In [1]:
```
import sqlite3
import pandas as pd
import seaborn as sns
import numpy as np
from matplotlib import pyplot as plt
```

1. Load the Data (sql db)

In [2]:
```
con = sqlite3.connect("bmarket.db")
```

In [3]:
```
cursor = con.cursor()

        # Query the sqlite_master table to get table names
cursor.execute("SELECT name FROM sqlite_master WHERE type='table';")

        # Fetch all results
table_names = [row[0] for row in cursor.fetchall()]
print("Tables in the database:", table_names)
```

```
Tables in the database: ['bank_marketing']
```

In [4]:
```
query = "SELECT * FROM bank_marketing"
df = pd.read_sql_query(query, con)

con.close()

df.head()
```

Out[4]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	Conta Meth
0	32885	57 years	technician	married	high.school	no	no	yes	C
1	3170	55 years	unknown	married	unknown	unknown	yes	no	telepho
2	32207	33 years	blue-collar	married	basic.9y	no	no	no	cellu
3	9404	36 years	admin.	married	high.school	no	no	no	Telepho
4	14021	27 years	housemaid	married	high.school	no	None	no	C

2. Initial Data Understanding

We first need to inspect the dataset, to gain a better understanding of what we are working with.

This includes:

-Number of rows & columns

-Column names & data types

-Summary of the statistics using .describe()

-Outliers/Data quality issues

In [5]:
```
df.columns
```

Out[5]:
```
Index(['Client ID', 'Age', 'Occupation', 'Marital Status', 'Education Level',
       'Credit Default', 'Housing Loan', 'Personal Loan', 'Contact Method',
       'Campaign Calls', 'Previous Contact Days', 'Subscription Status'],
      dtype='object')
```

In [6]:
```
df.shape
```

Out[6]:
```
(41188, 12)
```

By looking at the results from "df.describe(include='all').T", we immediately make a few observations:

-Under the 'top' result for the Age feature, it shows the highest age being 150 years old. As of now, the oldest person alive is 116 years old & the oldest ever recorded was 122. We need to dive into this later and verify the information

In [7]:
```
df.describe(include='all').T
```

Out[7]:

	count	unique	top	freq	mean	std	min
Client ID	41188.0	NaN	NaN	NaN	20594.5	11890.09578	1.0
Age	41188	77	150 years	4197	NaN	NaN	NaN
Occupation	41188	12	admin.	10422	NaN	NaN	NaN
Marital Status	41188	4	married	24928	NaN	NaN	NaN
Education Level	41188	8	university.degree	12168	NaN	NaN	NaN
Credit Default	41188	3	no	32588	NaN	NaN	NaN
Housing Loan	16399	3	yes	8595	NaN	NaN	NaN
Personal Loan	37042	3	no	30532	NaN	NaN	NaN
Contact Method	41188	4	Cell	13100	NaN	NaN	NaN
Campaign Calls	41188.0	NaN	NaN	NaN	2.051374	3.171345	-41.0
Previous Contact Days	41188.0	NaN	NaN	NaN	962.475454	186.910907	0.0
Subscription Status	41188	2	no	36548	NaN	NaN	NaN

Insights from running .duplicated().sum()

There are no duplicated entries inside the dataset, this helps to ensure reliable data that does not skew predictions

In [8]:
```
df.duplicated().sum()
```

Out[8]:
```
np.int64(0)
```

Insights from running .info()

There is 1 column currently stored as the 'object' type that is using the wrong data type, and needs to be changed:
-Age

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Client ID               41188 non-null  int64 
 1   Age                     41188 non-null  object
 2   Occupation              41188 non-null  object
 3   Marital Status          41188 non-null  object
 4   Education Level         41188 non-null  object
 5   Credit Default          41188 non-null  object
 6   Housing Loan            16399 non-null  object
 7   Personal Loan           37042 non-null  object
 8   Contact Method          41188 non-null  object
 9   Campaign Calls          41188 non-null  int64 
 10  Previous Contact Days   41188 non-null  int64 
 11  Subscription Status     41188 non-null  object
dtypes: int64(3), object(9)
memory usage: 3.8+ MB
```

In [10]:
```python
df.isna().sum()
```

Out[10]:
```
Client ID                    0
Age                          0
Occupation                   0
Marital Status               0
Education Level              0
Credit Default               0
Housing Loan             24789
Personal Loan             4146
Contact Method               0
Campaign Calls               0
Previous Contact Days        0
Subscription Status          0
dtype: int64
```

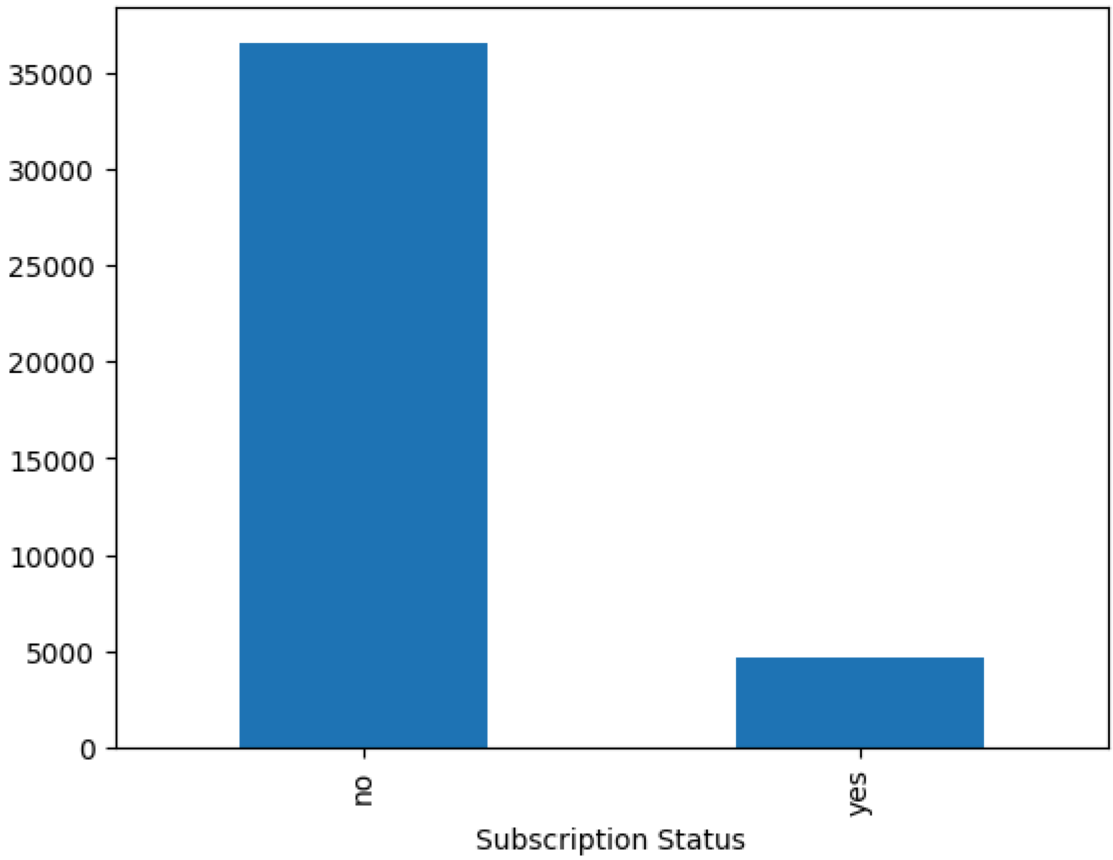
Check the target column for distribution

Insights

There is a very high class imbalance, hence we need to consider SMOTE or UnderSampling when training our model.

In [11]:
```python
df['Subscription Status'].value_counts().plot(kind='bar')
df['Subscription Status'].value_counts()/df.shape[0]
```

Out[11]:
```
Subscription Status
no     0.887346
yes    0.112654
Name: count, dtype: float64
```



(2a) Column by Column Data Understanding & Insights

Data Understanding & Insights for Client ID
From the description of Client ID, we can see that it is a unique identifier for each client.
This identifier column does not contain any missing values (41188 non-null values), which is equal to the total number of records in the dataset (41188).

In [12]:
```
display(df["Client ID"].nunique())
display(df["Client ID"].isna().sum())
display(df["Client ID"].describe())
```

```
41188
np.int64(0)
count    41188.00000
mean     20594.50000
std      11890.09578
min          1.00000
25%      10297.75000
50%      20594.50000
75%      30891.25000
max      41188.00000
Name: Client ID, dtype: float64
```

Data Understanding & Insights for Age

The "Age" feature in this dataset is stored as text, so it appears as an 'object' type.
There are 77 unique ages
The age "150 years" happens to appear in this dataset 4197 times, which is extremely unrealistic. The oldest person alive right now is 116 years old, which further solidifies the fact that there cannot be that many people who are significantly older.

Hence, we will treat this value as an outlier

The next oldest age after ""150 years" is "95 years", which is much more realistic.

In [13]:
```
display(df["Age"].dtype)
display(df["Age"].value_counts())
```

```
dtype('O')
Age
150 years    4197
31 years     1747
32 years     1646
33 years     1643
36 years     1606
             ...
92 years        4
89 years        2
91 years        2
98 years        2
95 years        1
Name: count, Length: 77, dtype: int64
```

In [14]:
```
print("The number of unique ages is",df["Age"].nunique())
```

```
The number of unique ages is 77
```

In [15]:
```
display(df["Age"].value_counts().sort_index(ascending=False).head(10))
display(df["Age"].value_counts().sort_index(ascending=False).tail(10))
```

```
Age
98 years     2
95 years     1
92 years     4
91 years     2
89 years     2
88 years    19
86 years     8
85 years    15
84 years     7
83 years    16
Name: count, dtype: int64
Age
25 years      536
24 years      414
23 years      207
22 years      123
21 years       90
20 years       62
19 years       38
18 years       27
17 years        5
150 years    4197
Name: count, dtype: int64
```

Data Understanding & Insights for Occupation

This feature has a total of 12 different categories, with zero missing values.

As this class is a categorical feature, we can use one-hot encoding.

Later on during the bivariate analysis, we will be able to check how the different occupations can affect the subscription rates.

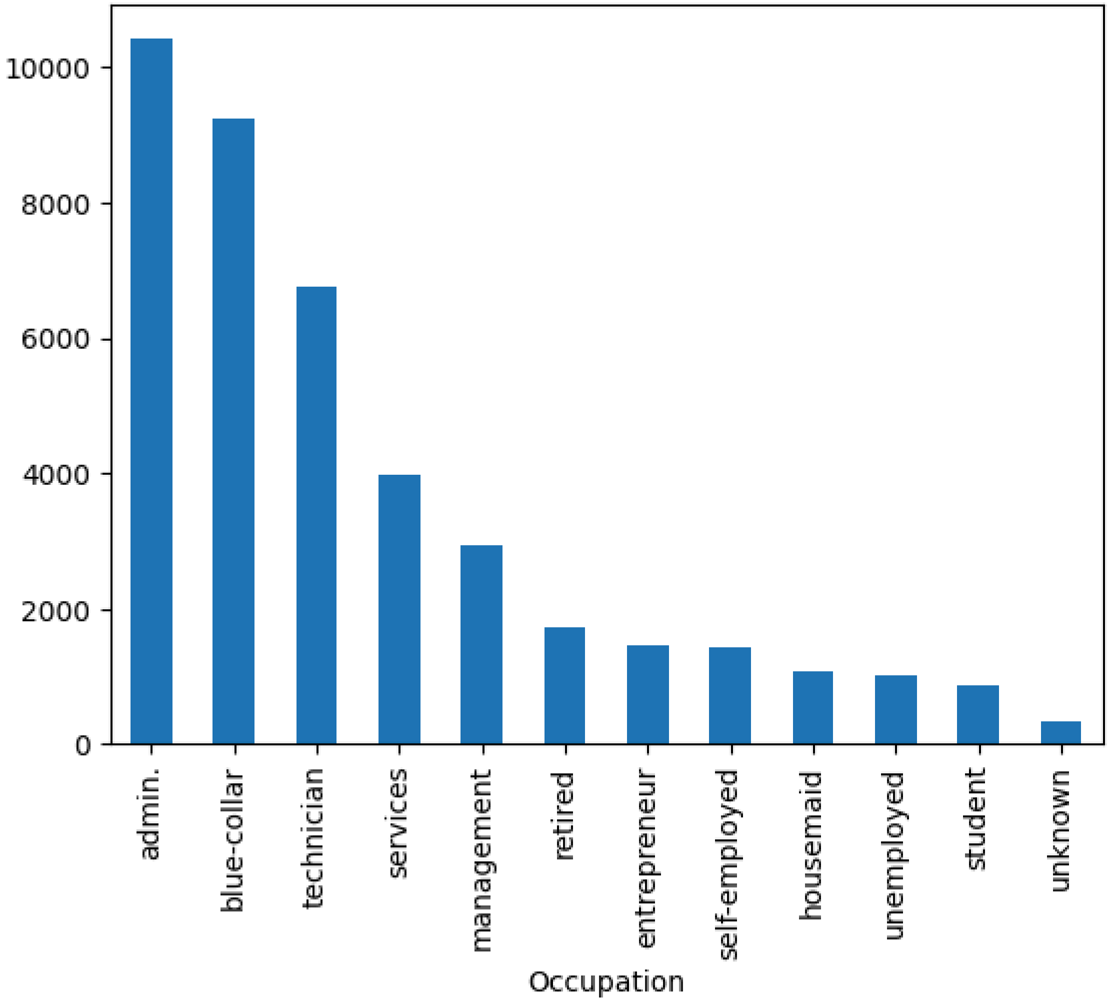
In [16]:
```
print("The number of occupations in this dataset is",df["Occupation"].nunique())
df["Occupation"].value_counts()
```

```
The number of occupations in this dataset is 12
```

Out[16]:
```
Occupation
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: count, dtype: int64
```

In [17]:
```
df['Occupation'].value_counts().plot(kind='bar')
df['Occupation'].info()
plt.show()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 41188 entries, 0 to 41187
Series name: Occupation
Non-Null Count  Dtype
--------------  -----
41188 non-null  object
dtypes: object(1)
memory usage: 321.9+ KB
```



Data Understanding & Insights for Marital Status

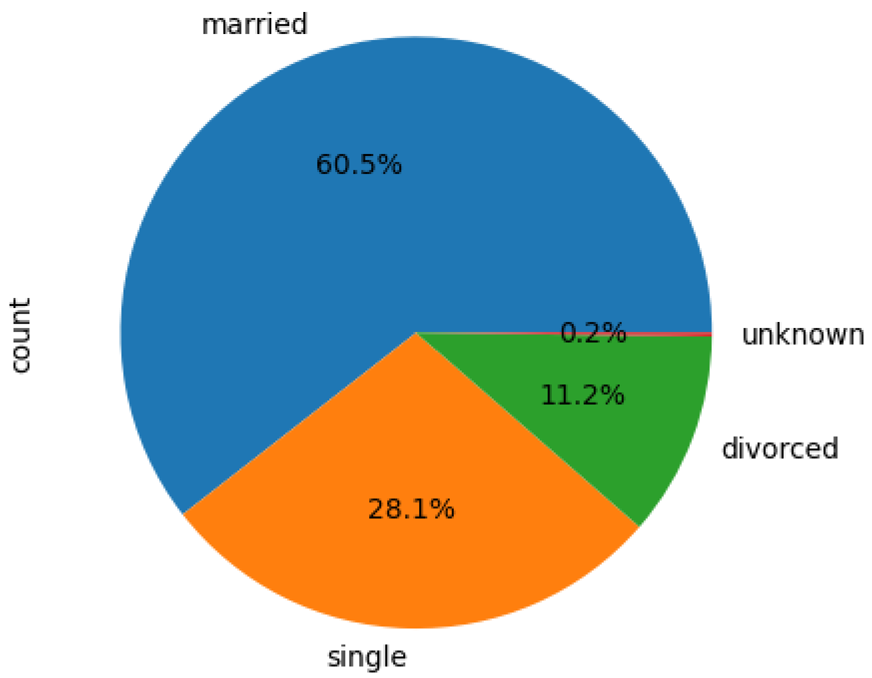
This feature has a total of 4 different categories, with zero missing values.
Similarly to the "Occupation" column, this class is a categorical feature, so we can use one-hot encoding.
Later on during the bivariate analysis, we will be able to check how the different marital statuses can affect the subscription rates.
It is particularly useful, as marital status can definitely influence financial decisions due to differing priorities and interests.

In [18]:
```
display(df["Marital Status"].value_counts())
display(df["Marital Status"].value_counts()/df.shape[0]*100)
```

```
Marital Status
married     24928
single      11568
divorced     4612
unknown        80
Name: count, dtype: int64
Marital Status
married     60.522482
single      28.085850
divorced    11.197436
unknown      0.194231
Name: count, dtype: float64
```

In [19]:
```python
df['Marital Status'].value_counts().plot(kind='pie', autopct='%1.1f%%')
df['Marital Status'].info()
plt.show()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 41188 entries, 0 to 41187
Series name: Marital Status
Non-Null Count  Dtype
--------------  -----
41188 non-null  object
dtypes: object(1)
memory usage: 321.9+ KB
```



Data Understanding & Insights for Education Level

This feature has a total of 8 different categories, with zero missing values.
This class is also a categorical feature, so we can use one-hot encoding.
Later on during the bivariate analysis, we will be able to check how the different education levels can affect the subscription rates.
Statistically, education generally correlates with income and financial literacy, which could affect the likelihood of individuals subscribing to the term deposit plan.

In [20]:
```python
print("The number of different Education Levels in this dataset is",df["Educatic
df["Education Level"].value_counts()
```

