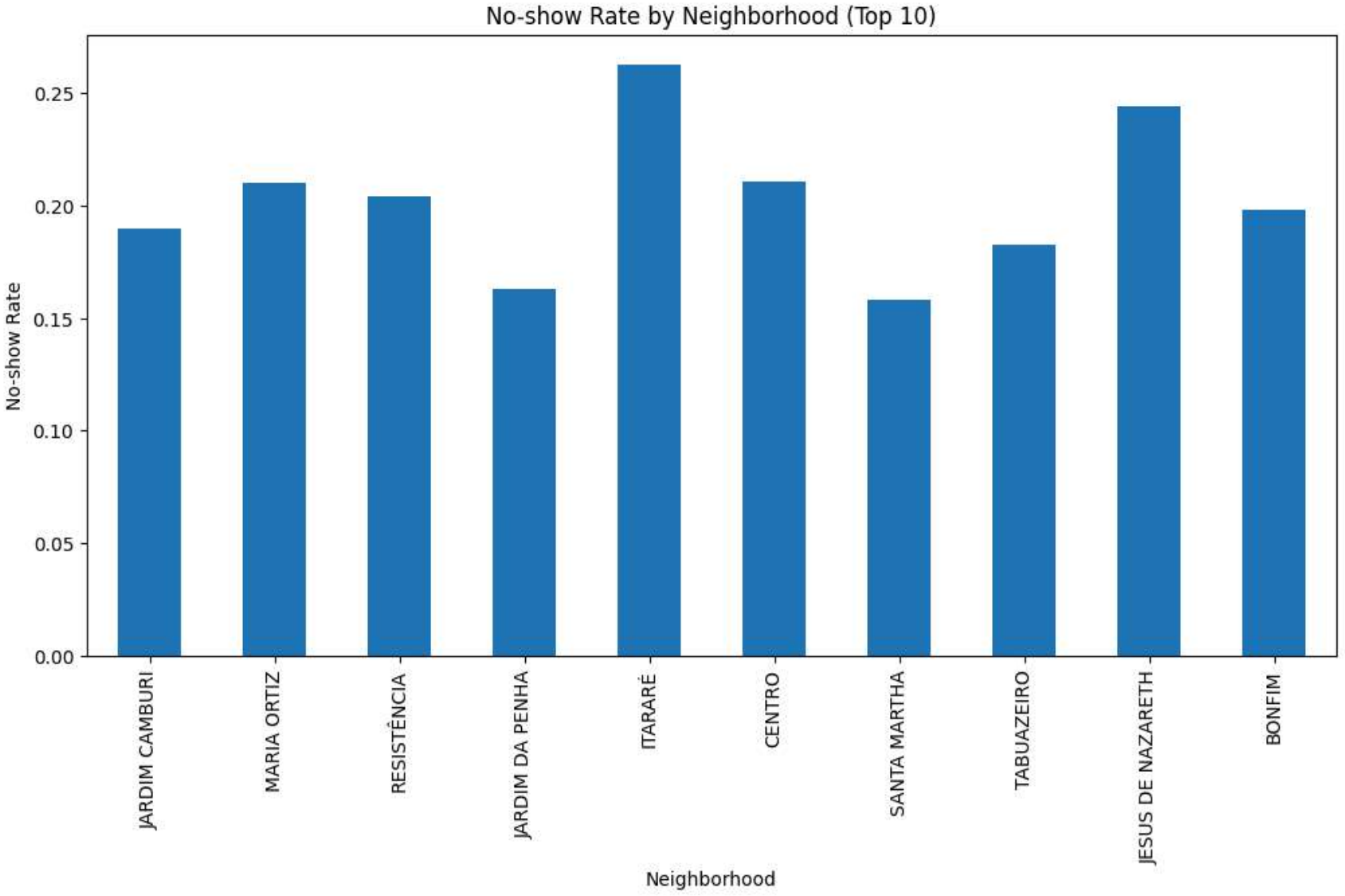
```
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday']
ax3 = df.groupby('day_of_week')['no_show_num'].mean().reindex(day_order).plot(
    kind='bar',
    figsize=(10, 6)
)

apply_plot_labels('No-show Rate by Day of Week', 'Day of Week', 'Rate')
```



the code focus from simple distributions to relational analysis. It examines how the day of the week might influence whether a person shows up for their appointment.