```
The number of different Education Levels in this dataset is 8
```

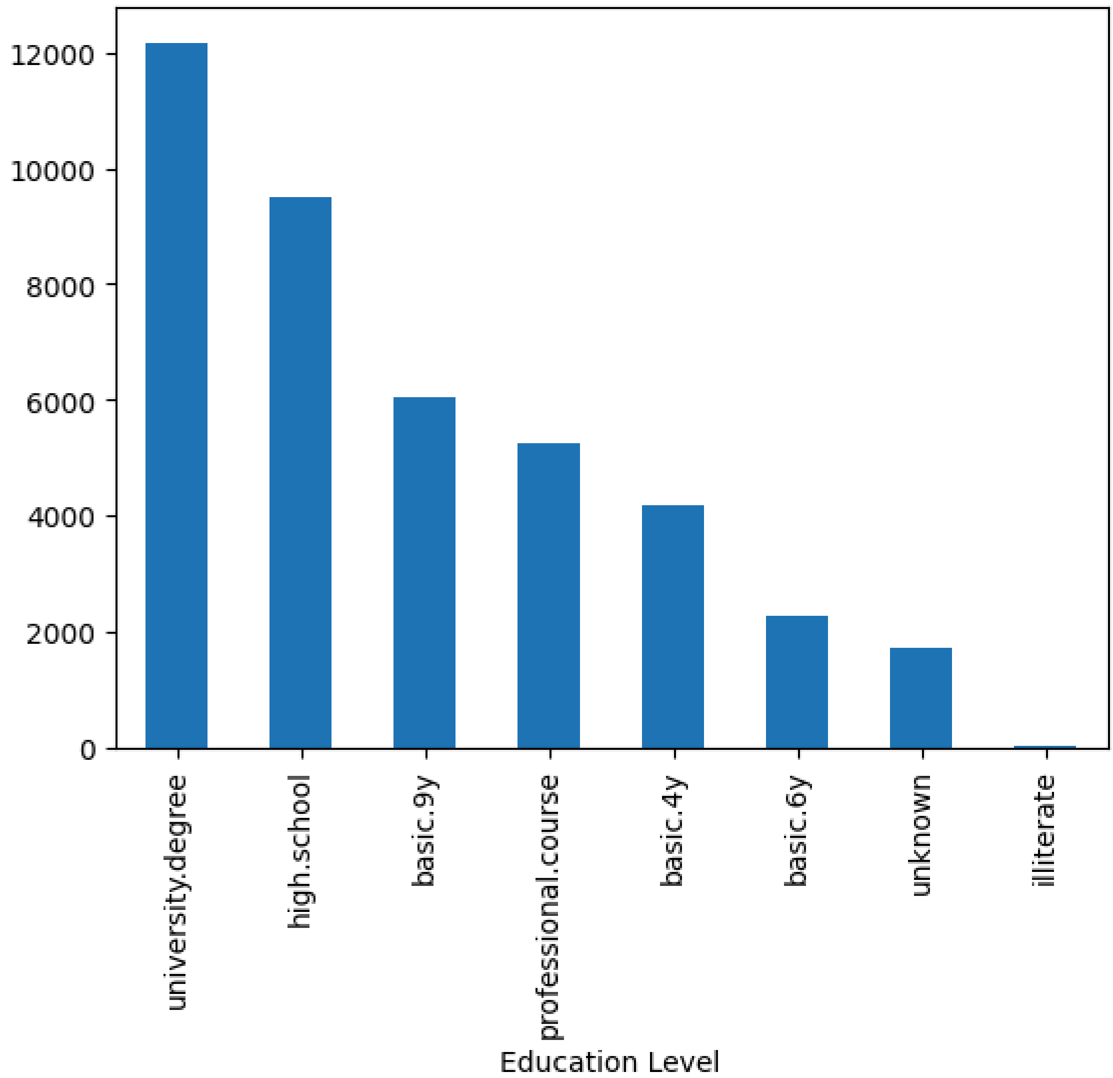
Out[20]:
```
Education Level
university.degree      12168
high.school             9515
basic.9y                6045
professional.course     5243
basic.4y                4176
basic.6y                2292
unknown                 1731
illiterate                18
Name: count, dtype: int64
```

In [21]:
```
df[df["Education Level"]=="illiterate"]["Subscription Status"].head()
```

Out[21]:
```
3824     no
5446     no
5742    yes
6342     no
8213     no
Name: Subscription Status, dtype: object
```

In [22]:
```
df['Education Level'].value_counts().plot(kind='bar')
df['Education Level'].info()
plt.show()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 41188 entries, 0 to 41187
Series name: Education Level
Non-Null Count  Dtype
--------------  -----
41188 non-null  object
dtypes: object(1)
memory usage: 321.9+ KB
```



Data Understanding & Insights for Credit Default

This feature has a total of 3 different categories, with zero missing values. However there is a decently large number of the "unknown" class
There is an extreme imbalance of data for this column, as seen below, where there are only three instances of "yes", which is 0.007% of the data.
We will need to consider how we use the "yes" class later on, due to its scarcity.

In [23]:
```
display(df["Credit Default"].value_counts())
display(df["Credit Default"].value_counts()/df.shape[0]*100)
```

```
Credit Default
no         32588
unknown     8597
yes            3
Name: count, dtype: int64
Credit Default
no         79.120132
unknown    20.872584
yes         0.007284
Name: count, dtype: float64
```

Data Understanding & Insights for Housing Loan

This feature has a total of 3 different categories.
There is a large number of null values for this column (24789), which is ~60% of the data.
We will need to consider how we classify the null values later on, due to how much of the data it constitutes.

In [24]:
```
display(df["Housing Loan"].isna().sum())
display(df["Housing Loan"].isna().sum()/df.shape[0]*100)
display(df["Housing Loan"].value_counts())
```

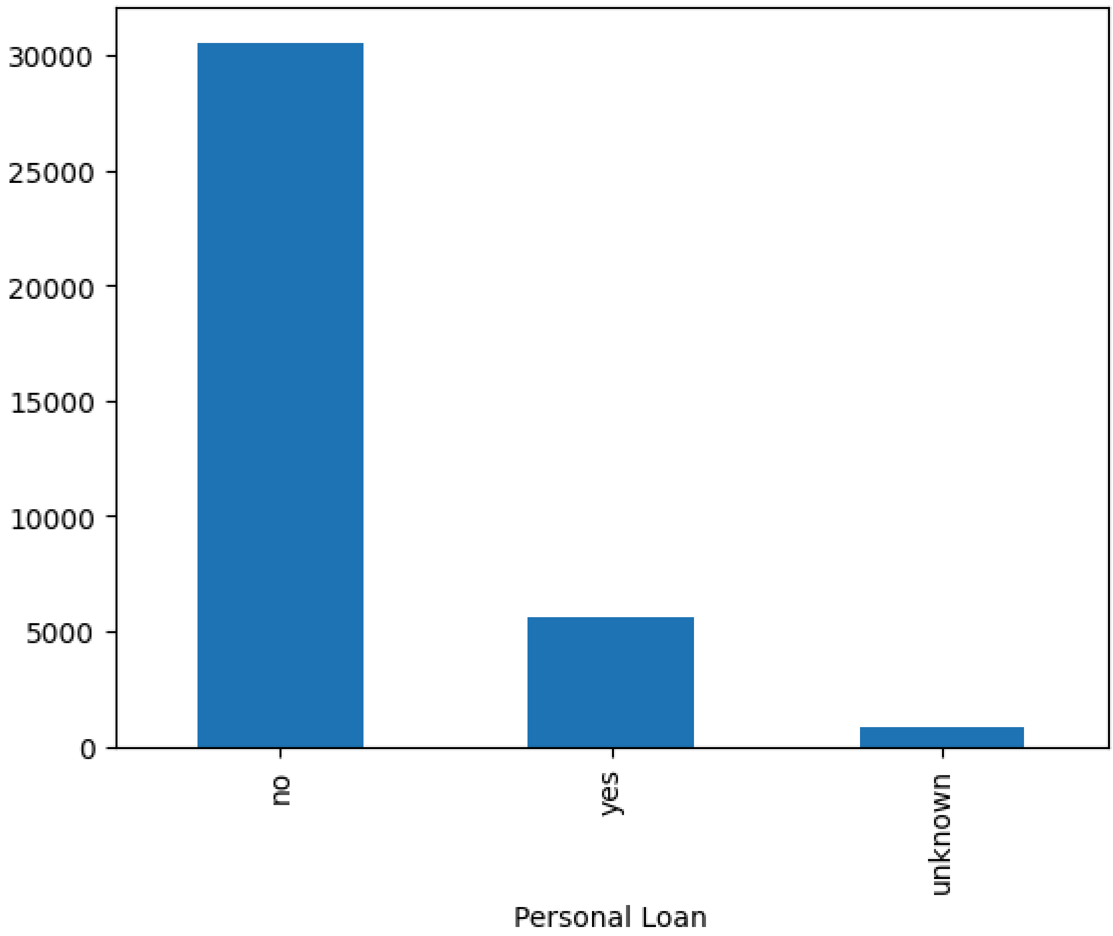
```
np.int64(24789)
np.float64(60.18500534136157)
Housing Loan
yes        8595
no         7411
unknown     393
Name: count, dtype: int64
```

Data Understanding & Insights for Personal Loan

This feature has a total of 3 different categories.
Similar to the previous column, Housing Loan, there are null values for this column (4146), which is ~10% of the data.
This feature will be useful as having personal loan(s) could indicate that the person already has financial commitments and this could reduce the likeliness of them subscribing to a new term deposit. We will need to consider how we classify the null values later on.

In [25]:
```
display(df["Personal Loan"].isna().sum())
display(df["Personal Loan"].isna().sum()/df.shape[0]*100)
display(df["Personal Loan"].value_counts())
display(df["Personal Loan"].value_counts()/df.shape[0]*100)
display(df["Personal Loan"].value_counts().plot(kind='bar'))
```

```
np.int64(4146)
np.float64(10.066038652034573)
Personal Loan
no         30532
yes         5633
unknown      877
Name: count, dtype: int64
Personal Loan
no         74.128387
yes        13.676313
unknown     2.129261
Name: count, dtype: float64
<Axes: xlabel='Personal Loan'>
```

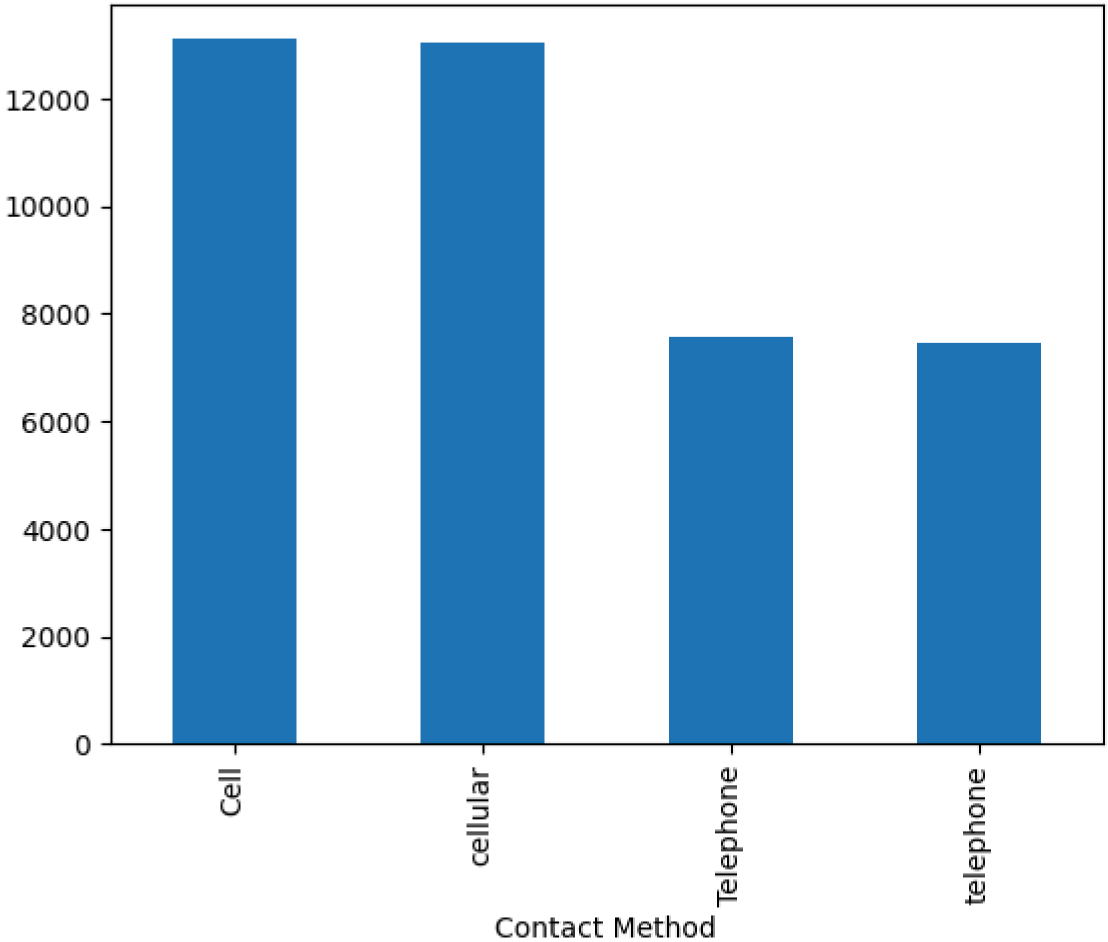


Data Understanding & Insights for Contact Method

This feature has a total of 4 different categories, with zero missing values.
This class is also a categorical feature, so we can use one-hot encoding.
However, it seems that the categories are inconsistent:
-Cell & cellular
-Telephone & telephone
Before encoding, we will standardise the data by combining these into fewer categories as they have the same meanings.

In [26]:
```
df["Contact Method"].value_counts()
df["Contact Method"].value_counts().plot(kind='bar')
```

Out[26]:
```
<Axes: xlabel='Contact Method'>
```



Data Understanding & Insights for Campaign Calls

This feature has zero missing values.
By looking at the output from the describe function, we can make some interesting insights:
-The maximum value is 56 calls, meaning there are some outliers with heavy-contact
-The minimum value is -41 calls, which is definitely an error as it is impossible to have negative calls

Upon closer inspection, there are multiple values in this feature with a negative value. These invalid values need to be handled later by adjusting rows where the "Campaign Calls" is less than zero.

In [27]:
```
display(df["Campaign Calls"].value_counts())
display(df["Campaign Calls"].describe())
```

```
Campaign Calls
 1      15874
 2       9446
 3       4807
 4       2405
-1       1768
        ...
 56         1
-41         1
 39         1
 37         1
-25         1
Name: count, Length: 70, dtype: int64
count    41188.000000
mean         2.051374
std          3.171345
min        -41.000000
25%          1.000000
50%          2.000000
75%          3.000000
max         56.000000
Name: Campaign Calls, dtype: float64
```

In [28]:
```python
display(df["Campaign Calls"].value_counts().sort_index(ascending=False).head(10))
display(df["Campaign Calls"].value_counts().sort_index(ascending=False).tail(10))
```

```
Campaign Calls
56     1
43     2
42     2
40     2
39     1
37     1
35     3
34     3
33     4
32     3
Name: count, dtype: int64
Campaign Calls
-20     3
-21     2
-22     3
-23     5
-25     1
-28     2
-29     1
-32     1
-35     2
-41     1
Name: count, dtype: int64
```

Data Understanding & Insights for Previous Contact Days

This feature has zero missing values.
Majority of the values in this feature are "999"
The project guide has stated that "999" means there has been no previous contact
However leaving this as a numerical value of 999 will heavily skew and distort the actual statistics.
Hence, we will create a different feature to address this later.

```
In [29]: display(df["Previous Contact Days"].value_counts().sort_index(ascending=False).h
         display(df["Previous Contact Days"].value_counts().sort_index(ascending=False).t
```

```
Previous Contact Days
999    39673
27         1
26         1
25         1
22         3
21         2
20         1
19         3
18         7
17         8
Name: count, dtype: int64
Previous Contact Days
9     64
8     18
7     60
6    412
5     46
4    118
3    439
2     61
1     26
0     15
Name: count, dtype: int64
```

Further Insights for the distribution of Subscription Status

Looking further into this feature, we can see that the no to yes ratio nearly reaches a 9:1. This shows that this dataset is heavily imbalanced and skewed.
When training our models during the pipeline, we definitely take some factors into consideration, such as:

-Proper sampling

-Appropriate metrics

-Assigning weights to the data

```
In [30]: df["Subscription Status"].value_counts()
         percentage_wise=df["Subscription Status"].value_counts()/df.shape[0]*100
         print(percentage_wise)
```

```
Subscription Status
no     88.734583
yes    11.265417
Name: count, dtype: float64
```

(3) Handling the null values / incorrect values / outliers

In order to convert the string inside the "Age" column into integer values, we must do the following:

```
In [31]: df["Age_numerical"]=(df["Age"].str.replace('years', '', regex=False).astype('int
```

For this next part, we addressed the outlier age of "150", by imputing the value using the median age. Firstly, we are commonly taught to drop the values if it is 5% of the total number of observations. However the total number of instances where the age is equal to 150 is ~10%, hence we decided on using imputation of values. Next we had to choose between median and mean imputation. Median imputation was chosen as the ages goes all the way up to 98 and median is more stable than mean, as it will not skew the cleaned dataset as much.

In [32]:
```
df_150=df[df["Age"]=="150 years"]
print(df_150.head(50))
```

	Client ID	Age	Occupation	Marital Status	Education Level	\
7	23758	150 years	admin.	divorced	university.degree	
13	21872	150 years	admin.	married	university.degree	
17	17689	150 years	technician	married	professional.course	
51	38203	150 years	retired	married	high.school	
59	29732	150 years	blue-collar	married	basic.4y	
61	4501	150 years	admin.	single	university.degree	
67	1632	150 years	admin.	married	high.school	
73	35637	150 years	services	single	high.school	
77	24445	150 years	admin.	single	high.school	
82	4244	150 years	blue-collar	married	basic.4y	
83	13927	150 years	services	single	high.school	
89	8086	150 years	blue-collar	married	basic.4y	
94	38325	150 years	services	married	basic.9y	
106	2001	150 years	self-employed	married	university.degree	
120	11097	150 years	technician	single	professional.course	
125	22364	150 years	blue-collar	married	basic.4y	
127	13029	150 years	admin.	single	professional.course	
129	10099	150 years	services	married	high.school	
135	15045	150 years	technician	divorced	high.school	
143	35754	150 years	admin.	divorced	high.school	
144	9591	150 years	technician	single	basic.9y	
147	22847	150 years	technician	married	university.degree	
150	37978	150 years	technician	married	professional.course	
164	13416	150 years	technician	married	university.degree	
166	33667	150 years	self-employed	single	professional.course	
183	20191	150 years	self-employed	married	university.degree	
189	40164	150 years	retired	divorced	basic.4y	
199	9255	150 years	technician	married	basic.9y	
212	24204	150 years	unemployed	married	university.degree	
219	29527	150 years	blue-collar	married	basic.9y	
223	41101	150 years	admin.	married	university.degree	
226	2005	150 years	entrepreneur	married	high.school	
246	37873	150 years	technician	single	professional.course	
270	9507	150 years	management	married	basic.4y	
279	14929	150 years	blue-collar	married	basic.4y	
294	26167	150 years	management	single	high.school	
304	1431	150 years	blue-collar	married	basic.6y	
305	13207	150 years	services	single	high.school	
306	21013	150 years	technician	married	professional.course	
315	11844	150 years	admin.	divorced	high.school	
317	24855	150 years	admin.	married	university.degree	
319	38125	150 years	management	married	university.degree	
322	37512	150 years	blue-collar	married	basic.9y	
344	28487	150 years	self-employed	married	university.degree	
373	20413	150 years	admin.	married	university.degree	
378	12958	150 years	blue-collar	divorced	basic.9y	
382	10931	150 years	admin.	married	university.degree	
392	28752	150 years	blue-collar	married	basic.4y	
395	24511	150 years	housemaid	married	university.degree	
402	5750	150 years	services	single	basic.9y	

	Credit Default	Housing Loan	Personal Loan	Contact Method	Campaign Calls	\
7	unknown	yes	None	Cell	7	
13	no	no	no	Cell	3	
17	no	None	yes	cellular	-11	
51	no	None	no	cellular	1	
59	unknown	None	no	cellular	1	
61	no	None	no	telephone	1	
67	no	None	no	Telephone	2	

73	no	None	no	Cell	6
77	no	None	no	cellular	1
82	no	yes	yes	Telephone	2
83	no	None	None	Cell	2
89	unknown	None	no	Telephone	2
94	no	None	no	Telephone	1
106	no	None	no	telephone	5
120	unknown	None	yes	Telephone	1
125	no	None	no	Cell	1
127	no	yes	yes	Cell	3
129	unknown	no	no	telephone	1
135	no	no	no	Cell	1
143	no	None	no	Telephone	2
144	no	None	no	Telephone	3
147	no	None	no	cellular	2
150	no	None	no	cellular	1
164	no	None	unknown	Telephone	1
166	no	None	no	cellular	2
183	no	None	None	cellular	2
189	no	None	no	Cell	2
199	no	no	no	Telephone	-2
212	no	None	unknown	Cell	1
219	unknown	None	yes	Cell	5
223	no	None	no	cellular	1
226	no	yes	no	Telephone	2
246	no	yes	no	Cell	1
270	no	no	None	telephone	2
279	unknown	yes	no	Cell	4
294	no	yes	yes	Cell	2
304	unknown	None	no	Telephone	2
305	no	None	no	cellular	-1
306	no	no	yes	Cell	2
315	no	no	no	telephone	3
317	no	no	no	cellular	1
319	no	yes	no	cellular	1
322	no	None	no	cellular	1
344	no	None	no	Cell	2
373	no	None	yes	Cell	1
378	no	None	no	cellular	1
382	no	yes	no	Telephone	5
392	no	None	no	cellular	1
395	no	None	no	cellular	1
402	no	None	no	telephone	-2

	Previous Contact Days	Subscription Status	Age_numerical
7	999	no	150
13	999	yes	150
17	999	no	150
51	999	no	150
59	999	no	150
61	999	no	150
67	999	no	150
73	999	no	150
77	999	no	150
82	999	no	150
83	999	no	150
89	999	no	150
94	999	yes	150
106	999	no	150
120	999	no	150

125	999	no	150
127	999	no	150
129	999	no	150
135	999	no	150
143	999	no	150
144	999	no	150
147	999	no	150
150	999	no	150
164	999	no	150
166	999	yes	150
183	999	no	150
189	6	yes	150
199	999	no	150
212	999	no	150
219	999	no	150
223	12	yes	150
226	999	no	150
246	999	no	150
270	999	no	150
279	999	no	150
294	6	no	150
304	999	no	150
305	999	no	150
306	999	no	150
315	999	no	150
317	999	no	150
319	999	no	150
322	999	no	150
344	999	yes	150
373	999	no	150
378	999	no	150
382	999	no	150
392	999	no	150
395	999	no	150
402	999	no	150

In [33]:
```
df["Age_Invalid"] = (df["Age_numerical"] == 150).astype('int')
valid_median_age=df.loc[df["Age_numerical"]!=150,"Age_numerical"].median()
df.loc[df["Age_numerical"]==150,"Age_numerical"]= valid_median_age
df["Age_numerical"].describe()
```

Out[33]:
```
count    41188.000000
mean        39.818928
std          9.909692
min         17.000000
25%         33.000000
50%         38.000000
75%         46.000000
max         98.000000
Name: Age_numerical, dtype: float64
```

Handling of unknown values in the "Occupation" Column

When inspecting the "Housing Loan" column, we can see that there are many different categories.
We have decided to remove the unknown values here alone as it constitutes to a very small minority of the data and we cannot combine it with another feature as there is no correlation.

Unlike unknown, we can keep the other categories, as we can combine them into larger groups later on for analysis.
The difference between unknown and the rest, is that unknown carries 0 value by itself

In [34]:
```
df["Occupation"].value_counts()
```

Out[34]:
```
Occupation
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
unknown            330
Name: count, dtype: int64
```

In [35]:
```
df=df[df["Occupation"]!="unknown"]
df["Occupation"].value_counts()
```

Out[35]:
```
Occupation
admin.           10422
blue-collar       9254
technician        6743
services          3969
management        2924
retired           1720
entrepreneur      1456
self-employed     1421
housemaid         1060
unemployed        1014
student            875
Name: count, dtype: int64
```

Handling of unknown values in the "Marital Status" Column

When inspecting the "Housing Loan" column, we can see that there are 4 different categories, "married", "single", "unknown" and "divorced".
We have decided to remove the unknown values here alone as it constitutes to a very small minority of the data.

In [36]:
```
df=df[df["Marital Status"]!="unknown"]
df["Marital Status"].value_counts()
```

Out[36]:
```
Marital Status
married     24694
single      11494
divorced     4599
Name: count, dtype: int64
```

Handling of unknown values in the "Education Level" Column

When inspecting the "Education Level" column, we can see that there are multiple different categories: university degree, high school, basic (4 years), basic (6 years), basic (9 years), professional course, unknown and illiterate.
A major thing we took note of was the uneven distribution of clients in the different categories for this column, and further inspection into the unknown and illiterate categories show that they total to less than 5% of the total data.
Although it is a good choice to have the "unknown" and "illiterate" columns, they face an extreme class imbalance. There are only a total of 1749 instances of these columns having data, and this is out of a total of around 40k. This means that it only constitutes to around 4.25%, which is quite low. Hence, these 2 categories would not affect training or evaluation of predictive models as it does not provide much meaning or value to prediction. These categories also cannot be merged with any other column, as they are each unique and have completely different meanings. Hence, we decided to exclude these 2 categories from the final cleaned dataset. This will be applied to the training of the selected models to prevent overfitting, as keeping these features would cause instability besides from not contributing any predictive value.

In [37]:
```
display(df["Education Level"].value_counts())
display(df["Education Level"].unique())
```

```
Education Level
university.degree      12096
high.school             9464
basic.9y                6006
professional.course     5225
basic.4y                4118
basic.6y                2264
unknown                 1596
illiterate                18
Name: count, dtype: int64
array(['high.school', 'basic.9y', 'professional.course',
       'university.degree', 'basic.4y', 'basic.6y', 'unknown',
       'illiterate'], dtype=object)
```

In [38]:
```
df=df[df["Education Level"]!="illiterate"]
df=df[df["Education Level"]!="unknown"]
```

In [39]:
```
df["Education Level"].value_counts()
```

Out[39]:
```
Education Level
university.degree      12096
high.school             9464
basic.9y                6006
professional.course     5225
basic.4y                4118
basic.6y                2264
Name: count, dtype: int64
```

Handling of the "Credit Default" Features

When inspecting the "Credit Default" column, we can see that there are 3 different categories, "yes", "no" and "unknown"
No credit default can indicate that the client has financial stability and is more

responsible with their money, which can affect their decision on whether they should or should not subscribe. The "unknown" class in this data indicate that the client has not have borrowed money from this bank before or the record could be incomplete. "Yes" in the context of credit default means that they did not manage to make the payments on time, and could signify that the person is tight on money. Although it is a good choice to have the "Yes" column, it faces an extreme class imbalance. There are only 3 instances of this being positive, and this is out of a total of 41188. This means that it only constitutes to around 0.00728%, which is extremely low. Hence, the "Yes" category would not affect training or evaluation of predictive models as it does not provide any meaning or value towards predictions. This category also cannot be merged with "unknown", as they have completely different meanings. Hence, we decided to exclude this category from the final cleaned dataset. This will be applied to the training of the selected models to prevent overfitting, as keeping this feature would cause instability besides from not contributing any predictive value.

In [40]:
```
df["Credit Default"].value_counts()
```

Out[40]:
```
Credit Default
no          31213
unknown      7957
yes             3
Name: count, dtype: int64
```

In [41]:
```
df=df[df["Credit Default"]!="yes"]
df["Credit Default"].value_counts()
```

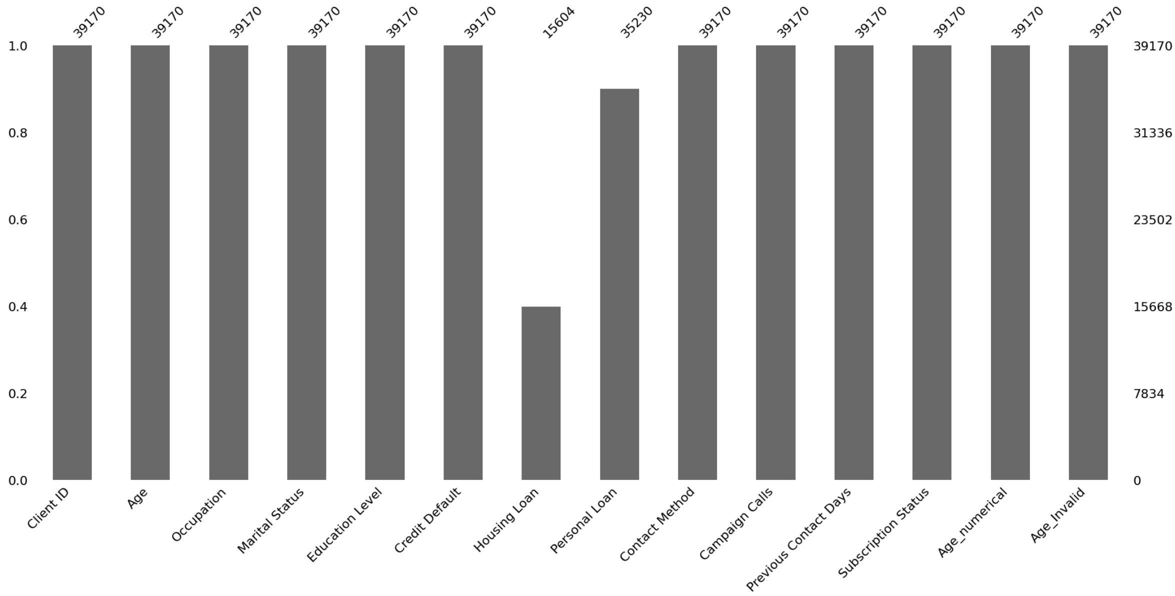
Out[41]:
```
Credit Default
no          31213
unknown      7957
Name: count, dtype: int64
```

Before moving on to the next features, we wanted to visualize and confirm that the next two rows we would be working on do indeed have null values.

In [42]:
```
import missingno as msno
```

In [43]:
```
msno.bar(df)
```

Out[43]:
```
<Axes: >
```



In [44]:
```
pd.options.display.max_rows = 999
nulls = df.isna().sum().sort_values(ascending=False)
nulls[nulls>0]
```

Out[44]:
```
Housing Loan     23566
Personal Loan     3940
dtype: int64
```

In [45]:
```
df.shape
```

Out[45]:
```
(39170, 14)
```

Cleaning of the "Housing Loan" Feature

When inspecting the "Housing Loan" column, we can see that there are 3 different categories, "yes", "no", "unknown" and the null values appear as as "None".
However, "None" and "no" do not mean the same thing in this case. "no" most likely refers to the client not having any housing loans, while "None" means that the bank has never recorded down the status of the client's housing loans, hence we are not able to verify whether they have or do not have any housing loans.
We have decided to remove the unknown values here alone as it constitutes to a very small minority of the data.

In [46]:
```
df[df["Housing Loan"].isna()].head(15)
```

Out[46]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan
4	14021	27 years	housemaid	married	high.school	no	None	no
5	17202	58 years	retired	married	professional.course	no	None	yes
8	10822	24 years	entrepreneur	married	university.degree	no	None	None
10	32312	34 years	blue-collar	married	basic.9y	no	None	no
12	13596	43 years	blue-collar	single	basic.9y	no	None	no
14	16736	58 years	blue-collar	married	basic.4y	no	None	yes
17	17689	150 years	technician	married	professional.course	no	None	yes
18	15508	37 years	entrepreneur	single	professional.course	no	None	no
20	17268	59 years	retired	married	basic.9y	unknown	None	no
21	1671	49 years	unemployed	single	professional.course	unknown	None	no
23	15756	30 years	admin.	single	high.school	no	None	yes
25	36916	45 years	admin.	married	basic.9y	no	None	no
27	22970	31 years	admin.	married	university.degree	no	None	no
28	8926	41 years	blue-collar	married	basic.4y	unknown	None	no
30	36969	47 years	housemaid	married	basic.6y	unknown	None	yes

In [47]:

```
df[df["Housing Loan"]=="no"].head(15)
```

Out[47]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Persor Lo
0	32885	57 years	technician	married	high.school	no	no	y
2	32207	33 years	blue-collar	married	basic.9y	no	no	
3	9404	36 years	admin.	married	high.school	no	no	
13	21872	150 years	admin.	married	university.degree	no	no	
24	20771	51 years	management	married	high.school	unknown	no	
31	36563	69 years	entrepreneur	married	high.school	no	no	
38	8726	30 years	blue-collar	married	basic.6y	no	no	
39	25810	30 years	management	married	university.degree	no	no	
64	40577	33 years	technician	single	professional.course	no	no	
70	18429	47 years	admin.	married	high.school	unknown	no	y
92	25159	40 years	admin.	divorced	basic.9y	no	no	
98	533	41 years	blue-collar	married	basic.6y	no	no	
108	17076	42 years	admin.	single	high.school	no	no	y
110	29676	33 years	blue-collar	married	high.school	no	no	
123	6223	36 years	services	married	high.school	unknown	no	

In [48]:
```
df[df["Housing Loan"]=="unknown"].head(15)
```

Out[48]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Persor Lo
169	36548	50 years	admin.	single	basic.9y	no	unknown	unknov
211	14241	27 years	blue-collar	single	basic.9y	no	unknown	unknov
244	14423	32 years	admin.	single	university.degree	no	unknown	unknov
401	31694	38 years	technician	married	university.degree	no	unknown	unknov
404	6661	54 years	admin.	married	high.school	no	unknown	unknov
468	9332	40 years	admin.	married	university.degree	unknown	unknown	unknov
804	15179	29 years	unemployed	married	university.degree	no	unknown	unknov
860	26664	34 years	unemployed	married	high.school	no	unknown	unknov
906	19859	49 years	technician	married	professional.course	unknown	unknown	unknov
952	20069	43 years	admin.	married	university.degree	no	unknown	unknov
962	26267	32 years	admin.	married	professional.course	no	unknown	unknov
1206	1034	40 years	blue-collar	married	basic.4y	unknown	unknown	unknov
1242	6003	49 years	blue-collar	married	basic.4y	no	unknown	unknov
1311	29585	35 years	admin.	single	university.degree	no	unknown	unknov
1328	13421	150 years	technician	married	university.degree	no	unknown	unknov

In [49]:

```
display(df["Housing Loan"].value_counts())
```

```
Housing Loan
yes        8193
no         7035
unknown     376
Name: count, dtype: int64
```

In [50]:

```
df=df[df["Housing Loan"]!="unknown"]
df["Personal Loan"].value_counts()
df["Housing Loan"]=df["Housing Loan"].fillna("no_info")
```

```
display(df["Housing Loan"].isna().value_counts())
display(df["Housing Loan"].value_counts())
```

```
Housing Loan
False    38794
Name: count, dtype: int64
Housing Loan
no_info    23566
yes         8193
no          7035
Name: count, dtype: int64
```

Similar to the "Housing Loan" column, there are 3 different categories, "yes", "no", "unknown" and null values as "None".
However, "None" and "no" do not mean the same thing in this case. "no" most likely refers to the client not having any personal loans, while "None" means that the bank has never recorded down the status of the client's personal loans, hence we are not able to verify whether they have or do not have any personal loans.
We have decided to remove the unknown values as it constitutes to a very small minority of the data.

In [51]:
```
display(df["Personal Loan"].value_counts())
```

```
Personal Loan
no         29020
yes         5370
unknown      509
Name: count, dtype: int64
```

In [52]:
```
display(df[df["Personal Loan"].isna()].head(5))
display(df[df["Personal Loan"]=="no"].head(5))
df[df["Personal Loan"]=="unknown"].head(5)
```

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	
7	23758	150 years	admin.	divorced	university.degree	unknown	yes	None	
8	10822	24 years	entrepreneur	married	university.degree	no	no_info	None	t
58	39197	41 years	admin.	divorced	university.degree	no	yes	None	
63	3420	45 years	blue-collar	married	basic.4y	no	no_info	None	T
80	33318	41 years	management	married	high.school	unknown	yes	None	

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	Conta Methc
2	32207	33 years	blue-collar	married	basic.9y	no	no	no	cellul
3	9404	36 years	admin.	married	high.school	no	no	no	Telephor
4	14021	27 years	housemaid	married	high.school	no	no_info	no	Ce
6	880	48 years	services	married	high.school	unknown	yes	no	Telephor
10	32312	34 years	blue-collar	married	basic.9y	no	no_info	no	Ce

Out[52]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan
164	13416	150 years	technician	married	university.degree	no	no_info	unknown
188	8815	30 years	technician	single	professional.course	no	no_info	unknown
212	24204	150 years	unemployed	married	university.degree	no	no_info	unknown
225	26419	38 years	admin.	married	high.school	no	no_info	unknown
239	8202	38 years	student	single	university.degree	no	no_info	unknown

In [53]:

```
df=df[df["Personal Loan"]!="unknown"]
display(df["Personal Loan"].isna().sum())
df["Personal Loan"]=df["Personal Loan"].fillna("no_info")
display(df["Personal Loan"].isna().value_counts())
display(df["Personal Loan"].value_counts())
```