Days of the week are discrete/categorical data. Bar charts excel at comparing values across categories side-by-side.

In [13]:
```
top_neighborhoods = df['neighbourhood'].value_counts().nlargest(10).index
ax4 = df[df['neighbourhood'].isin(top_neighborhoods)].groupby('neighbourhood')['no_show_num'].mean().reindex(top_neig
    kind='bar',
    figsize=(12, 6)
)
apply_plot_labels('No-show Rate by Neighborhood (Top 10)', 'Neighborhood', 'No-show Rate')
```



Geographic Variance To see if location is a factor, the no-show rates were analyzed for the most active neighborhoods. Neighborhoods are categorical groups. Bar charts are ideal for comparing a metric (no-show rate) across different categories

In [14]:
```
df.to_csv('noshow_final_processed.csv', index=False)
df.head()
```

Out[14]:

	patient_id	appointment_id	gender	scheduledday	appointmentday	age	neighbourhood	scholarship	hypertension	dia
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	
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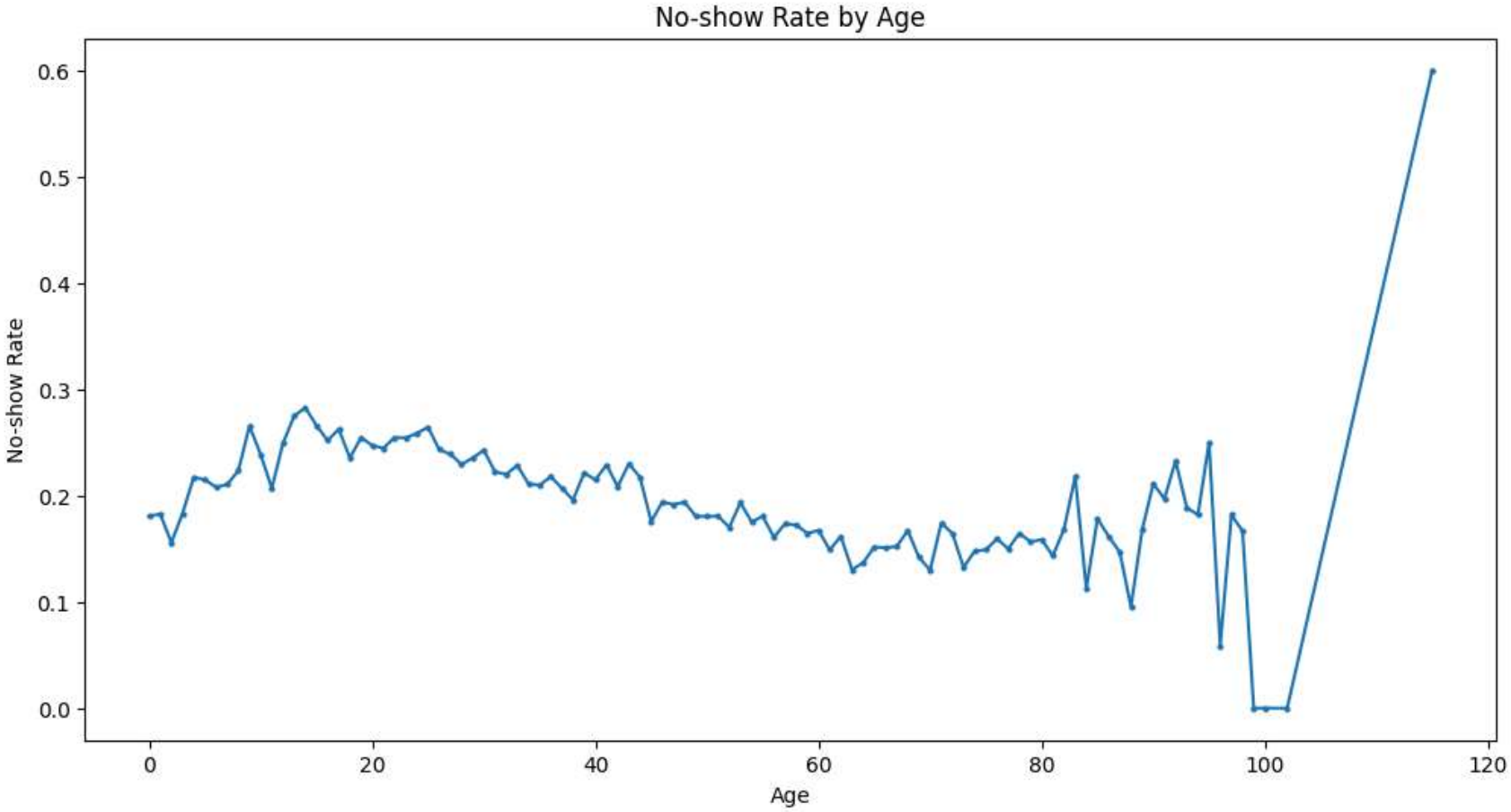
3	8.679512e+11	5642828	F	2016-04-29 17:29:31+00:00	2016-04-29 00:00:00+00:00	8	PONTAL DE CAMBURI	0	0	
4	8.841186e+12	5642494	F	2016-04-29 16:07:23+00:00	2016-04-29 00:00:00+00:00	56	JARDIM DA PENHA	0	1	