```
np.int64(3895)
Personal Loan
False    38285
Name: count, dtype: int64
Personal Loan
no         29020
yes         5370
no_info     3895
Name: count, dtype: int64
```

Cleaning of the "Contact Method" Feature

When inspecting the "Contact Method" column, we can see that there are 4 different categories, "Cell", "cellular", "Telephone" and "telephone".

To clean this, we will convert them into similar, lowercase terms:

"Telephone" & "telephone" --> "telephone"

"Cell" & "cellular" --> "cellular"

In [54]:
```
df["Contact Method"].value_counts()
```

Out[54]:
```
Contact Method
Cell         12257
cellular     12201
Telephone     6933
telephone     6894
Name: count, dtype: int64
```

In [55]:
```
df["Contact Method"]= df["Contact Method"].replace({"Cell":"cellular", "Telephon
df["Contact Method"].value_counts()
```

Out[55]:
```
Contact Method
cellular     24458
telephone    13827
Name: count, dtype: int64
```

Cleaning of the "Campaign Calls" Feature

When inspecting the "Campaign" column, we can see that there are many values that are negative.

To clean this, we must first check the number of negative values, before we make a decision.

In [56]:
```
df[df["Campaign Calls"]<0].shape[0]
```

Out[56]:
```
3847
```

In [57]:
```
df["Campaign Calls"].value_counts().sort_index(ascending=True).head(50)
```

Out[57]:
```
Campaign Calls
-41        1
-35        2
-32        1
-29        1
-28        2
-25        1
-23        5
-22        3
-21        2
-20        3
-19        1
-18        3
-17        5
-16        5
-15        4
-14       10
-13        8
-12       15
-11       19
-10       15
-9        27
-8        34
-7        59
-6        82
-5       144
-4       231
-3       486
-2      1051
-1      1627
 1     14759
 2      8781
 3      4473
 4      2238
 5      1360
 6       830
 7       525
 8       339
 9       232
 10      193
 11      147
 12      100
 13       68
 14       54
 15       43
 16       40
 17       49
 18       28
 19       22
 20       27
 21       17
Name: count, dtype: int64
```

In [58]:
```
df["Campaign Calls"].value_counts().sort_index(ascending=False).head(50)
```

Out[58]:
```
Campaign Calls
 43         2
 42         2
 40         2
 39         1
 37         1
 35         3
 34         3
 33         4
 32         3
 31         7
 30         7
 29         8
 28         6
 27        11
 26         7
 25         6
 24        15
 23        11
 22        14
 21        17
 20        27
 19        22
 18        28
 17        49
 16        40
 15        43
 14        54
 13        68
 12       100
 11       147
 10       193
 9        232
 8        339
 7        525
 6        830
 5       1360
 4       2238
 3       4473
 2       8781
 1      14759
-1       1627
-2       1051
-3        486
-4        231
-5        144
-6         82
-7         59
-8         34
-9         27
-10        15
Name: count, dtype: int64
```

In [59]:
```
df[df["Campaign Calls"]<0].sort_index(ascending=True).head(50)
```

Out[59]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Persor Lo
17	17689	150 years	technician	married	professional.course	no	no_info	y
23	15756	30 years	admin.	single	high.school	no	no_info	y
36	23686	33 years	admin.	single	university.degree	no	yes	
48	23462	44 years	technician	married	professional.course	no	yes	
52	2465	36 years	blue-collar	married	basic.9y	unknown	no_info	
56	24130	52 years	technician	divorced	university.degree	no	no_info	
66	38247	77 years	retired	married	university.degree	no	no_info	y
69	37778	57 years	retired	married	university.degree	no	yes	
70	18429	47 years	admin.	married	high.school	unknown	no	y
72	32715	51 years	entrepreneur	married	professional.course	unknown	no_info	
84	3271	46 years	blue-collar	single	basic.4y	no	no_info	
96	28108	44 years	management	divorced	university.degree	no	yes	
105	16549	49 years	self-employed	divorced	university.degree	no	no_info	y
108	17076	42 years	admin.	single	high.school	no	no	y
113	7946	54 years	admin.	married	high.school	unknown	yes	
139	22233	45 years	technician	single	university.degree	no	no	
146	34534	26 years	blue-collar	single	basic.9y	no	no	
173	6113	53 years	self-employed	married	university.degree	no	no_info	y
177	19566	41 years	unemployed	divorced	university.degree	unknown	no_info	
197	26891	43 years	technician	married	professional.course	no	no	

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Persor Lo
199	9255	150 years	technician	married	basic.9y	no	no	
250	35029	32 years	admin.	divorced	high.school	no	no_info	
259	33470	35 years	admin.	single	basic.9y	no	no_info	
260	34182	27 years	self-employed	married	basic.9y	no	yes	
273	37483	62 years	retired	married	university.degree	unknown	no_info	y
275	22783	50 years	housemaid	married	basic.4y	no	no	
278	21100	38 years	technician	divorced	university.degree	unknown	no_info	
280	15639	30 years	management	single	university.degree	no	no_info	
293	23085	55 years	technician	divorced	university.degree	no	no_info	
303	11811	40 years	housemaid	married	basic.4y	unknown	no_info	
305	13207	150 years	services	single	high.school	no	no_info	
312	30880	39 years	blue-collar	married	basic.9y	no	no_info	
321	12514	47 years	admin.	married	basic.9y	no	yes	
325	17378	44 years	blue-collar	single	high.school	unknown	no_info	
330	15918	57 years	admin.	married	university.degree	no	yes	
348	1078	29 years	admin.	single	university.degree	no	no_info	
349	6189	55 years	admin.	married	high.school	no	no_info	
359	37701	32 years	admin.	married	university.degree	no	no_info	no_ir
368	29911	41 years	blue-collar	married	professional.course	no	no_info	
391	2993	26 years	unemployed	single	basic.9y	no	no_info	

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Person Lo
397	9286	48 years	management	married	basic.9y	no	yes	
402	5750	150 years	services	single	basic.9y	no	no_info	
403	41162	33 years	admin.	married	university.degree	no	yes	
414	31991	38 years	technician	married	university.degree	no	no_info	
419	586	150 years	admin.	single	university.degree	no	no_info	y
430	8553	58 years	services	married	basic.4y	no	no_info	
443	37055	45 years	admin.	married	university.degree	no	no_info	
448	21742	30 years	technician	single	professional.course	no	yes	y
449	5458	31 years	services	single	basic.6y	no	no_info	
464	25542	38 years	management	married	professional.course	unknown	no_info	

After looking at the values, ~10% of the data is less than 0, so it is not wise to drop these rows.
Instead, we decided to impute the values, similar to what we did for the cleaning of the "Age" column.
We decided to use the absolute value method, where we convert the negative values into positives, as the there are no set boundaries for this data column, and change -41 to 41 would still be less than the maximum value of the data.
Also, the distribution of the data does follow the general trend, where there is an inversely proportional relationship between the number of calls and number of clients.

In [60]:
```
df["Campaign Calls"]=df["Campaign Calls"].abs()
display(df["Campaign Calls"].describe())
```

```
count    38285.000000
mean         2.566984
std          2.766944
min          1.000000
25%          1.000000
50%          2.000000
75%          3.000000
max         43.000000
Name: Campaign Calls, dtype: float64
```

In [61]:
```
Q1 = df["Campaign Calls"].quantile(0.25)
Q3 = df["Campaign Calls"].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
print(f"IQR Bounds for 'Campaign Calls': Lower Bound = {lower_bound}, Upper Boun
```

```
IQR Bounds for 'Campaign Calls': Lower Bound = -2.0, Upper Bound = 6.0
```

Cleaning of the "Previous Contact Days" Feature

As seen in the project guide, values like "999" are placeholders for "No previous contact". Hence, we cannot treat this as a numeric value, or it will skew the other data.
We decided to replace 999 with NaN and create a new column with binary features to show whether there has been contact or not, using "1" and "0".
This helps to remove any instances which could heavily imbalance our data, and still preserve the knowledge of knowing which clients have had contact or no previous contact.
Keeping this information is extremely important for our project, as it can influence a person's decision.

In [62]:
```
df["no_previous_contact"] = (df["Previous Contact Days"] == 999)
df["no_previous_contact"]=df["no_previous_contact"].astype(int)
df["Previous Contact Days_clean"]= df["Previous Contact Days"].replace(999, np.n
```

In [63]:
```
display(df["Previous Contact Days"].head())
display(df["no_previous_contact"].head())
display(df["Previous Contact Days_clean"].head())
```

```
0    999
2    999
3    999
4    999
5    999
Name: Previous Contact Days, dtype: int64
0    1
2    1
3    1
4    1
5    1
Name: no_previous_contact, dtype: int64
0   NaN
2   NaN
3   NaN
4   NaN
5   NaN
Name: Previous Contact Days_clean, dtype: float64
```

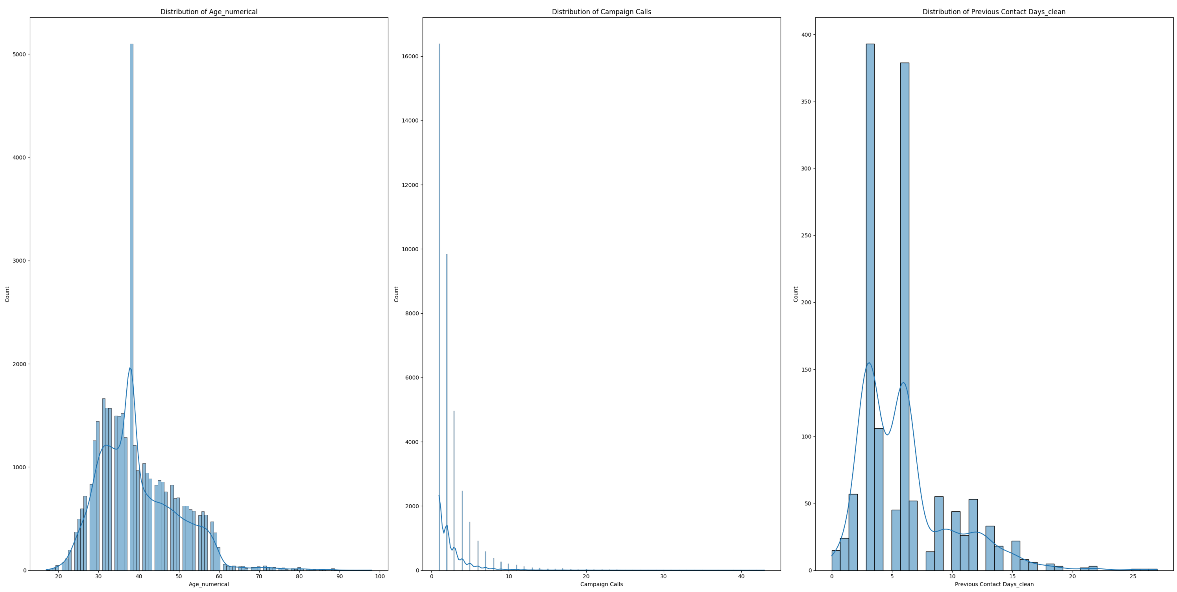
In [64]:
```
df.head()
```

Out[64]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	
0	32885	57 years	technician	married	high.school	no	no	yes	
2	32207	33 years	blue-collar	married	basic.9y	no	no	no	
3	9404	36 years	admin.	married	high.school	no	no	no	te
4	14021	27 years	housemaid	married	high.school	no	no_info	no	
5	17202	58 years	retired	married	professional.course	no	no_info	yes	

In [65]:
```
df=df.reset_index(drop=True)
```

In [66]:
```
num_cols = ["Age_numerical", "Campaign Calls", "Previous Contact Days_clean"]

plt.figure(figsize=(30,15))
for i, col in enumerate(num_cols, 1):
    plt.subplot(1, 3, i)
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```



(4) Bivariate Analysis

Our main target variable for this EDA is "Subscription Status". However It is currently categorical (yes/no)
In order to conduct this bivariate analysis, we first have to encode it into numeric characters in order for this to work.
The following changes will be made:

"1"-> subscribed ("yes")

"0"-> not subscribed ("no")

In [67]:
```
df["Subscription_Status_Code"]=df["Subscription Status"].map({"yes":1, "no":0})
df["Subscription_Status_Code"].value_counts()
```

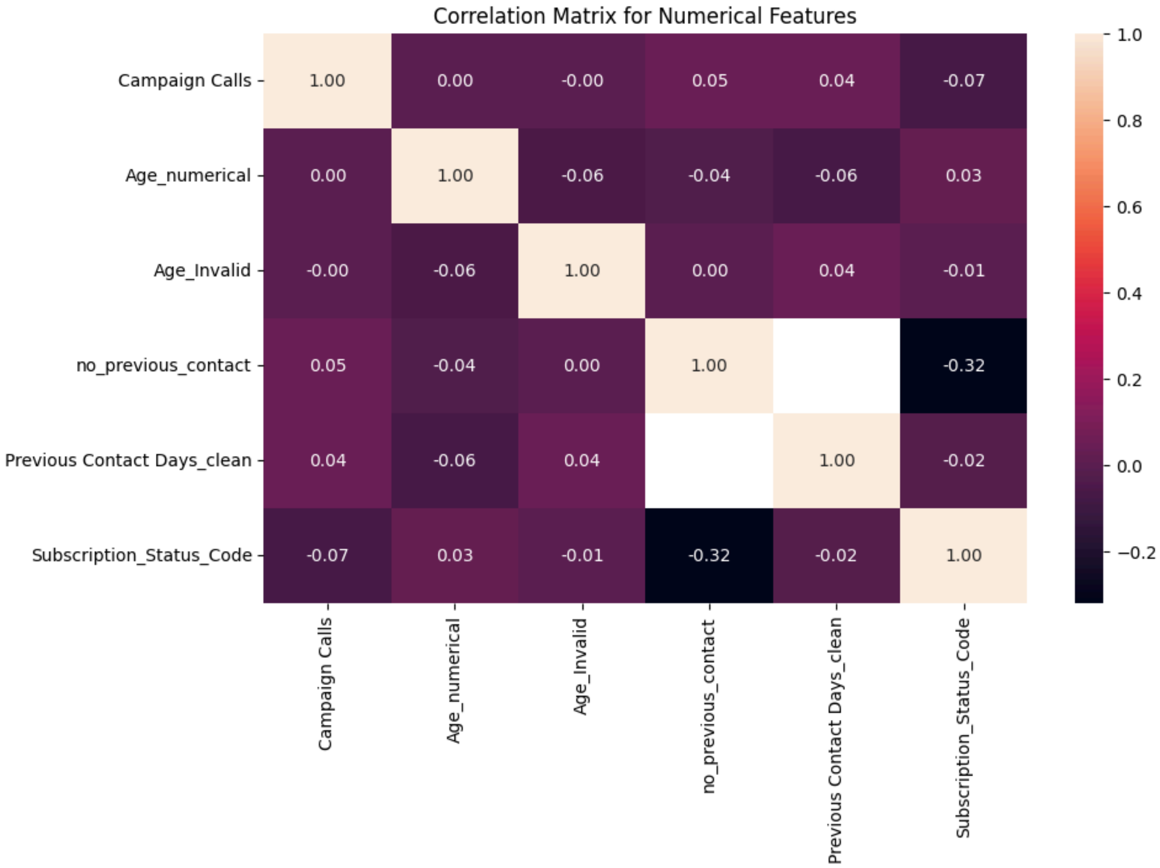
Out[67]:
```
Subscription_Status_Code
0    34025
1     4260
Name: count, dtype: int64
```

In [68]:
```
df_cleaned = df.drop(columns=["Age", "Previous Contact Days"])
```

In [69]:
```
df_cleaned.info()
```

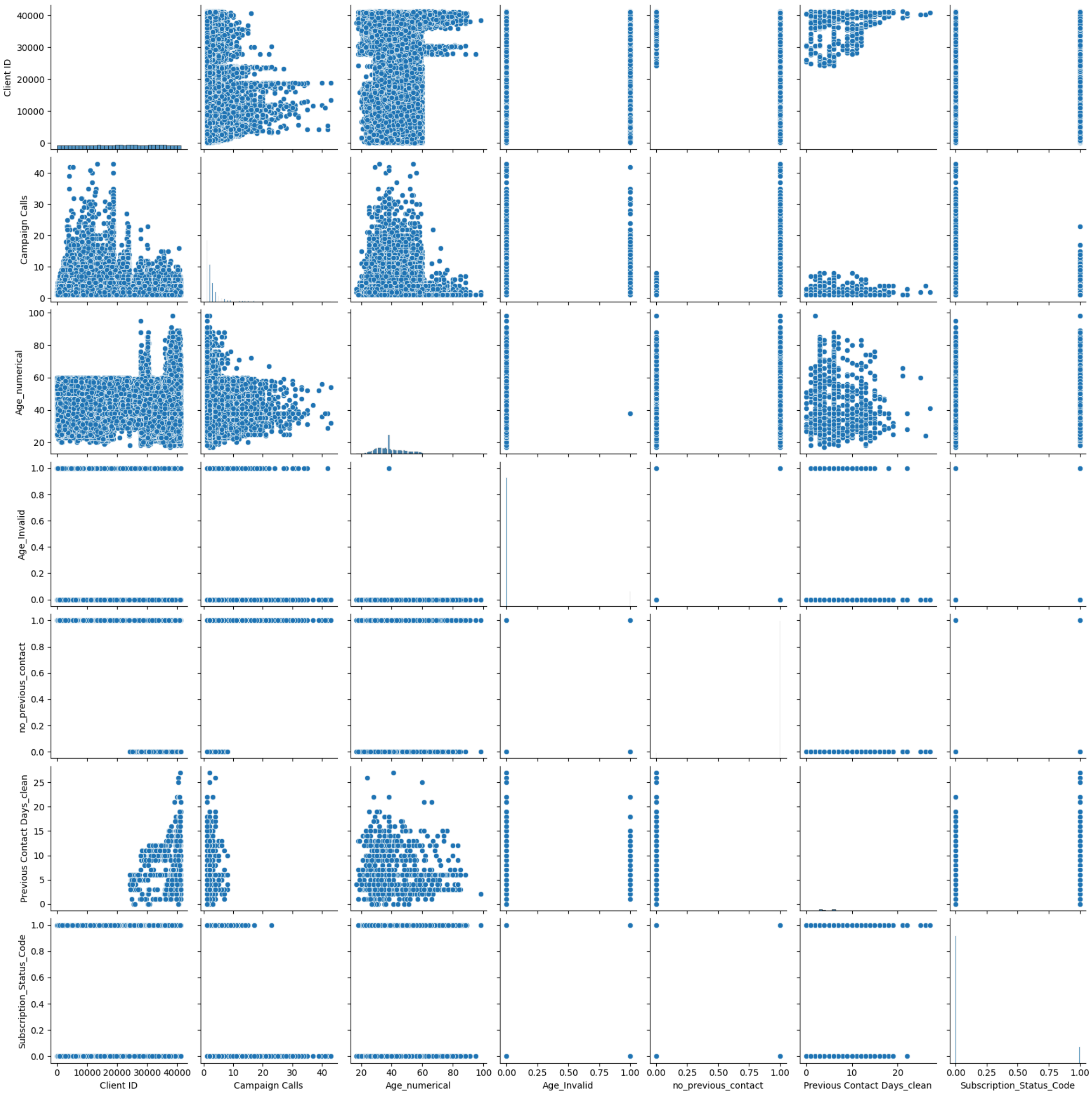
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 38285 entries, 0 to 38284
Data columns (total 15 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Client ID                    38285 non-null  int64  
 1   Occupation                   38285 non-null  object 
 2   Marital Status               38285 non-null  object 
 3   Education Level              38285 non-null  object 
 4   Credit Default               38285 non-null  object 
 5   Housing Loan                 38285 non-null  object 
 6   Personal Loan                38285 non-null  object 
 7   Contact Method               38285 non-null  object 
 8   Campaign Calls               38285 non-null  int64  
 9   Subscription Status          38285 non-null  object 
 10  Age_numerical                38285 non-null  int64  
 11  Age_Invalid                  38285 non-null  int64  
 12  no_previous_contact          38285 non-null  int64  
 13  Previous Contact Days_clean  1366 non-null   float64
 14  Subscription_Status_Code     38285 non-null  int64  
dtypes: float64(1), int64(6), object(8)
memory usage: 4.4+ MB
```

In [70]:
```
plt.figure(figsize=(10,6))
num_cols= ["Campaign Calls", "Age_numerical", "Age_Invalid", "no_previous_contac
df_numerical_relationship=df_cleaned[num_cols]
sns.heatmap(df_numerical_relationship.corr(numeric_only=True), annot=True, fmt="
plt.title("Correlation Matrix for Numerical Features")
plt.show()
```

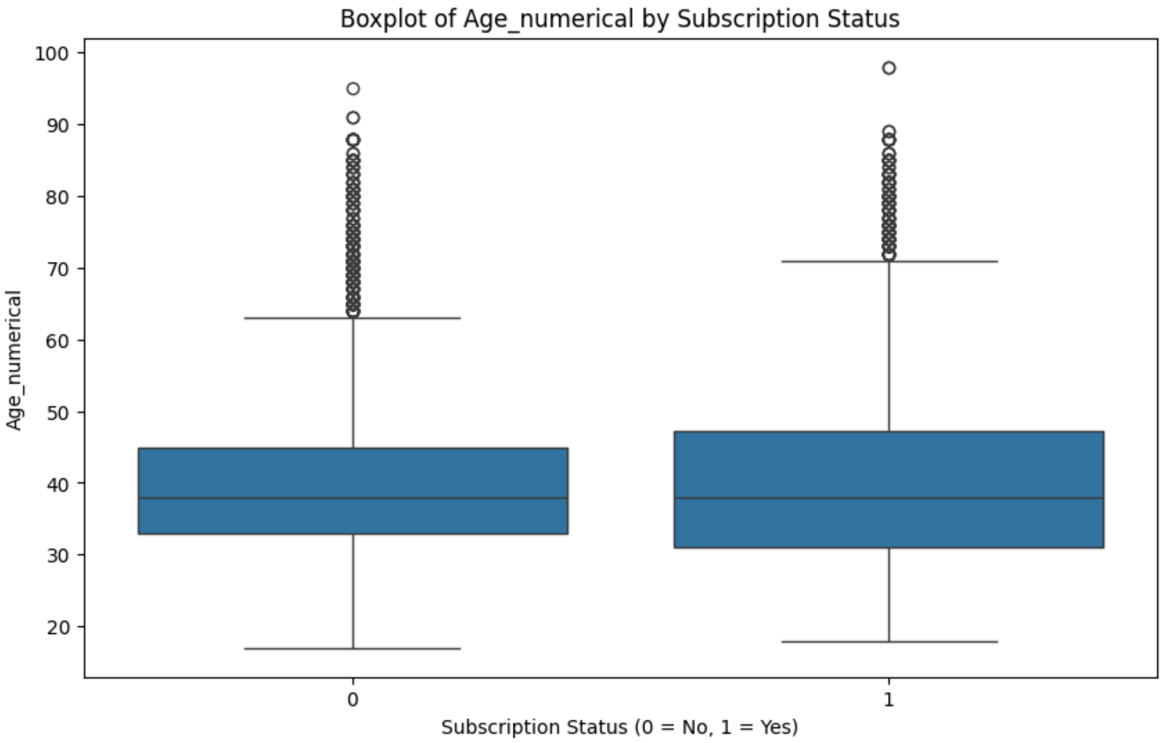


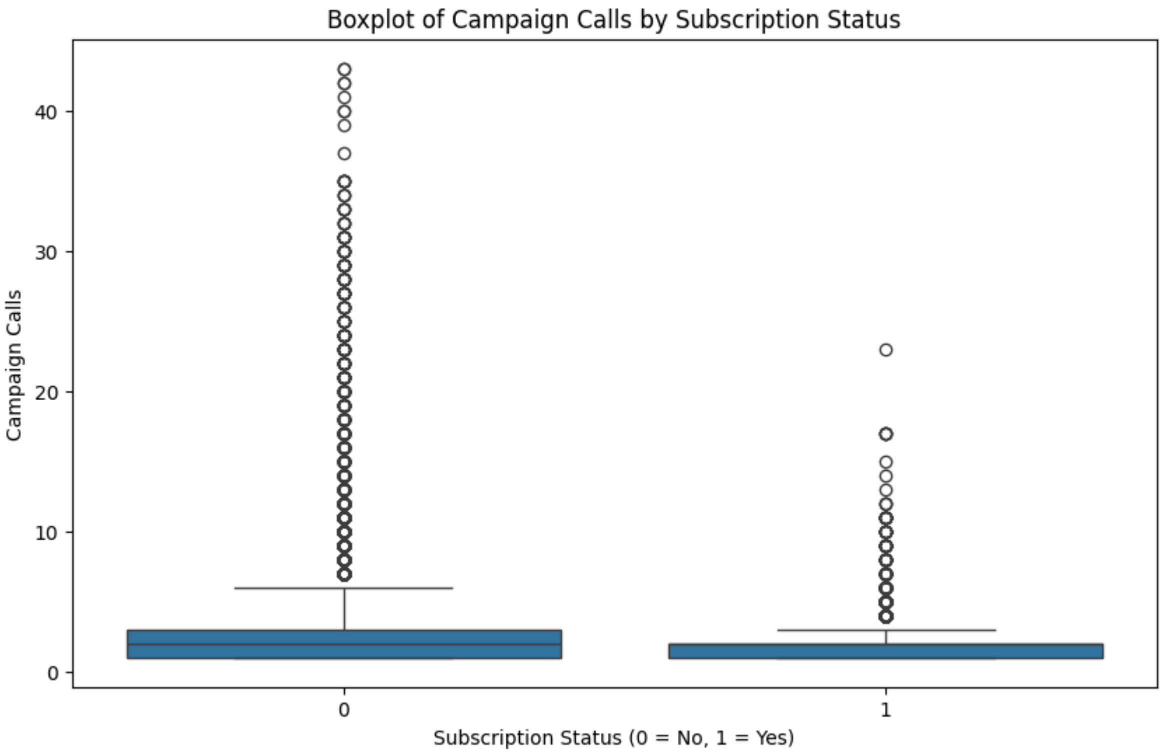
In [71]:
```
sns.pairplot(df_cleaned)
```

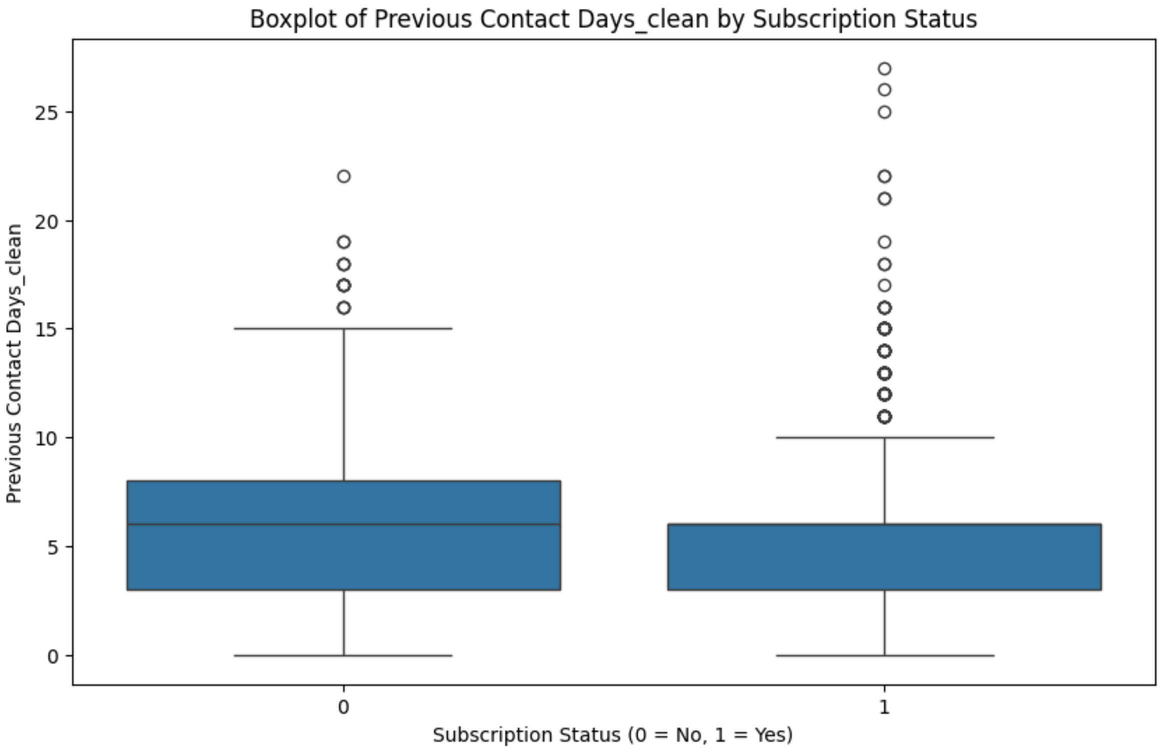
Out[71]: <seaborn.axisgrid.PairGrid at 0x140fbb8a3c0>



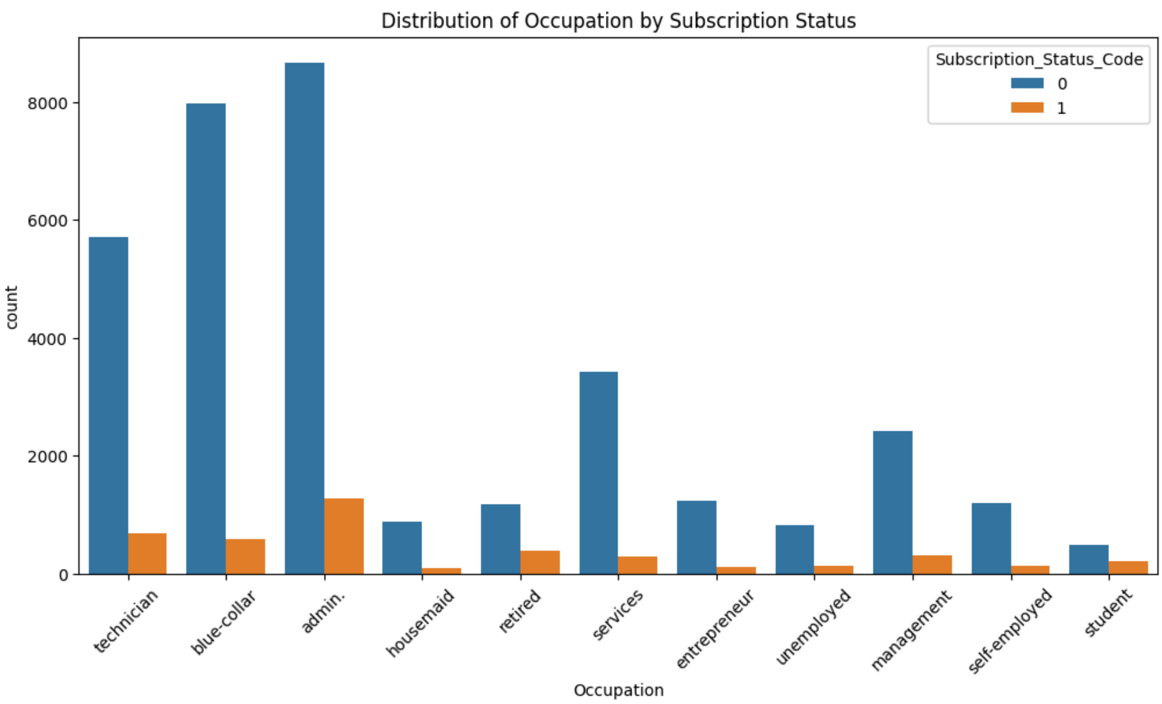
In [72]:
```
continuous_features = ["Age_numerical", "Campaign Calls", "Previous Contact Days
for feature in continuous_features:
    plt.figure(figsize=(10,6))
    sns.boxplot(x='Subscription_Status_Code', y=feature, data=df_cleaned)
    plt.title(f'Boxplot of {feature} by Subscription Status')
    plt.xlabel('Subscription Status (0 = No, 1 = Yes)')
    plt.ylabel(feature)
    plt.show()
```

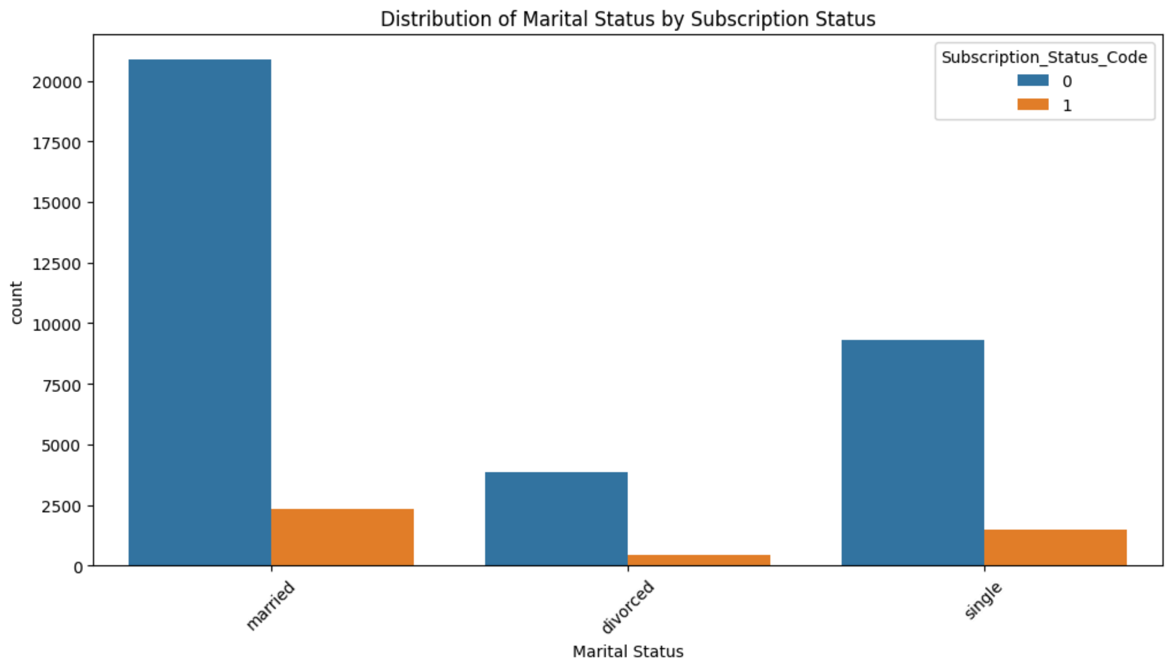

Boxplot of Age_numerical by Subscription Status
Age_numerical
Subscription Status (0 = No, 1 = Yes)
100
90
80
70
60
50
40
30
20
0
1

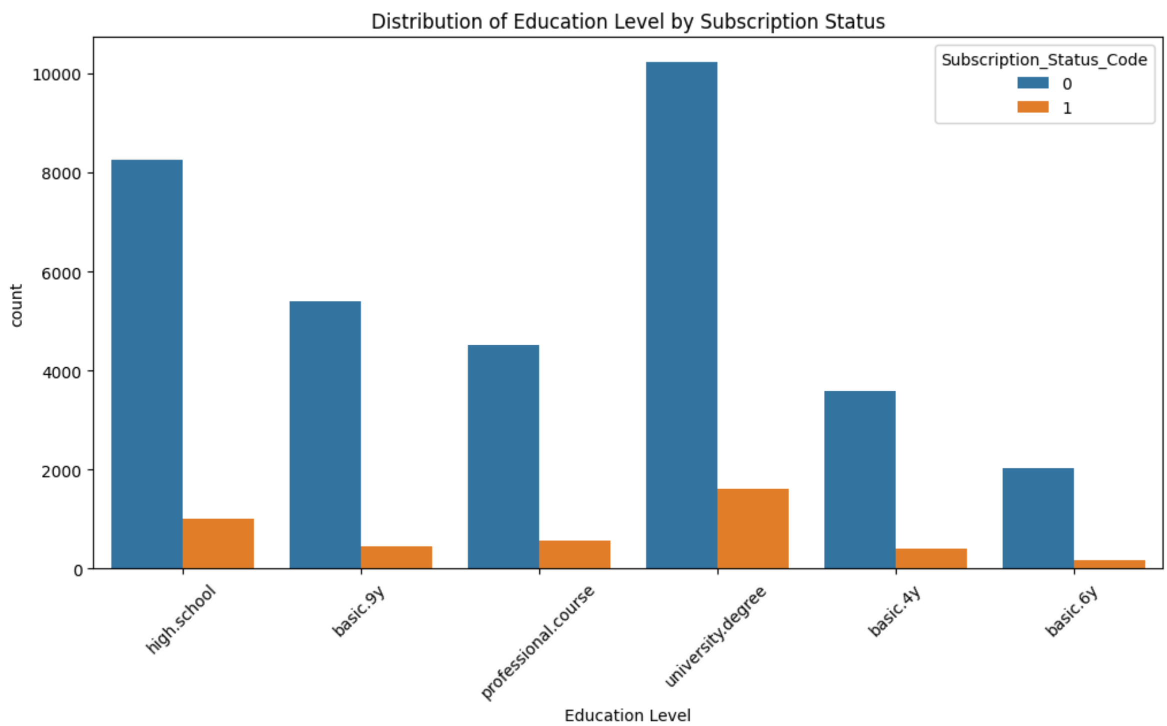

Boxplot of Campaign Calls by Subscription Status
Campaign Calls
Subscription Status (0 = No, 1 = Yes)
40
30
20
10
0
0
1

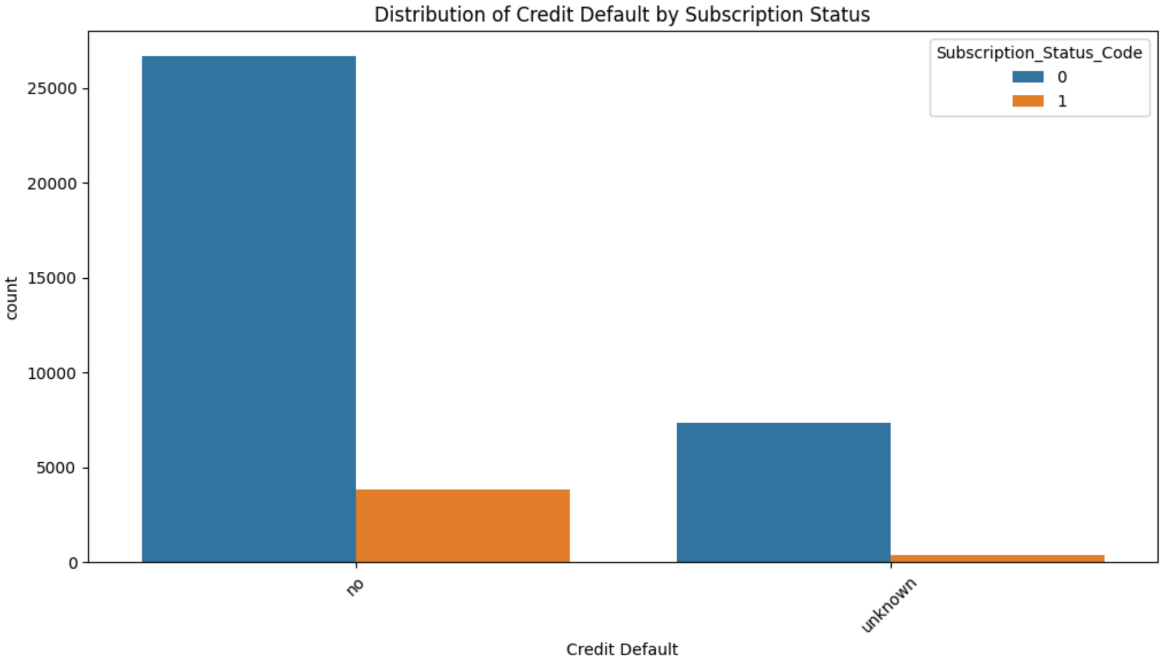


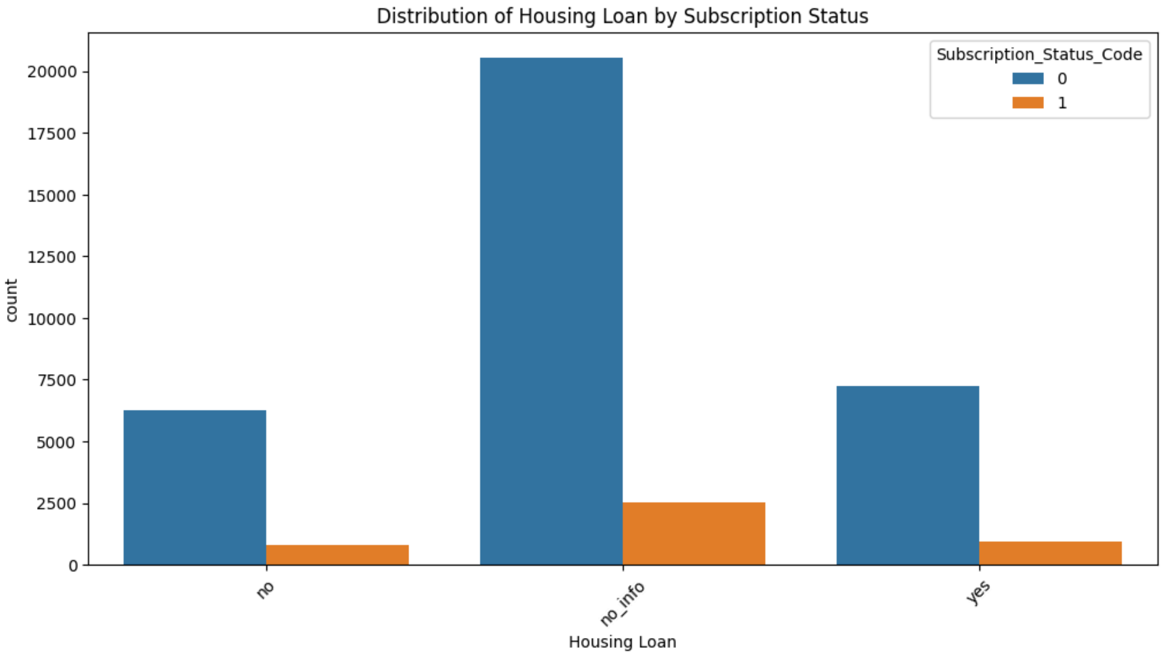
In [73]:
```
cat_cols = ["Occupation", "Marital Status", "Education Level", "Credit Default",