Q1 : **Age Impact:** Does a patient's age correlate with their likelihood of missing an appointment?

In [15]:
```
age_analysis = df.groupby('age')['no_show_num'].mean()

ax_age = age_analysis.plot(kind='line', figsize=(12, 6), marker='o', markersize=2)
apply_plot_labels('No-show Rate by Age', 'Age', 'No-show Rate')
```

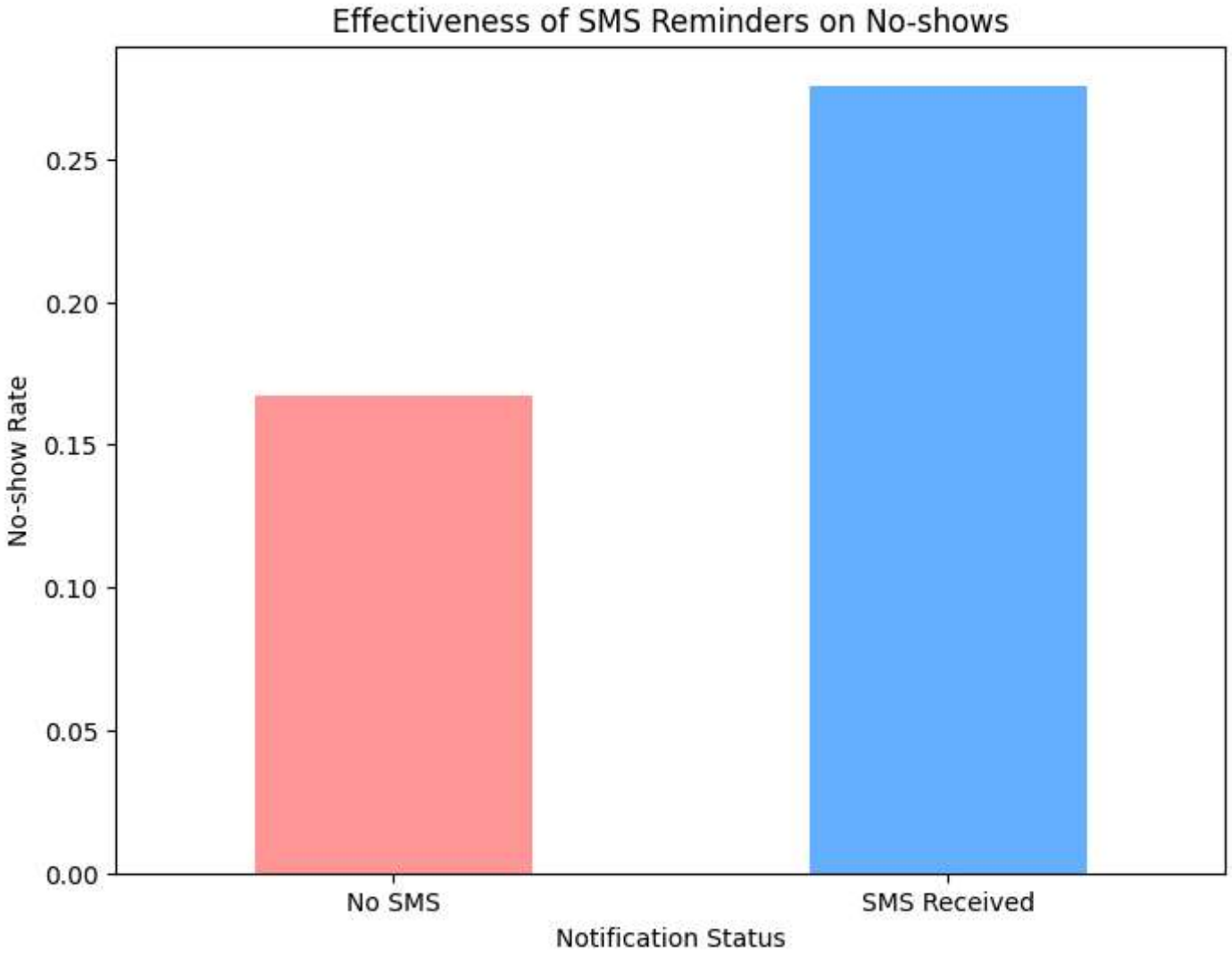


Age is continuous, and a line chart shows how no-show rates trend across the age spectrum, revealing patterns that bars wouldn't highlight as clearly.

Q2 : **SMS Reminders:** How effective are SMS notifications in reducing the number of missed appointments?

In [16]:
```
sms_analysis = df.groupby('sms_received')['no_show_num'].mean()
ax_sms = sms_analysis.plot(kind='bar', figsize=(8, 6), color=['#ff9999','#66b3ff'])
ax_sms.set_xticklabels(['No SMS', 'SMS Received'], rotation=0)
apply_plot_labels(
    'Effectiveness of SMS Reminders on No-shows',
```

```
    'Notification Status',
    'No-show Rate'
)
```



Only two categories (SMS received vs. no SMS), making a bar chart ideal for direct comparison.

Final Conclusion

In this investigation, we explored the factors influencing patient no-shows for medical appointments using a dataset of over 110,000 records. We specifically addressed two research questions:

Age Impact: Does a patient's age correlate with their likelihood of missing an appointment?

SMS Reminders: How effective are SMS notifications in reducing the number of missed appointments?

Age and Attendance: Younger patients and infants are more likely to miss appointments; no-show rates decrease with age.

Waiting Time Impact: Longer gaps between booking and appointment increase no-show likelihood; same-day appointments have the highest attendance.

SMS Effectiveness: Patients who received SMS reminders showed higher no-show rates, likely because reminders were sent for appointments with longer waiting times rather than the SMS causing the absence.

Further Research