for col in cat_cols:
    plt.figure(figsize=(12,6))
    sns.countplot(data=df_cleaned, x=col, hue="Subscription_Status_Code")
    plt.title(f"Distribution of {col} by Subscription Status")
    plt.xticks(rotation=45)
    plt.show()
```

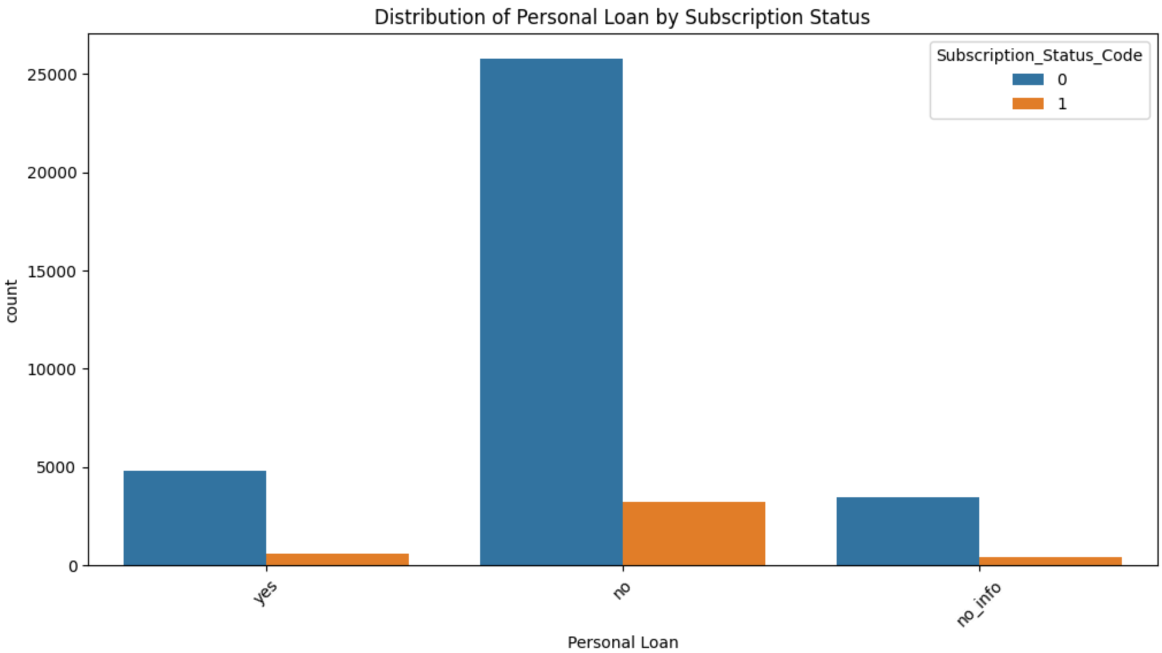


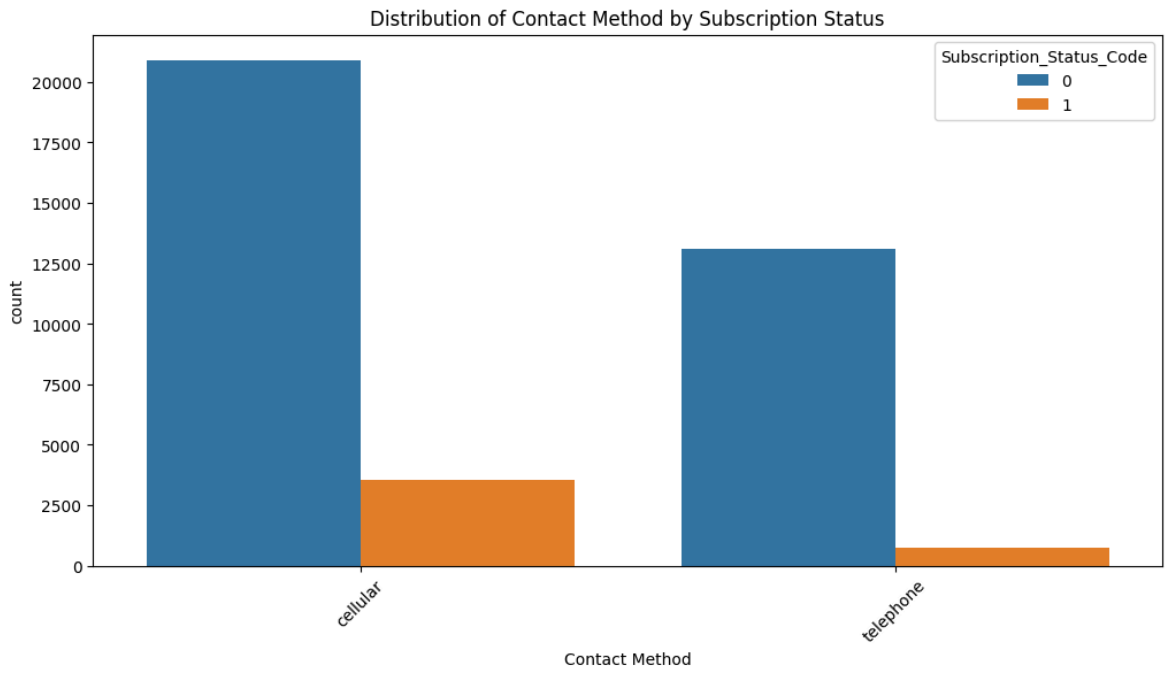

Distribution of Marital Status by Subscription Status
Subscription_Status_Code
0
1
count
20000
17500
15000
12500
10000
7500
5000
2500
0
married
divorced
single
Marital Status


Distribution of Education Level by Subscription Status
Subscription_Status_Code
0
1
count
10000
8000
6000
4000
2000
0
high.school
basic.9y
professional.course
university.degree
basic.4y
basic.6y
Education Level


Distribution of Credit Default by Subscription Status
Subscription_Status_Code
0
1
count
0
5000
10000
15000
20000
25000
no
unknown
Credit Default


Distribution of Housing Loan by Subscription Status
Subscription_Status_Code
0
1
count
0
2500
5000
7500
10000
12500
15000
17500
20000
no
no_info
yes
Housing Loan


Distribution of Personal Loan by Subscription Status
Subscription_Status_Code
0
1
count
0
5000
10000
15000
20000
25000
yes
no
no_info
Personal Loan



(5) Feature Engineering

In order to make more meaningful insights, we will engineer some features such as:
-Job Type Category (Job_Type):
-Age Grouping (Age_Group):
-Education Type Category (Education_Rank):
-Loan Count (Loan_Count):

What is the Job_Type feature and how does it help the project?

Job_Type_Classification helps to group the original detailed occupations into a smaller number of meaningful categories.
They include:
White Collar: Contains people working in administration, management and entrepreneurs.
Blue Collar: Includes technicians, people who work in the services sector and blue collared workers
No Active Income: Consists of students, retirees and the unemployed, which are all groups that currently do not have an income, but may still have savings
Other: Contains unknown cases

White collar roles tend to usually earn more than blue collar roles.
Positions with a fixed salary are likely to be more financially stable than those who are unemployed or not working.
People with a higher income are likely to have a higher disposable income and may be more willing to commit their funds into a term deposit, which is a long term product.

This feature helps to decrease the wide spread of data across the many categories found in "Occupation", by combining them into broader but still meaningful groups. This helps to increase the sample count while capturing the general importance of each category, and would lead to more reliable analysis and patterns.

In [74]:
```
def Job_Type_Classification(job):
    if job in ["admin.", "management", "entrepreneur", "self-employed"]:
        return "White-Collar"
    elif job in ["blue-collar", "technician", "services", "housemaid"]:
        return "Blue-Collar"
    elif job in ["student", "unemployed", "retired"]:
        return "No Active Income"
    else:
        return "Other"

df_cleaned["Job_Type"]=df_cleaned["Occupation"].apply(Job_Type_Classification)
```

What is the Age_Group feature and how does it help the project?

Age_group helps to convert the numerical age into bins

Youth (<= 25 years old)

Young Adult (26-35 years old)

Adult (36-50 years old)

Mature (51-65 years old)

Senior (>65 years old)

Age is and has always been an extremely popular feature in the financial sector: Younger people will generally tend to have lower savings, but they have This helps to improve the scope of the data and generalize the data into more meaningful variables. Also, based on research and other financial datasets I have looked at online, the relationship between age and the subscription is not strictly linear. Hence, binning helps to capture the relationship better by age groups than just singular numeric age values.

This feature helps to reduce noise and captures non-linear patterns better.

In [75]:
```
bins=[0, 25, 35, 50, 65, 100]
labels=["Youth", "Young Adult", "Adult", "Mature", "Senior"]
df_cleaned["Age_Group"]=pd.cut(df_cleaned["Age_numerical"], bins=bins, labels=la
```

What is the Loan Count feature and how does it help the project?

Loan_Count aggregates the "Housing Loan" and "Personal Loan" into a singular integer, where 0 means no loans, 1 means one of the two loans, and 2 means both housing and personal loans.

This helps to improve the scope of the data and generalize the data into more meaningful variables.

Customers with 0 loans may have more disposable income and might be more willing to place their money in a term deposit.

Customers with 1 loan are likely to be in a moderate financial position.

Customers with 2 loans are likely to have less disposable income and might not be able to afford to place their funds into a term deposit.

This feature helps to combine information from both "Housing Loan" and "Personal Loan", and could reveal patterns that could not be captured separately in the two columns.

In [76]:
```
df_cleaned["Loan_Count"]=((df_cleaned["Housing Loan"]=="yes").astype(int) + (df_
```

(6) Label Encoding

For the final bivariate analysis, we will convert all the meaningful categorical columns into numerical, to improve the visualization.\

In [77]:
```
for col in ["Job_Type", "Age_Group"]:
    if col not in cat_cols:
        cat_cols.append(col)
```

In [78]:
```
df_cleaned[cat_cols].head()
```

Out[78]:

	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	Contact Method	Job_
0	technician	married	high.school	no	no	yes	cellular	C
1	blue-collar	married	basic.9y	no	no	no	cellular	C
2	admin.	married	high.school	no	no	no	telephone	W C
3	housemaid	married	high.school	no	no_info	no	cellular	C
4	retired	married	professional.course	no	no_info	yes	cellular	No A Inc

In [79]:
```
for col in cat_cols:
    df_cleaned[col + "_code"]=df_cleaned[col].astype('category').cat.codes
```

In [80]:
```
for col in cat_cols:
    print(f"Mapping for {col}:")
    categories = df_cleaned[col].astype('category').cat.categories
    mapping_df = pd.DataFrame({col: categories,
                               col + 'Code': range(len(categories))})
    display(mapping_df)
```

```
Mapping for Occupation:
```

	Occupation	OccupationCode
0	admin.	0
1	blue-collar	1
2	entrepreneur	2
3	housemaid	3
4	management	4
5	retired	5
6	self-employed	6
7	services	7
8	student	8
9	technician	9
10	unemployed	10

```
Mapping for Marital Status:
```

	Marital Status	Marital StatusCode
0	divorced	0
1	married	1
2	single	2

```
Mapping for Education Level:
```

	Education Level	Education LevelCode
0	basic.4y	0
1	basic.6y	1
2	basic.9y	2
3	high.school	3
4	professional.course	4
5	university.degree	5

```
Mapping for Credit Default:
```

	Credit Default	Credit DefaultCode
0	no	0
1	unknown	1

```
Mapping for Housing Loan:
```

	Housing Loan	Housing LoanCode
0	no	0
1	no_info	1
2	yes	2

```
Mapping for Personal Loan:
```

	Personal Loan	Personal LoanCode
0	no	0
1	no_info	1
2	yes	2

```
Mapping for Contact Method:
```

	Contact Method	Contact MethodCode
0	cellular	0
1	telephone	1

```
Mapping for Job_Type:
```

	Job_Type	Job_TypeCode
0	Blue-Collar	0
1	No Active Income	1
2	White-Collar	2

```
Mapping for Age_Group:
```

	Age_Group	Age_GroupCode
0	Youth	0
1	Young Adult	1
2	Adult	2
3	Mature	3
4	Senior	4

In [81]:

```
df_cleaned.info()
```

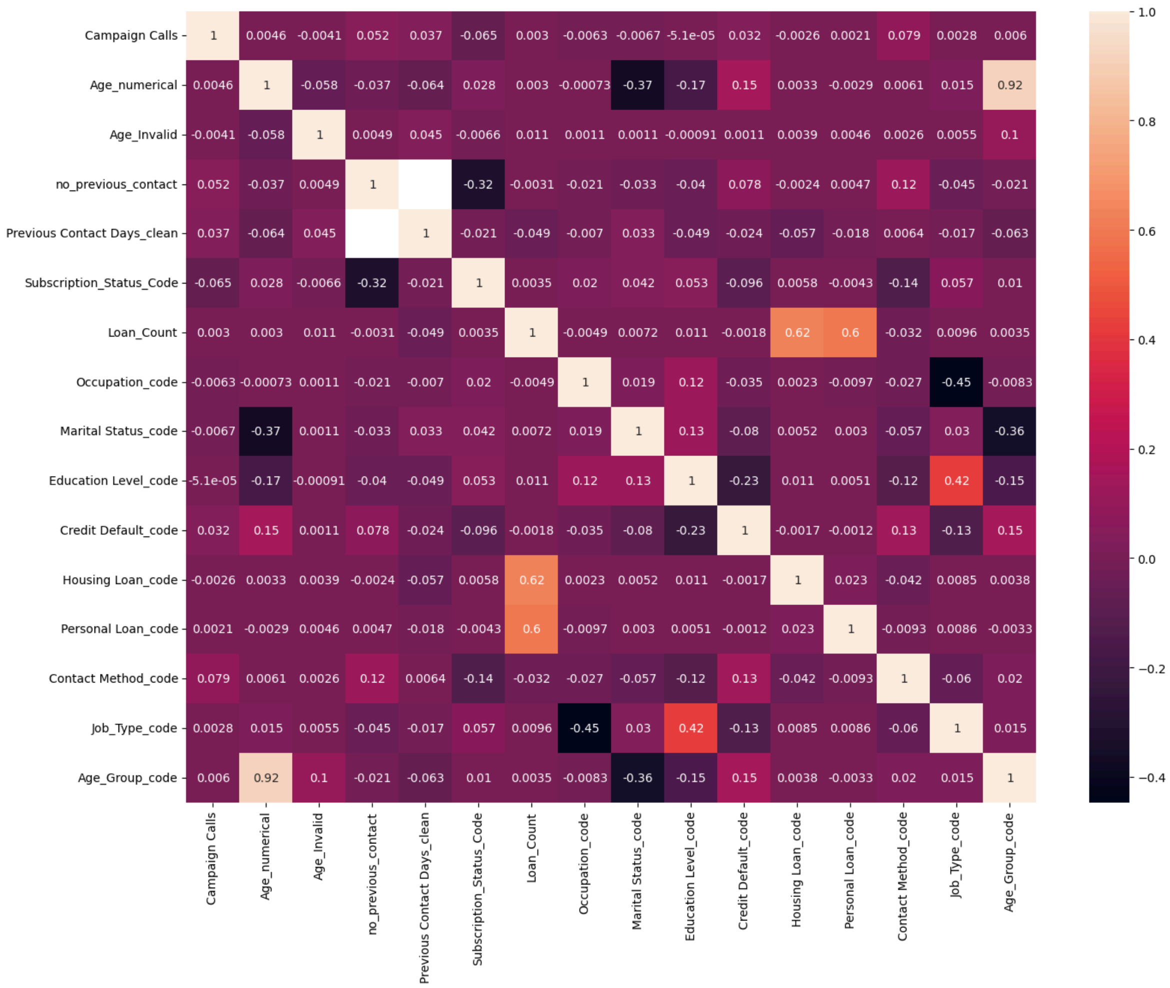
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 38285 entries, 0 to 38284
Data columns (total 27 columns):
 #   Column                        Non-Null Count  Dtype   
---  ------                        --------------  -----   
 0   Client ID                     38285 non-null  int64   
 1   Occupation                    38285 non-null  object  
 2   Marital Status                38285 non-null  object  
 3   Education Level               38285 non-null  object  
 4   Credit Default                38285 non-null  object  
 5   Housing Loan                  38285 non-null  object  
 6   Personal Loan                 38285 non-null  object  
 7   Contact Method                38285 non-null  object  
 8   Campaign Calls                38285 non-null  int64   
 9   Subscription Status           38285 non-null  object  
 10  Age_numerical                 38285 non-null  int64   
 11  Age_Invalid                   38285 non-null  int64   
 12  no_previous_contact           38285 non-null  int64   
 13  Previous Contact Days_clean   1366 non-null   float64 
 14  Subscription_Status_Code      38285 non-null  int64   
 15  Job_Type                      38285 non-null  object  
 16  Age_Group                     38285 non-null  category
 17  Loan_Count                    38285 non-null  int64   
 18  Occupation_code               38285 non-null  int8    
 19  Marital Status_code           38285 non-null  int8    
 20  Education Level_code          38285 non-null  int8    
 21  Credit Default_code           38285 non-null  int8    
 22  Housing Loan_code             38285 non-null  int8    
 23  Personal Loan_code            38285 non-null  int8    
 24  Contact Method_code           38285 non-null  int8    
 25  Job_Type_code                 38285 non-null  int8    
 26  Age_Group_code                38285 non-null  int8    
dtypes: category(1), float64(1), int64(7), int8(9), object(9)
memory usage: 5.3+ MB
```

Final bivariate analysis takeaways

There are no features with high linearity, although it may appear that there are some. Those few that have above a 60% linearity is due to them being engineered features. We kept in the original features as well to see if there are any nuanced relationships

In [82]:
```
numeric_cols= df_cleaned.select_dtypes(include=['number']).columns

numeric_cols= numeric_cols.drop(['Client ID'])

plt.figure(figsize=(16,12))
sns.heatmap(df_cleaned[numeric_cols].corr(numeric_only=True), annot=True)
```

Out[82]: <Axes: >



Important Insights from the charts

We can make a few important insights from the charts below, especially based on these few classes:

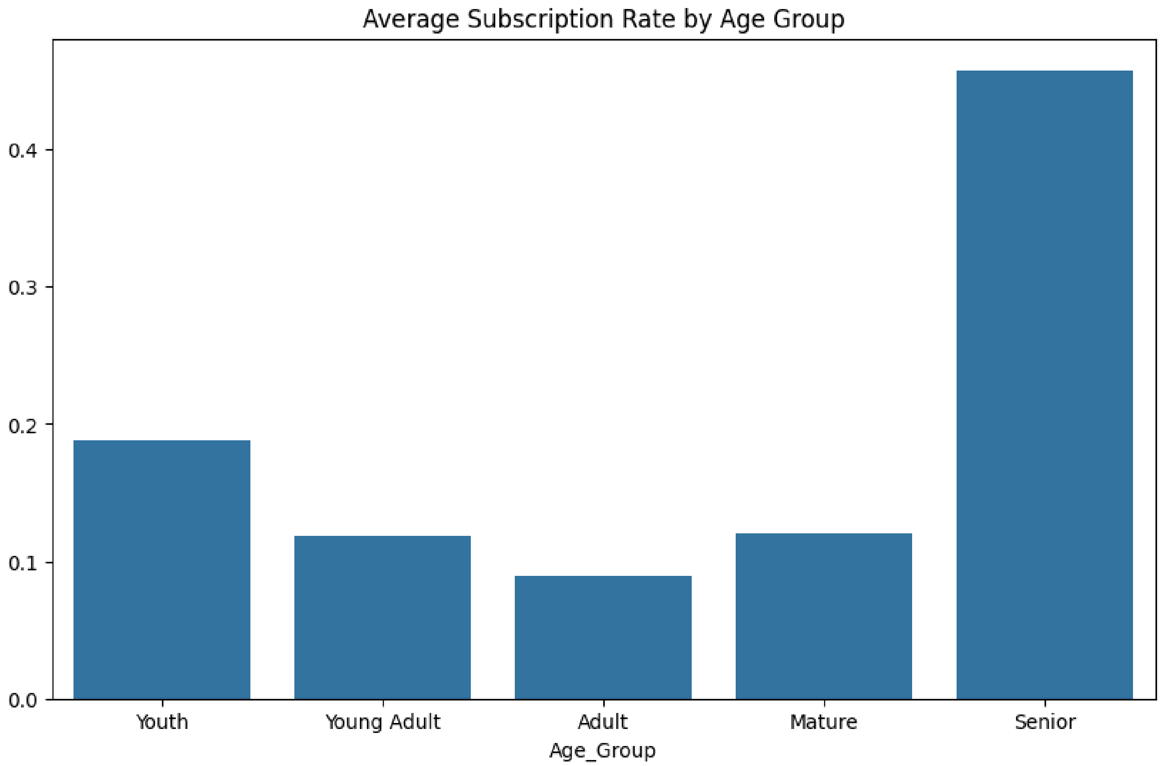
no_previous_contact ("0" category): For people who were previously contacted, there was a significantly higher chance of them subscribing to the term deposit, with a percentage of 63%. This could point to the fact that having contact could boost or already signify the fact that the client already has a strong interest and wants to gather more information on the terms and conditions of the term deposit.

Contact Method ("cellular" category): Clients who were last contacted with through cellular, had a slightly higher subscription rate of 14% compare to 4% by those contacted through telephone.

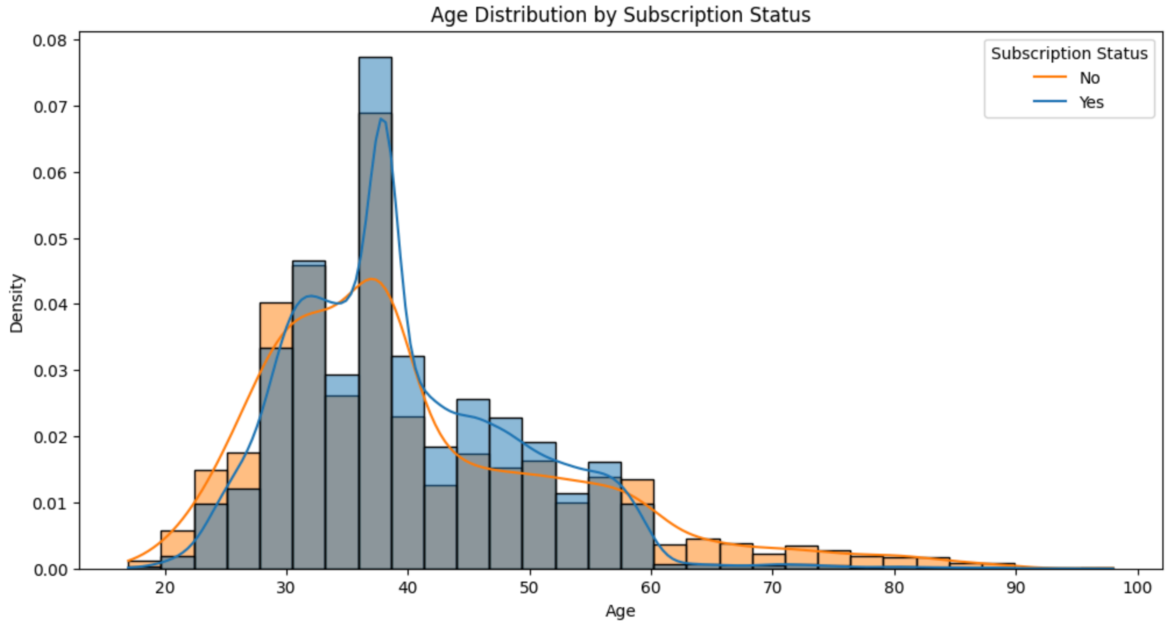
Age_Group ("Senior" category) & Age_numerical ("" category): Looking at the Age_Group chart, we can see that there is a generally trend of Seniors (>65 age) having a higher subscription rate of over 40% and is double of the next highest category which is the Youth.

Job_Type ("No Active Income" category) & Occupation ("student", "retired", "unemployed" category): Generally, the graphs show how people with no active income are having a higher subscription rate that is about twice the amount of other job types. Looking deeper into the specific occupations, we can see how students have the highest rate followed by the retired and the unemployed.\

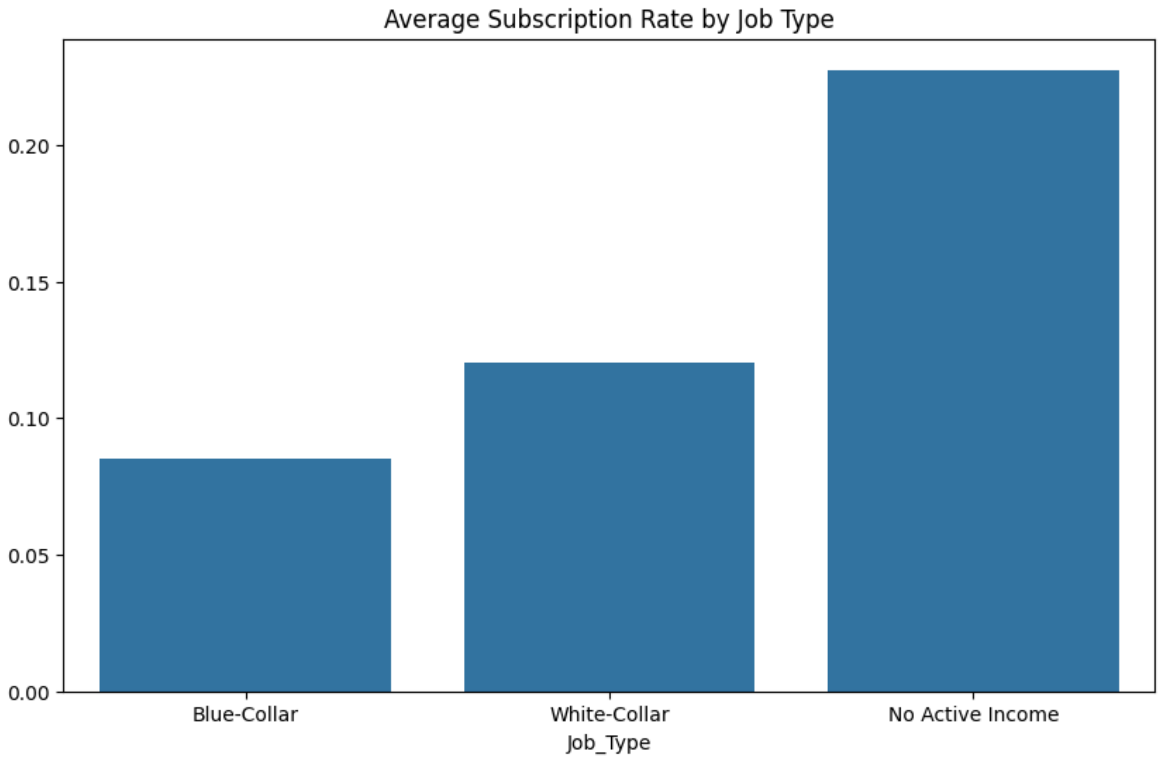
In [83]:
```
age_group_sub = df_cleaned.groupby("Age_Group", observed=True)["Subscription_Sta

plt.figure(figsize=(10,6))
sns.barplot(x=age_group_sub.index, y=age_group_sub.values)
plt.title("Average Subscription Rate by Age Group")
plt.show()
```



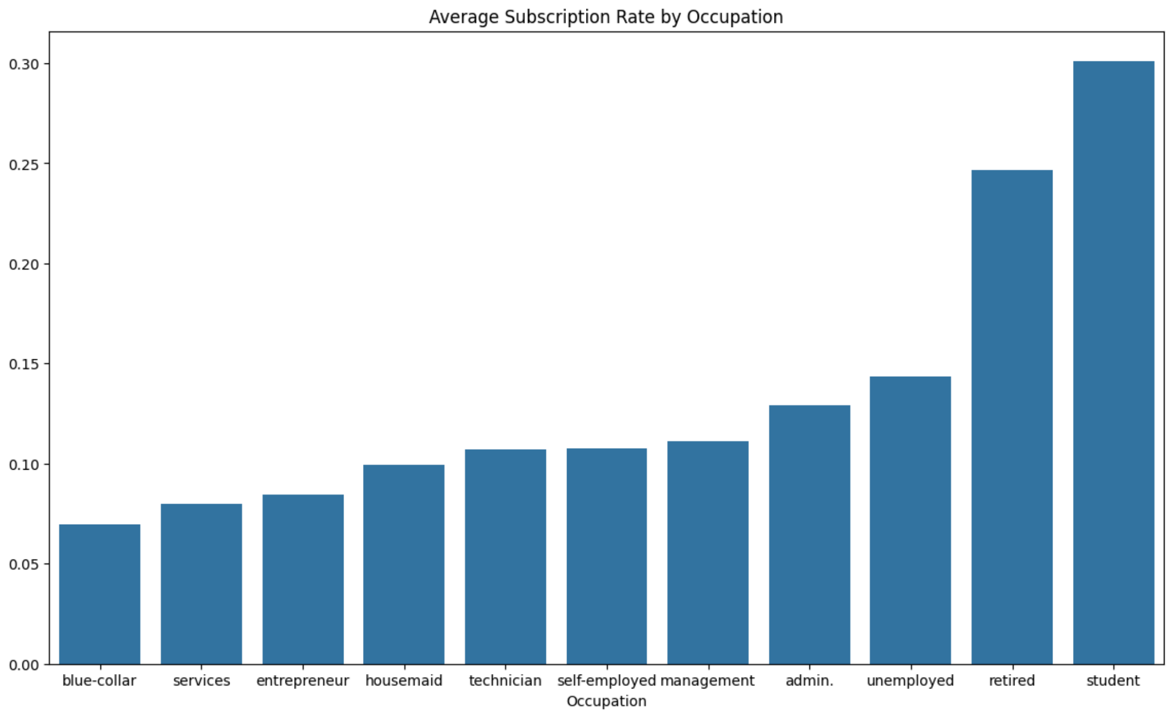
In [84]:
```
plt.figure(figsize=(12,6))
sns.histplot(data=df_cleaned, x="Age_numerical", hue="Subscription_Status_Code",
plt.title("Age Distribution by Subscription Status")
plt.xlabel("Age")
plt.ylabel("Density")
plt.legend(title="Subscription Status", labels=["No", "Yes"])
plt.show()
```



In [85]:
```
job_type_sub= df_cleaned.groupby("Job_Type")["Subscription_Status_Code"].mean().

plt.figure(figsize=(10,6))
sns.barplot(x=job_type_sub.index, y=job_type_sub.values)
plt.title("Average Subscription Rate by Job Type")
plt.show()
```

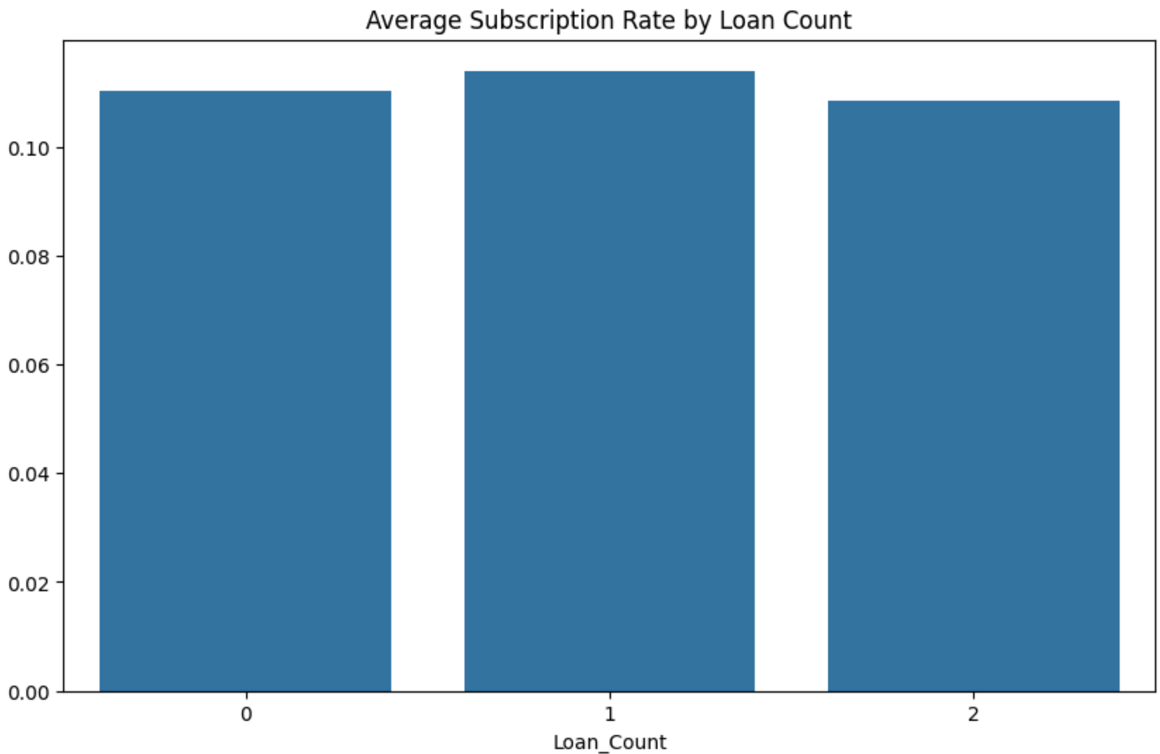


In [86]:
```
occupation_sub= df_cleaned.groupby("Occupation")["Subscription_Status_Code"].mea
plt.figure(figsize=(14,8))
sns.barplot(x=occupation_sub.index, y=occupation_sub.values)
plt.title("Average Subscription Rate by Occupation")
plt.show()
```