Socioeconomic and Geographic Factors: While the current analysis looks at individual patient variables, a deeper dive into the neighbourhood and scholarship features could be revealing. Future research could explore whether no-show rates are significantly higher in specific neighborhoods and if those areas correlate with lower socioeconomic status or limited access to public transportation.

Predictive Modeling: The current project focuses on descriptive analysis and identifying correlations. A logical next step would be to develop a machine learning model to predict the probability of a no-show for a given appointment. This would move from understanding "what happened" to predicting "what might happen," allowing clinics to proactively manage their schedules.

Time-of-Day Analysis: The scheduledday column contains timestamp information. Investigating whether appointments scheduled early in the morning versus late in the afternoon have different no-show rates could provide actionable insights for clinic staffing and scheduling.

Limitations

Limited Scope: The dataset covers only public clinics in Brazil during May 2016, limiting generalizability across regions, cultures, and seasons.

Correlation vs. Causation: The analysis shows relationships between variables and no-show rates but cannot establish causality (e.g., higher no-shows among SMS recipients likely reflect longer waiting times, not the effect of SMS itself).

Incomplete Data: Important factors affecting attendance—such as employment status, weather, and medical specialty—are missing, and some variables (like handicap levels) lack clear definitions.

Cleaning Assumptions: Removing records with invalid ages (e.g., -1) corrects errors but assumes they are random and not systematic.

In [ ]:
```
!python -m nbconvert --to html project.ipynb
```

```
[NbConvertApp] Converting notebook project.ipynb to html
[NbConvertApp] WARNING | Alternative text is missing on 6 image(s).
[NbConvertApp] Writing 522752 bytes to project.html
```