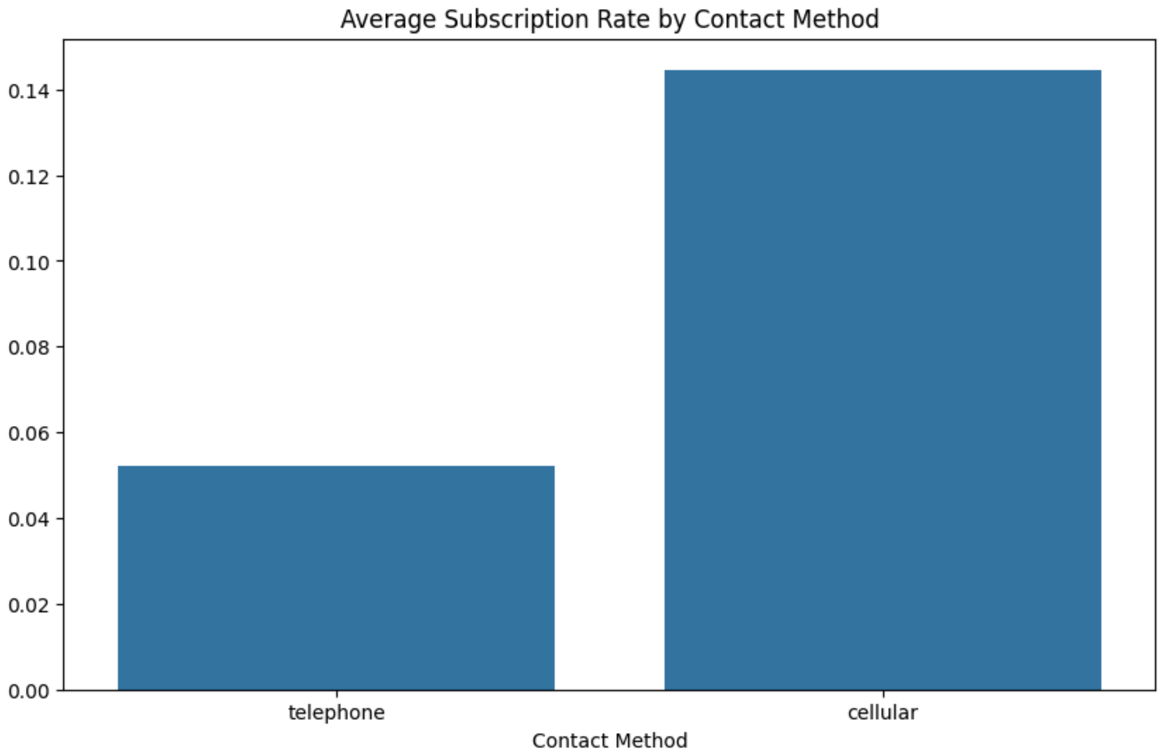
In [87]:

```
loan_count_sub= df_cleaned.groupby("Loan_Count")["Subscription_Status_Code"].mea

plt.figure(figsize=(10,6))
sns.barplot(x=loan_count_sub.index, y=loan_count_sub.values)
plt.title("Average Subscription Rate by Loan Count")
plt.show()
```

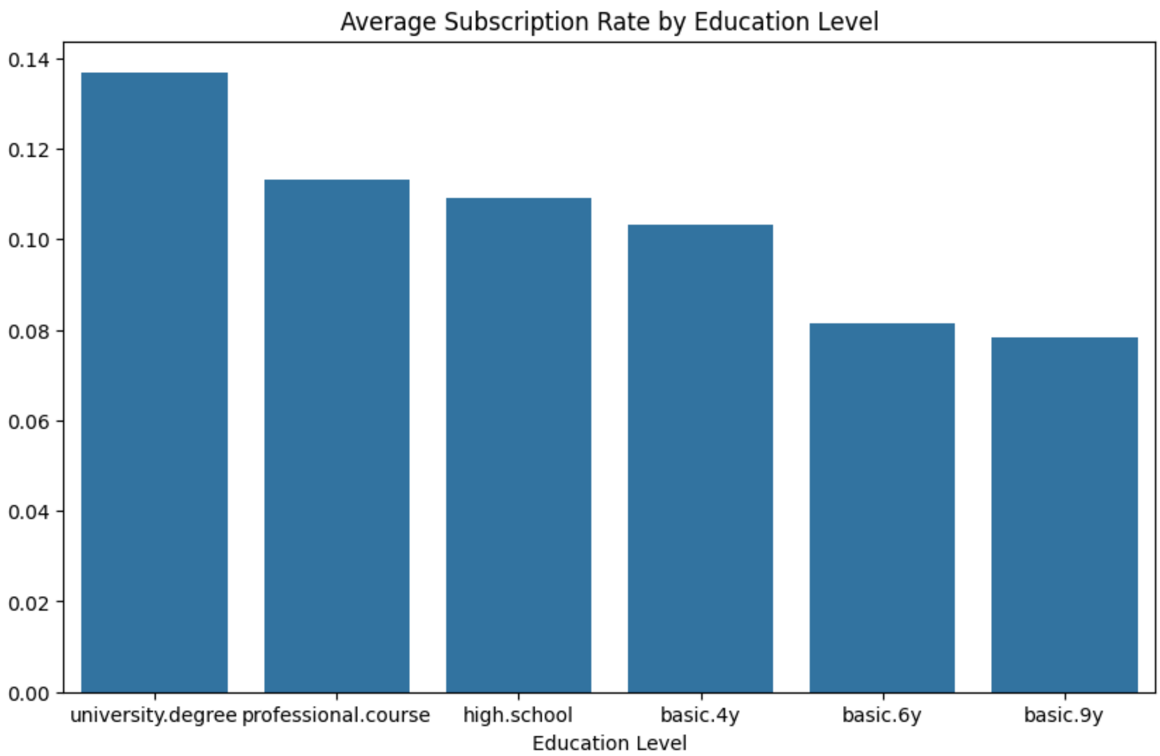


In [88]:

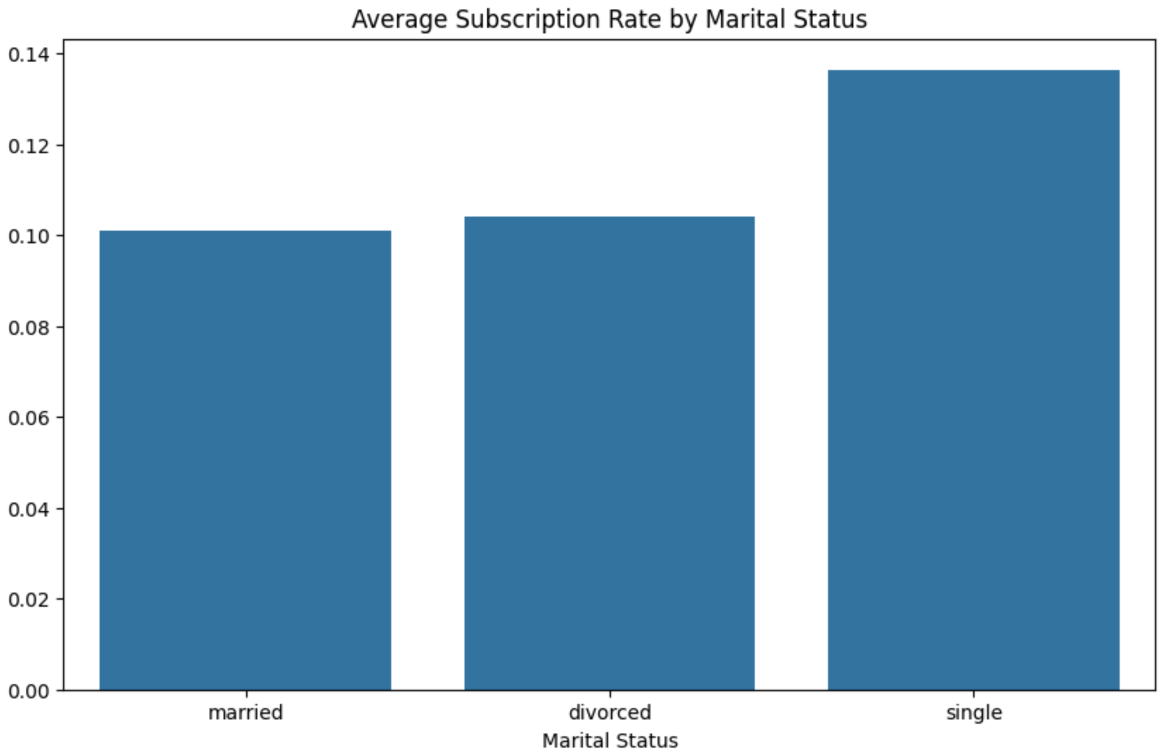
```
contact_method_sub= df_cleaned.groupby("Contact Method")["Subscription_Status_Co
plt.figure(figsize=(10,6))
sns.barplot(x=contact_method_sub.index, y=contact_method_sub.values)
plt.title("Average Subscription Rate by Contact Method")
plt.show()
```



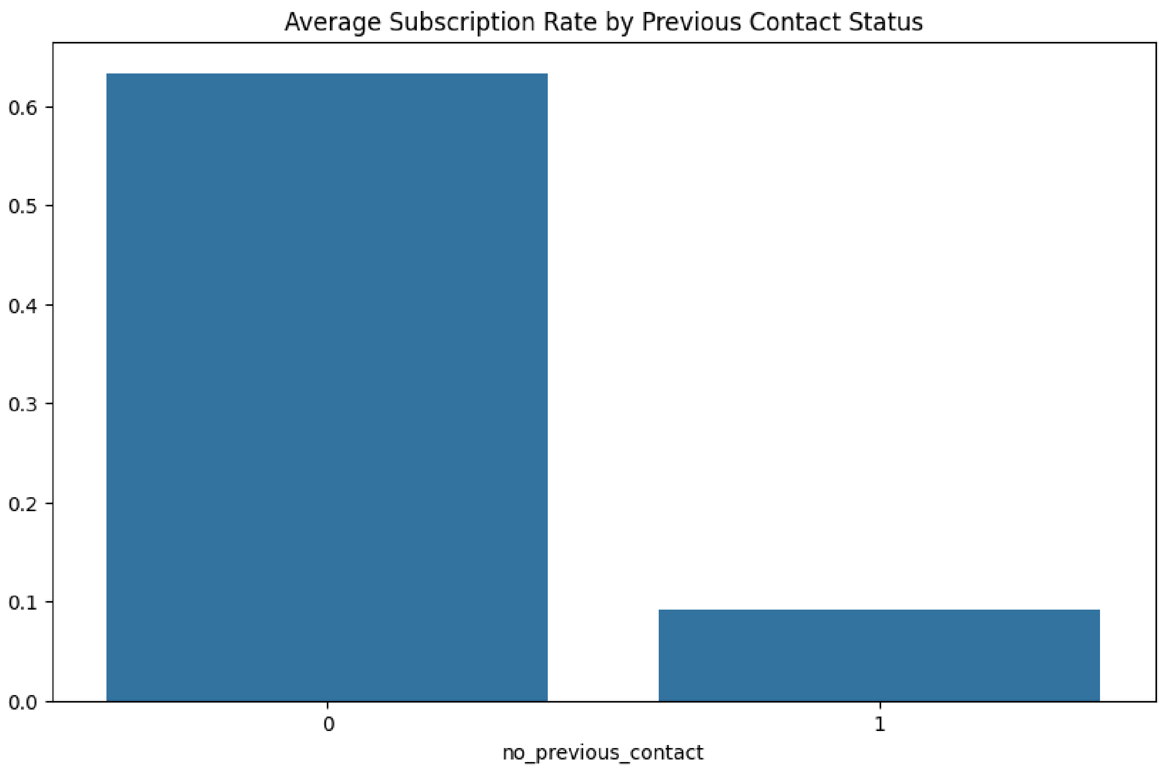
In [89]:
```
education_level_sub= df_cleaned.groupby("Education Level")["Subscription_Status_
plt.figure(figsize=(10,6))
sns.barplot(x=education_level_sub.index, y=education_level_sub.values)
plt.title("Average Subscription Rate by Education Level")
plt.show()
```



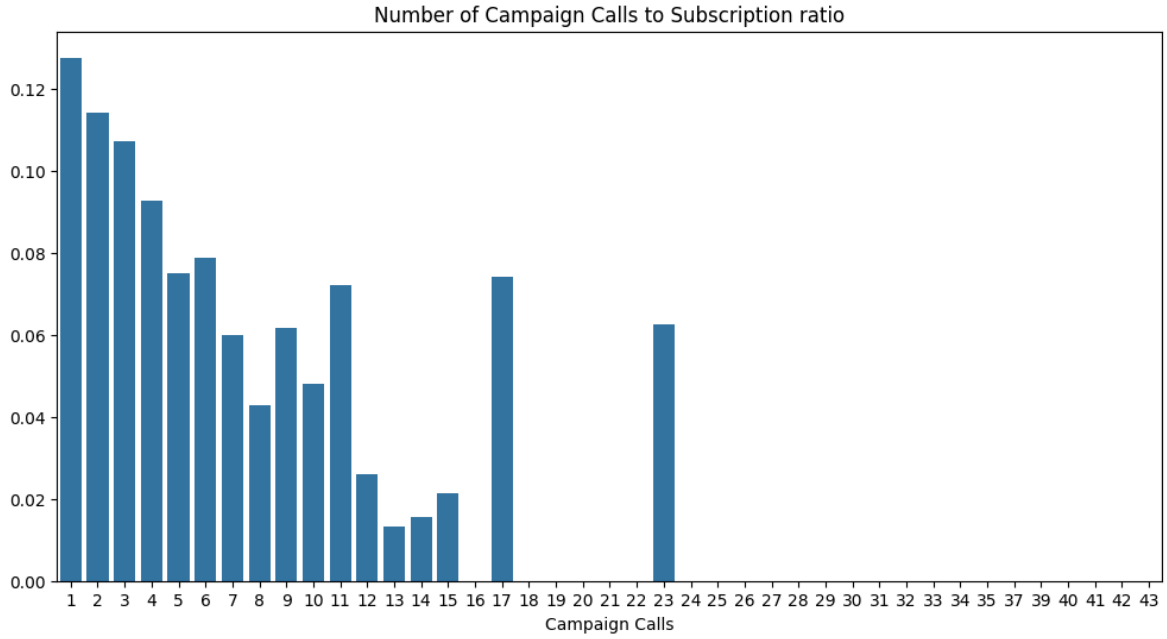
In [90]:
```
marital_status_sub= df_cleaned.groupby("Marital Status")["Subscription_Status_Co
plt.figure(figsize=(10,6))
sns.barplot(x=marital_status_sub.index, y=marital_status_sub.values)
plt.title("Average Subscription Rate by Marital Status")
plt.show()
```



In [91]:
```
prev_contact_sub= df_cleaned.groupby("no_previous_contact")["Subscription_Status
plt.figure(figsize=(10,6))
sns.barplot(x=prev_contact_sub.index, y=prev_contact_sub.values)
plt.title("Average Subscription Rate by Previous Contact Status")
plt.show()
```



In [92]:
```
calls_sub= df_cleaned.groupby("Campaign Calls")["Subscription_Status_Code"].mean
plt.figure(figsize=(12,6))
sns.barplot(x=calls_sub.index, y=calls_sub.values)
plt.title("Number of Campaign Calls to Subscription ratio")
plt.show()
```



(7) Key Insights Summary

Based on the exploratory data analysis conducted on this bank marketing dataset, we have observed many important patterns based on the clients' behaviours and different demographics. These insights we have concluded, can definitely help the bank refine their future marketing strategies, as well as which customer segments have high potential to be subscribers to the term deposits.

1. The overall subscription rate is very low
   -Only ~11% of the clients subscribed to the term deposit.
   -The dataset is extremely imbalanced, with almost 9/10 clients not going through with the subscription.
   -This could suggest how the mass-marketing approaches done by the company are not efficient and are expensive .

2. Having a previous contact history significantly boosts subscription likelihood
   -Clients who had been previously contacted showed a ~63% subscription rate, which is very good.
   -Extremely different from first-time contacts which constitutes to ~9 of the subscription rate.
   -This has been shown to be the predictor with the highest impact out of all the features we have analysed.

3. Age-Subscription Trend
   -The subscription rate varies and it resembles a "U" shape, with Seniors having 45% of the distribution and the Youth having 19% out of all the people who subscribed.
   -This shows how seniors show the highest interest. Followed by the Youth and then the Young Adults and Mature clients.
   -The Adult age group has the lowest subscription rate, and this could indicate possible financial commitments such as saving for a house, or paying off their car, or even raising a family.

-Hence, this U-shaped pattern helps to highlight that the youngest and oldest age groups are the most receptive and responsive to the term deposit offer

4. Job type influences the subscription rate
   -No Active Income clients have a higher subscription rate than the rest, at ~23%.
   -This also aligns with the Age Group results as seniors and students are more likely to subscribe.
   -White-collar clients have a higher subscription rate than blue-collar clients.
   -This could suggest how financial stability and the current available savings can contribute to the client's decision to subscribe.

5. Contact method's effect on subscription rates
   -Although not extreme, cellular methods of contacting the clients have shown to perform better than the traditional telephone method.
   -Moving forward, a digital-first method will likely prove to be a more viable strategy.

6. Education Level scales with subscription rates
   -There is a general trend that the higher the education level of a client, the more likely it is for the client to subscribe to the term deposit. This shows that there is a linear relationship between the two features.
   -This in fact proves how the higher the education level, the more knowledge the client has about finances and they tend to be more financially literate.

7. Loan Count and Marital Status are not major factors in influencing the client's decision
   -We have observed how the number of loans and the marital status of the client do not have a noticeable effect on whether the client decides to subscribe or not.